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affiliée à l'Université de Montréal

Modelling the factors influencing car ownership

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Département des génies civil, géologique et des mines

Thèse présentée en vue de l'obtention du diplôme de *Philosophiæ Doctor*

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Modelling the factors influencing car ownership

présentée par **Jérôme LAVIOLETTE**

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DEDICATION

*...to all those who seek to challenge the status quo and improve quality of life for all within the
limits of our planet.*

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RÉSUMÉ

Les sociétés actuelles sont largement dépendantes de l'automobile. Leurs systèmes de transport centrés sur sa possession et son utilisation entraînent des conséquences négatives importantes sur les changements climatiques, l'environnement, la qualité de vie, la santé, les inégalités sociales et les finances publiques et privées. Alors que beaucoup d'efforts sont mis pour réduire l'utilisation de l'auto, trop peu sont mis pour limiter la croissance de la motorisation. Pourtant, la possession automobile favorise grandement son utilisation au détriment des autres modes de transport et influence plusieurs autres aspects des comportements de mobilité. De plus, les taux de possession automobile sont en augmentation dans de nombreuses villes et régions du monde incluant au Québec et dans sa métropole, Montréal. Une première contribution de ce projet de thèse a démontré que la réduction des taux de possession véhiculaire n'est pas abordée dans les documents de planification des transports et de l'aménagement du territoire de la province. De plus, une analyse des projets planifiés d'infrastructures indique que les projets d'ajout de capacité routière sont encore favorisés par le gouvernement provincial, allant ainsi à l'encontre de la vision et des objectifs fixés dans ses documents de planification. Ceci suggère une résistance politique à un changement de paradigme en mobilité et la poursuite du développement d'un développement territorial centré sur l'automobile, lesquels pourraient expliquer en partie la croissance observée de la motorisation.

La motivation pour ce projet de recherche découle de ces constats. L'objectif principal est de raffiner notre compréhension des facteurs d'influence de la motorisation, et plus largement, de la façon dont les ménages accèdent à l'automobile. Une revue de la littérature scientifique portant sur la modélisation de la possession automobile a permis d'identifier plusieurs aspects sous-étudiés. Ces aspects font l'objet de trois principales contributions, chacune ayant leurs questions de recherche spécifiques contribuant à l'objectif principal de la thèse. La méthodologie générale repose sur le développement d'une base de données géospatiale intégrée rassemblant plusieurs ensembles de données. À partir de celle-ci, plusieurs représentations de la possession automobile sont élaborées et un large éventail de variables explicatives sont calculées afin d'être testées dans les modèles développés pour chacune des contributions.

Pour la première contribution, des modèles économétriques spatiaux sont utilisés avec des données sur l'ensemble des véhicules immatriculés afin d'étudier les effets de la dépendance spatiale sur

les taux de possession automobile. Les modèles développés confirment la présence d'une forte autocorrélation spatiale, et ce même lorsque plusieurs variables sociodémographiques et de l'environnement bâti sont incluses. Ceci suggère la présence d'autres facteurs non observés et spatialement corrélés influençant les taux de possession automobile. Les modèles confirment aussi l'association entre les niveaux de service de transport collectif, l'accès aux opportunités locales (p. ex., les épiceries et ressources de mobilité) et les taux de possession automobile.

Pour la seconde contribution, une approche par apprentissage machine, les arbres de décision par descente de gradient, est utilisée pour évaluer si la taille des quartiers utilisés pour calculer les variables de l'environnement bâti influence les résultats de modélisation. À l'aide de l'enquête Origine-Destination 2018 de Montréal, les résultats suggèrent qu'une taille unique de zone tampon autour des ménages ne permet pas de bien capturer les effets de l'ensemble des variables de l'environnement bâti évaluées. Les mesures d'accessibilité à pied sont notamment très sensibles à la taille des tampons utilisés alors que les caractéristiques de la forme urbaine comme la densité, la diversité d'usage des sols et le design du réseau le sont moins. Le modèle permet aussi d'établir que les variables de l'environnement bâti ont, collectivement, une influence relative sur la possession automobile plus grande que les caractéristiques sociodémographiques des ménages. De plus, la méthode permet de confirmer que presque toutes les variables présentent des relations non linéaires avec la possession automobile. Finalement, la densité de population, la distance d'accès au métro et la disponibilité de véhicules d'autopartage sont les variables d'environnement bâti avec la plus haute influence relative sur la possession automobile.

Dans la troisième contribution, une modélisation conjointe des décisions de possession automobile et d'abonnement à l'autopartage est réalisée afin de comprendre les effets de substitution entre les deux méthodes d'accès à l'automobile et le rôle des attitudes sur ces décisions. La modélisation est réalisée à l'aide d'une enquête de mobilité de la Ville de Montréal collectée en 2019 dans laquelle des attitudes à l'égard de la voiture étaient mesurées. Comme premier objectif, un modèle de choix discret par classe latente où les attitudes sont incluses uniquement dans le modèle de segmentation est proposé afin de tester leur effet modérateur sur les caractéristiques sociodémographiques et de l'environnement bâti. Les résultats suggèrent la présence de deux profils psychologiques (les « pro-automobile » et les « non-pro automobile ») en proportions similaires (46 % et 54 %). Les deux segments présentent des façons distinctes d'intégrer l'autopartage dans leur portfolio d'outils de mobilité. Ainsi, les ménages « pro-auto » possèdent

davantage de véhicules et sont moins abonnés à l'autopartage. À l'inverse, les ménages « non-pro auto » choisissent davantage l'autopartage et sont plus sensibles à l'influence des caractéristiques sociodémographiques, de la densité de population et de la disponibilité des véhicules d'autopartage à proximité de leur domicile. Le deuxième objectif de cette contribution est de mieux comprendre la relation entre le choix d'accès à l'automobile et le choix de localisation résidentielle. Pour ce faire, la méthode d'analyse de profils latents est utilisée pour identifier deux segmentations des ménages. La première permet d'identifier quatre types de quartier et la seconde quatre profils psychologiques. La comparaison des deux segmentations permet de confirmer une forte relation entre les attitudes à l'égard de l'automobile et le type de quartier choisi. Ceci suggère que les attitudes influencent le choix de localisation résidentielle (principe d'autosélection résidentielle), que le type de quartier influence les attitudes ou un peu des deux effets sans toutefois permettre de confirmer la direction principale d'influence. Une asymétrie est aussi observée dans la correspondance entre les attitudes de mobilité et la localisation résidentielle. Près de 30 % des « pro-auto » habitent dans le type de quartier le plus central alors que presque aucun « anti-auto » n'habite dans les quartiers les plus suburbains de l'Île de Montréal. De plus, les « pro-automobile » ont davantage de voitures dans tous les types de quartier que les autres profilés. Finalement, un modèle de choix discret confirme que le type de quartier maintient une influence significative sur le choix de possession automobile et d'autopartage même lorsque les effets des attitudes, du stationnement résidentiel et des caractéristiques sociodémographiques sont contrôlés.

La revue de littérature et les résultats des trois contributions sont synthétisés au sein d'un modèle conceptuel des facteurs influençant la motorisation. De celui-ci, plusieurs avenues de recherche sont suggérées. Tout d'abord, il est nécessaire de mieux comprendre les mécanismes causaux par lesquels les changements dans la disponibilité des ressources de mobilité (transport collectif, autopartage, etc.) et l'accès aux opportunités locales mènent à des changements dans la façon dont les ménages accèdent à l'automobile. Ceci inclut la compréhension de ce qui permet aux ménages de ne pas augmenter le nombre de véhicules possédés et ce qui mène à la démotorisation volontaire. Les prochaines recherches doivent aussi investiguer comment le changement de contexte et les changements dans les attitudes interagissent et se répercutent sur la hiérarchie des décisions de mobilité : localisation résidentielle, possession automobile et comportements de mobilité quotidiens. Finalement, davantage de recherches sont requises pour comprendre comment

les changements attitudinaux se diffusent dans la population via les interactions sociales et comment ceci affecte les choix de mobilité des individus.

ABSTRACT

Today's societies are highly dependent on automobiles for personal mobility. Excessive car use puts a high burden on climate change, the environment, quality of life, public health, social inequalities, and public and private finances that have been well documented for decades. At the heart of car-centred societies and transportation systems is car ownership. Ownership of cars is linked to higher car use, reduced use of other modes, longer distances travelled and various other aspects of travel behaviour. While car use and ownership reductions are needed to limit their externalities on societies, the trends point in the opposite direction. Car ownership is on the rise in many cities and regions worldwide. The province of Québec and its largest city, Montréal, taken as a case study in this thesis, are no exception. An early contribution of this thesis revealed that targeting car dependency and setting goals to stop the growth and, ultimately, reduce car ownership is too often forgotten in municipal, metropolitan and provincial transportation planning documents. Furthermore, analysis of planned transportation infrastructure projects indicates that road expansions are still favoured by the provincial government, running against the vision and objective of its planning documents. This suggests a political resistance to a paradigm shift and the pursuit of car-oriented transportation planning that likely fuel some of the observed growth in car ownership.

This context provided motivation for this dissertation's objective to refine our understanding of factors influencing car ownership decisions and, more broadly, decisions about how households decide to access automobiles in urban settings. A review of the car ownership modelling literature revealed several gaps. This gave rise to three specific contributions, each with specific objectives and research questions. The research relies on developing an integrated spatial database that fuses numerous datasets. The database allows for the preparation of different representations of car ownership and the computation of a large variety of explanatory variables to be tested and incorporated into various car ownership and mobility tool ownership models developed in the three contributions.

The first contribution investigates the effects of sociodemographic and built environment characteristics on car ownership, taking into consideration spatial correlation effects. It does so by modelling car ownership at a finely aggregated scale using advanced spatial econometric models and administrative data of all registered vehicles. The models confirmed a strong spatial

correlation effect on car ownership rates even when sociodemographic and built environment variables were controlled for. This suggests the presence of still unexplained spatial autocorrelation. The models also confirm a strong association between built environment characteristics, including transit level of service and local commercial accessibility (e.g., to grocery stores), with neighbourhood car ownership levels.

The second contribution investigates if the size of the neighbourhood (i.e., buffer) used to compute built environment variables influence results. The analyses are conducted using a machine learning method known as Gradient boosting decision tree (GBDT). Using the large-scale 2018 Montréal Origin-Destination survey, results confirm that no one-size-fits-all household-specific buffer size best captures the effect of all built environment variables. Accessibility measures were very sensitive to the size of the buffers, while density, diversity, and design were less so. The model indicates that, collectively, built environment characteristics have a slightly stronger relative influence than sociodemographic on car ownership. Furthermore, the method confirms that all tested variables presented threshold effects on car ownership, thus invalidating the assumption of linear-in-parameter relationship assumed in many discrete choice models. Population density, distance to a metro station and carsharing vehicle access had the strongest relative influence among built environment characteristics.

In the third contribution, the complex substitution patterns between car ownership and carsharing membership in the presence of high availability of carsharing vehicles are investigated. This is achieved by modelling the joint decision to own cars and/or subscribe to the local carsharing services at the household level using a mobility survey with attitudes collected for the City of Montréal in 2019. First, how travel and car-related attitudes moderate the influence of built environment and sociodemographic characteristics on car ownership / carsharing decisions is investigated through a latent-class discrete choice framework where latent attitudes are entered only in the segmentation part of the model. Results indicate the presence of two psychological profiles (“car-oriented” and “social-conscious / non-car-oriented”) in similar proportions (46 % and 54 %). The two segments show different ways of incorporating carsharing in their portfolio of car accessibility tools. “Car-oriented” households systematically own more cars and are less likely to subscribe to carsharing. “Social-conscious” households are also more sensitive to sociodemographic, population density and the number of carsharing vehicles available near their home.

Second, to further investigate the joint choice of car ownership and carsharing along with residential location choice, two segmentation models are built using latent-profile analysis (LPA). The first identifies four neighbourhood types, and the second, four latent attitude profiles. Then cross-classification analysis and tests of association confirm a strong relationship between attitudinal profiles and neighbourhood types. This suggests evidence of either residential self-selection (attitudes influencing residential choice location), residential determinism (built environment influencing attitudes) or both. Results also indicate the presence of an asymmetric mismatch between travel-related attitudes and residential location: 30 % of “car-lovers” live in the most central neighbourhood type, but no “car-dislikers” reside in the most suburban neighbourhoods. In all neighbourhood types, “car lovers” own more cars than the other profiles, suggesting that attitudes matter in all types of environments. A discrete choice model with neighbourhood types and attitude profiles used as explanatory variables while controlling for sociodemographic confirms that the built environment still affects car ownership / carsharing decisions when attitudes are included.

The literature review and findings from the three main contributions enriched the knowledge of factors influencing car ownership decisions. This is summarized in a proposed conceptual framework of factors influencing how households access cars. From this, avenues for future research are presented. First, there is a need for a deeper understanding of the causal mechanism by which changes to the built environment, including the rapidly evolving availability of mobility resources in cities, lead to changes in how households decide to access cars (ownership / carsharing). Identifying what allows households not to increase their car ownership levels and, ultimately, allow some to voluntarily demotorize is critical. This also requires investigation into the role of attitudes and, more importantly, how *changes in attitudes* influence the hierarchy of choices: residential location, car ownership and short-term travel behaviour decisions. More research is also needed to refine our understanding of how attitudinal changes are diffusing in the population through social interactions and how this affects travel-related decisions.

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LIST OF SYMBOLS AND ABBREVIATIONS

This list presents the symbols and abbreviations used in the thesis or dissertation in alphabetical order, along with their meanings.

ARTM	Autorité régionale de transport métropolitain
ATT	Attitude
BE	Built environment
CO	Car ownership
CS	Carsharing
DA	Dissemination area
GHG	Greenhouse gas
HH	Household
MAUP	Modifiable areal unit problem
MNL	Multinomial logistic
OD	Origin-Destination
SAAQ	Société d'assurance automobile du Québec
SD	Sociodemographic
TB	Travel behaviour
VEH	Vehicle

CHAPTER 1 INTRODUCTION

1.1 Context

An unaccustomed eye looking at the streets of our modern world would quickly notice something ubiquitous to almost any city, town, or village: the cars and the infrastructure dedicated to them. Their ownership and use have proliferated worldwide following the S curve of the Gompertz function (J. Dargay & Gately, 1999; J. Dargay, Gately, & Sommer, 2007). Slow at first, then increasingly fast, before slowing down again when approaching a saturation point. First in the wealthiest countries, led by the United States after the Second World War, and, more recently, in every developing country, starting with their major cities.

In developed countries, this growth is argued to be the result of the development of car-dependent transportation systems, or systems of *automobility*, underpinned by several interlinked components reinforcing each other to ensure its expansion and preservation (Mattioli, Roberts, Steinberger, & Brown, 2020; Urry, 2004).

The first component is the suburbanization of cities through policies that encourage sprawling low-density and non-mixed land-use development patterns (e.g., Gössling, 2017). This goes in tandem with the provision of government-funded road infrastructure to accommodate the expanding number of private cars and a transportation planning approach that prioritizes the flow of motor vehicles over all other modes of transport (e.g., Newman & Kenworthy, 2015b). This creates a form of “lock-in” mechanism where the car becomes almost essential to satisfy human needs (e.g., Mattioli, 2016) and where the experience of the car as a tool of high accessibility in a system designed to facilitate its use generates political support for pro-car policies. This entrenchment of car dependency spurs demand for automobile and petroleum consumption, thus alighting a powerful techno-industrial complex of car manufacturing in symbiosis with fossil fuel industries (Mattioli et al., 2020; Urry, 2004). This is interlinked with a political discourse of being beneficial for regional and national economic developments and prosperity and embedded with the development of a “car culture” that leads to a self-reinforcing dynamic (Mattioli et al., 2020).

The development of this car culture happened through different interconnected mechanisms, including extensive marketing and advertising strategies to present the car not only as a practical tool to get from A to B but as a way of life. Making the car part of what constitutes the “good life”

(Urry, 2004, 2006). Car culture also manifests itself by presenting the car as the ultimate tool and symbol of “freedom” and “independence” and as a means to express oneself, one’s wealth, and one’s social status (Stokes & Hallett, 1992). An object from which one could derive pleasure, happiness, excitement, adventures and socialization (Sheller, 2004) and thus, theorized to create a strong psychological attachment for its owner (e.g., Jensen, 1999; Marsh & Collett, 1986).

Unfortunately, cars are an energy-intensive form of transportation powered, until very recently, almost exclusively by fossil fuels. Due to the interlinkage between these various components, car-dependent transportation systems represent a form of “carbon lock-in” that appears to be particularly complex to unlock (e.g., Erickson, Kartha, Lazarus, & Tempest, 2015; Unruh, 2000). Indeed, today’s systems of *automobility* are a leading source of greenhouse gas emissions. Worldwide, the estimations put the road transport sector at 11.9 % of global emissions (Our World in Data, 2020). The percentage is much higher in the wealthiest economies. For example, it is 22.8 % in the US (EPA, 2020), 19.5 % in Canada (Environment and Climate Change Canada, 2022), and a staggering 34.4 % in the province of Québec. One would be quick to point out that those numbers also include the transport of goods. In Québec, road passenger transport by private light-duty vehicles represents 22 % of the entire GHG of the province, so about 64 % of all road transport emissions (MELCC, 2021).

The consequences of our societal dependence on automobiles go well beyond the impacts on the climate. The effects on societies have been well documented over the decades (e.g., Gärling & Steg, 2007; Gössling, Choi, Dekker, & Metzler, 2019; Héran, 2011; Parry, Walls, & Harrington, 2007; The World Bank, 2014). These include impacts on public health (e.g., air pollution, road crashes, sedentary lifestyles, psychological stress, noise-induced stress and more) (e.g., Glazener et al., 2021). Economic tolls on cities due to perpetually increasing congestion levels and costs (e.g., Litman, 2011) due to private cars’ inefficiency in terms of space. While the initial development of a car-oriented transportation system and car manufacturing and associated industries brought economic growth to specific regions and nations, there is an increasing financial burden on all levels of government to maintain the aging infrastructure of sub-efficient sprawling urban areas (e.g., Thompson, 2013). This is in parallel to the economic burden of a “predict and provide” approach to transportation planning, which consistently requires adding more lanes and highway extensions to accommodate, in vain, increasing traffic volumes (e.g., Duranton & Turner, 2011; Newman & Kenworthy, 2015b). The rising transport inequalities where lower income and

marginalized communities suffer disproportionately from traffic externalities while having reduced access to opportunities (e.g., Gössling, 2016; King, Smart, & Manville, 2019). These lower-income communities may suffer reduced access because they are often priced out of central neighbourhoods and are thus forced to live without a car in areas poorly served by public transit and other alternatives. This increasing economic burden is not only felt by low-income households but also by middle-income households having to own multiple cars to serve their mobility needs. One's quality of life is degraded by the omnipresence of the automobile (Gärling & Steg, 2007). The list goes on.

While some of those consequences are systemic, others, most apparent in cities, are due specifically to the overuse of private cars, which are becoming evermore apparent as the number of people joining the “club” of automobile ownership is increasing (Gabriel Dupuy, 1999). Indeed, as demonstrated in numerous research further detailed in the literature review section, travel behaviour in general and specifically car use is strongly influenced by car ownership itself. Simply put, when people own cars, they tend to use them.

Unfortunately, current trends indicate that ownership continues to rise in many developed countries, although at a slower pace than before, including in Canada, the province of Québec, and its main city of Montréal, the studied region for the present thesis (further detailed in Chapter 2). With the emergence of shared mobility, trends in transportation electrification and improvements in vehicle automation along with the urgency of climate action, it remains to be seen how motorization will keep evolving in the future.

For all these reasons, it remains highly relevant to identify which specific factors influence car ownership, specifically those upon which public policies have leverage (e.g., built environment characteristics, transportation infrastructure, travel demand management) and how these interact with household and individual characteristics (e.g., sociodemographic and attitudes). The best way to do that is through modelling.

1.2 Problems

For the reasons laid out in the previous section and because of their importance in travel demand forecasting, car ownership has been a much-studied topic in transportation research. While car ownership modelling is not one of the four steps in the classical sequential modelling procedure,

the number of cars owned by households is an essential variable because modal choice and trip generation models often use the output of external car ownership models to complement the classical approach (de Jong, Fox, Daly, Pieters, & Smit, 2004). Beyond use as input for regional travel models, certain models, such as aggregate models, are relevant for understanding and forecasting general mobility trends, pollutant emissions and energy demand at the regional or national level. These models can be used to guide public policy with respect to passenger transportation. Alternatively, disaggregate models where the modelling unit is the household, or the individual can provide insightful knowledge on the behavioural mechanism shaping car ownership decisions (Anowar, Eluru, & Miranda-Moreno, 2014).

A vast array of modelling methodologies has been used to investigate car ownership at the aggregate and, most notably, at the household or individual level (Anowar, Eluru, et al., 2014; Bunch & Chen, 2007; de Jong et al., 2004). Many published articles on car ownership have focused on developing, testing, and comparing alternative modelling methods that can best represent car ownership decisions by households. Decisions about *how many cars to own*, what *types of vehicles* (brands, vintages, segments, used/new, etc.), *purchase decisions*, *how much these cars are driven* and more. There have also been attempts to jointly model car ownership with long-term residential location choice, with short-term travel behaviour decisions and even with all three levels of decisions as the decisions are acknowledged to be endogenous to one another.

It is thus not surprising that the published reviews about car ownership have focused on reviewing the modelling methods. de Jong et al. (2004) reviewed many aggregated and disaggregated modelling methods developed since 1995 and classified them into nine categories. Bunch and Chen (2007) reviewed discrete choice models of vehicle ownership, vehicle-purchase models, vehicle holding and usage models and vehicle transaction models. de Jong and Kitamura (2009) conducted a review of dynamic holding models versus dynamic transaction models. Anowar, Eluru, et al. (2014) conducted the most recent and most comprehensive review of disaggregate car ownership modelling methods. They classified the approach into four categories: exogenous static, exogenous dynamic, endogenous static and endogenous dynamic. In their summary table, they also include which types of variables have been included (household and individual demographics, employment attributes, life-cycle attributes, built environment, transit attributes, policy and unobserved effects). However, they do not report how any of those variables are associated with

car ownership. Shaygan, Mamdoohi, and Masoumi (2017) conducted a review of methods and determinants of car ownership with a focus on Iran and the Middle East.

Here lies a **first gap in the literature**: to the best of our knowledge, at the time of starting this Ph.D. research project, there was no review (of any type) focusing on the range of *factors* influencing car ownership decisions. Since the beginning of this project, one literature review of factors influencing *demotorization* (household-level car ownership reduction) has been published (Aguilera & Cacciari, 2020). The review goes a long way in identifying those factors and the gaps and needs of the literature on that narrower scope. However, it does not cover what allows households to live without a car or what leads households to add cars to their fleet. Furthermore, they considered only studies using true panel data (the same household surveyed multiple times). A second review published in the summer of 2022 focuses on enablers and barriers to car ownership and trends within the automotive industry (Fronteli & Pacheco Paladini, 2022). The review covers only the period from 2019 to 2021 and draws from a large variety of studies, not only car ownership modelling.

Significant gaps remain to be filled, which is a key motivation behind this research project and a first implicit¹ contribution to the existing literature. The literature review in Chapter 3 presents an overview of factors influencing the decisions of how many cars to own, classified by categories of variables (sociodemographic, built environment, attitudes, others) and by modelling methods (aggregate, disaggregate static and dynamic, with and without control of attitude-induced residential self-selection).

A second gap in the literature on car ownership relates to spatial dependence effects. In disaggregate car ownership models, spatial dependence effects are seldom investigated or controlled for. This is likely due to extreme computational difficulties in estimating discrete choice models which control for observed and unobserved sources of distance-based spatial interactions (Paleti, Bhat, Pendyala, & Goulias, 2013). Only a few studies have included such interactions using various methods (M. Adjemian & Williams, 2009; M. K. Adjemian, Cynthia Lin, &

¹ The contribution is considered implicit because contained within the dissertation but was not the subject of a publish article. A literature review conducted *for* a dissertation does not count as a contribution to the requirement of obtaining that Ph.D at Polytechnique Montréal.

Williams, 2010; Goetzke & Weinberger, 2012; Paleti et al., 2013; X. Q. Wang, Shao, Yin, & Zhuge, 2018), most of them focusing on vehicle type choice. This is problematic since all those studies concluded that spatial dependence effects were significant and *substantial* in their effects. This quasi-absence of consideration in the car ownership modelling literature is thus jeopardizing the accuracy of the effects inferred from any model that does not control for spatial interactions. Alternatively, consideration for spatial dependence is more common among zonal aggregate car ownership models, but these models have been mostly shunned in recent years in favour of disaggregate models. Among the few models found, only some tested spatial models (e.g., M. K. Adjemian et al., 2010; S. Clark, 2007; S. Clark & Finley, 2009; Trendle, 2019; Whelan, Crockett, & Vitouladiti, 2010). However, none used the most advanced and state-of-the-art spatial modelling methods that integrate more than one source of spatial dependence (endogenous, contextual, and unobserved effects) (Elhorst, 2010; LeSage, 2014). Furthermore, only a handful of built environment variables were included in those models and the zones used as modelling units were relatively large, thus precluding the investigation of small-scale effects.

The **third gap in the vehicle ownership literature** became apparent when reviewing the effects of built environment characteristics on household car ownership decisions. The question is simple: does it matter how built environment variables are computed? First, a wide variety of variables have been used to describe the most common aspects of the built environment. The same type of attribute, for example, density, can be included using different variables (population density, household density, employment density, residential density where the population is only divided by residential land-use surface area, combined job and housing density, built-up index, etc.). This makes it hard to compare effects across studies. This is something not unique to car ownership modelling but to travel behaviour modelling in general (Næss, 2019). In addition, there is also a wide range of *scales* used to compute those variables. The most common method uses fixed spatial zones within which the households reside (Transport Analysis Zones, Census Tract, etc.). These zones vary in size and shape, causing the well-known modifiable areal unit problem (MAUP). Because all households within the same zone will have the same value for all the built environment variables, this violates the assumption of independence of observations. Multilevel models could alleviate the problem but have rarely been used for car ownership modelling until recently (see, for example, Ding & Cao, 2019; Ding, Wang, Tang, Mishra, & Liu, 2018; X. Q. Wang et al., 2018). In short, it goes against the best-recommended practice of using “variable neighbourhoods”

or “buffers” unique to each observed household (Gehrke & Wang, 2020; J. Y. Guo & Bhat, 2007). However, even when used, they can be circular or based on network distance. They are also most often of commonly used sizes in travel behaviour research (500 m, 1 km, ½ mile, 1 mile, etc.) without much justification for the size's choice. Finally, many built environment variables are often included as continuous variables in discrete choice models, thus assuming a linear-in-parameter relationship. This assumption is likely erroneous as most attributes often have threshold effects on household car ownership decisions (Klein & Smart, 2019; W. Zhang, Sun, & Zegras, 2021).

The **fourth gap identified in the literature** relates to the emergence and growing popularity of new mobility options to easily access a car. Notably, carsharing in various forms (free floating, station-based, peer-to-peer) is becoming more present in many cities around the world, thus providing households with alternatives to private car ownership (Shaheen, Cohen, & Jaffe, 2018). When the number of carsharing vehicles available is high, the influence of having a carsharing membership on car ownership decisions cannot be neglected, nor can it be included as a mere exogenous variable to explain car ownership due to obvious endogeneity issues. This suggests a need to expand car ownership models toward a broader modelling approach of how households choose to access cars. The inclusion of carsharing membership in *observed* household mobility tool ownership decisions seems to have been conducted only once by Becker, Loder, Schmid, and Axhausen (2017) in Switzerland. Furthermore, because car ownership and, to a greater extent, carsharing seem to be influenced by typically “unobserved” effects arising from personal preferences and attitudes, it appears necessary to include those factors in the joint modelling of household car ownership / carsharing decisions. The direct incorporation of attitudes in models offers one way to control for residential self-selection effects.

1.3 General objective and specific contributions

The broad objective of this thesis is to expand the sphere of knowledge about the factors influencing car ownership. A coherent framework of factors influencing medium- and long-term car ownership decisions and, more broadly, the decision of *how* households choose to access cars (ownership or carsharing) is proposed. This is rooted in a broader discussion about the difficulty for societies to move beyond car-oriented transportation and urban planning and toward a more sustainable mobility paradigm. This early thesis question was investigated in a case study of the

province of Québec, Canada, and presented in a paper published in the French journal *FLUX* (Laviolette, Morency, & Waygood, 2020) (0).

Three approaches, each with specific objectives, are proposed to contribute to the general objective. Each method represents a novel contribution to the existing literature on car ownership and mobility tool ownership and is covered within one of four papers included in this thesis.

The first contribution analyzes what factors influence car ownership levels at the neighbourhood scale. When modelling a phenomenon at an aggregate level, an important issue is spatial autocorrelation where zones next to each other might exhibit similar values of the analyzed variable. Thus, the objective is to understand how the neighbourhoods' built environment and sociodemographic characteristics affect aggregate car ownership rates while controlling for potential spatial correlation and, ultimately, uncovering potential sources for this correlation. Instead of relying on survey data, this is done using administrative data of *all* registered vehicles in the studied region. This contribution is covered in Chapter 6 and is the subject of one published article (Laviolette, Morency, Waygood, & Goulias, 2021).

The second contribution takes a closer look at household car ownership decisions to investigate if the *scale* at which built environment characteristics are measured matters. The effect of the *scale* and *shape* of the “neighbourhood” within which built environment and accessibility measures are calculated has been largely overlooked in travel behaviour research and even more so in car ownership modelling studies. Can different scales lead to different effects (magnitude, sign, significance) and thus affect policy recommendations?

This contribution also investigates possible threshold (or non-linear) effects of various built environment attributes. While most models assume a linear-in-parameter relationship between explanatory variables and the outcome (e.g., number of cars), this assumption might only hold for some measured attributes of the built environment and thus lead to an erroneous estimate of their effect. This is presented in Chapter 7 and covered in a second published paper (Laviolette, Morency, & Waygood, 2022).

The third contribution aims to expand the scope of analysis beyond the traditional ownership of cars by incorporating carsharing as an alternative way for households to access automobiles. As carsharing services are expanding in cities around the world, it becomes essential to investigate this alternative within a broader mobility tools ownership framework where the decision to own

cars and to have a carsharing membership are modelled jointly. Furthermore, previous research has indicated that households have heterogeneous preferences regarding car ownership and even more so when carsharing is integrated into the mix. The first objective of this third contribution is to uncover how car-related and travel attitudes influence taste heterogeneity by moderating the effect of sociodemographic and built environment characteristics on households' joint decision of car ownership and carsharing. This objective is investigated in a third paper presented in Chapter 8 (Laviolette, Morency, & Waygood, 2022, under review-a).

The second objective is to explore further the relationship between residential location choice, built environment characteristics, travel and car-related attitudes and car ownership / carsharing decisions. This is achieved by using latent cluster analysis to create two segmentations. The first segmentation aims to uncover neighbourhood types in Montréal based on built environment characteristics. The second aims to identify latent psychological profiles of the survey's respondents according to their car and travel attitudes. The two segmentations are then cross-analyzed to uncover patterns of relationships between the various neighbourhood types and attitude profiles identified. Car ownership and carsharing decisions are then modelled using the uncovered neighbourhood types and attitude profiles as explanatory variables while controlling for sociodemographic and household access to off-street parking. This analysis is presented in Chapter 9.

1.1 Outline of the Dissertation

This dissertation is organized as follows. Chapter 2 presents some statistics on car ownership trends in Québec and Canada over the last 40 years. Chapter 3 extensively reviews the literature about numerous aspects of car ownership. Specifically, section 3.1 gives a summary of the concept of car dependency. Section 3.2 reviews the impacts of car ownership on travel behaviour, residential choice, and attitudes. Section 3.3 describes the aggregate and disaggregate methods used to model car ownership. Section 3.4 presents a review of factors influencing car ownership. Section 3.5 describes the concept of mobility tool ownership and the modelling methods used to investigate those joint decisions. Section 3.6 concludes with the impact of shared mobility on car ownership. Chapter 4 presents the overall methodological framework for the thesis and the datasets used. It also summarizes the methods chosen for the three main contributions. Then 0 presents a paper published in a French journal that analyzes transportation and planning policies in Québec

and their potential to reduce car dependency. Chapter 6 presents the paper published as the first contribution (*Car ownership and the Built environment: A spatial modelling approach*), Chapter 7 presents the paper published as the second contribution (*A kilometer or a mile? Does buffer size matter when it comes to car ownership?*), Chapter 8 contains the article submitted as the first part of the third contribution (*Car ownership or carsharing? Latent class model of mobility tools ownership decisions incorporating car-related attitudes*). Chapter 9 presents a complimentary analysis of the third contribution that explores the relationship between attitudes, built environment and car ownership/carsharing decisions. Finally, the dissertation is concluded with a general discussion in Chapter 10 of the main findings, their limitations, and their relevance for future research and transport policy. The chapter ends with avenues for future car ownership/mobility tools ownership research. A proper conclusion follows this in Chapter 11, which includes a summary of the thesis and perspectives.

CHAPTER 2 CAR OWNERSHIP TRENDS IN QUÉBEC

This chapter compiles aggregate level statistics of vehicle registration data to analyze the trends in car ownership since 1980 within the province of Québec. In Québec, vehicle registration and driver's licenses are managed by the *Société de l'assurance automobile du Québec* (SAAQ). Aggregate registration data are published yearly by the SAAQ and are publicly available. When new data is published, the media coverage commonly focuses on the increase in the total number of registered vehicles. That is, they report only the values in absolute terms, failing to control for population changes that might explain some of that growth. Four indicators reflecting the evolution of motorization trends in Québec and Canada are defined and calculated from several data sets to overcome these limitations.

2.1 Defining the Indicators

The **first indicator** considered is the evolution of the number of passenger vehicles registered in Québec. While there is little doubt that the number of vehicles is increasing year after year, the question is to know at what rate it is increasing and if that rate has been changing over the decades. For this first and all subsequent indicators, only passenger vehicles, i.e., those registered in the name of individuals, are considered. Vehicles classified by the SAAQ for institutional, commercial, or industrial use are excluded.

However, because Québec's population is also changing, it is necessary to evaluate the relationship between population growth and the increase in the vehicle fleet. Three relative indicators of car ownership are computed. The **second indicator** is thus the number of **vehicles per thousand people** (VEH / 1000 people). It is commonly used in international comparisons. However, this indicator is not optimal, as it does not control for the evolution of certain factors, such as the aging of the population, changes in driver's licensing laws or the reduction in household size. In Québec, the adult population has been growing faster than the entire population in recent years. For this reason, the **third indicator** is the **number of vehicles per adult** of driving age. To obtain a driver's licence, one must be 16 years old in Québec. Driving age adults thus refers to all those aged 16 and above.

As explained in the literature review section, car ownership is considered a household-level decision. Thus, the **fourth indicator** is the **number of vehicles per household** (VEH / HH). There

is currently no Canada-wide or Québec-wide travel survey. Furthermore, unlike office statistics in other countries, Statistic Canada does not collect information about vehicle ownership, including in its census conducted every five years. This means that the number of vehicles per household cannot be measured directly. An alternative is to obtain it by dividing the total number of registered residential vehicles (obtained from the SAAQ) by the number of households (obtained from the census). Unlike population for which yearly estimates are provided, the number of households is only provided for each census year (5-year intervals).

The figures in the following subsections show the evolution of these four indicators for the last 40 years for the province of Québec. Québec is then compared with the other Canadian provinces and the United States.

2.2 Data sources

Four data sources are used to compute those indicators:

1. The *Institut de la Statistique du Québec* compiles every year the registration data released by the SAAQ. Their tables provide information on the number of registered vehicles by type (car, light truck, heavy truck, motorcycle, etc.) and by permitted usage (residential, commercial/institutional/industrial, off-road, etc.). These are also broken down by administrative regions (17 in total). These tables have been freely available online since 2000 onward (SAAQ, 2022). The total number of vehicles, total residential vehicles and drivers licences by gender and age group are available since 1978 for the province in the yearly statistical report of the SAAQ (2021).
2. Statistics Canada compiles data from each provincial registration authority on the number of vehicles registered from 1999 to the present (Statistics Canada, 2020). However, the vehicle classification is different from that used by the SAAQ. Vehicles are classified by weight (<4,500 kg, 4,500 kg to 15,000 kg, > 15,000 kilograms), and within the category of vehicles under 4,500 kg, there are no distinctions between cars and light trucks as in the SAAQ data. There is also no distinction on the type of use (residential or commercial). Thus, strictly comparing passenger vehicles registered for non-commercial purposes across provinces is not possible.

- Aggregate data about registered vehicles per capita in the United States were extracted from David and Boundy (2021)'s Transportation Energy Data Book. They compile data from the Federal Highway Administration. They include "light-duty vehicles" (cars, pickups, SUVs, and vans). However, whether it includes vehicles used for commercial purposes or only those owned by individuals is unclear. Population data by provinces are obtained from Statistics Canada (2022b)'s annual estimates and household data are from census years (Statistics Canada, 2019). Data for 2005, 2010 and 2017 for the European Union were obtained from the European Environment Agency (EEA, 2019).

2.3 Trends since 1980

Registration data before 2000 are only aggregated at the provincial level. Figure 2.1 shows the growth in the adult population, registered residential passenger cars and driver's licence for the province of Québec since 1980.

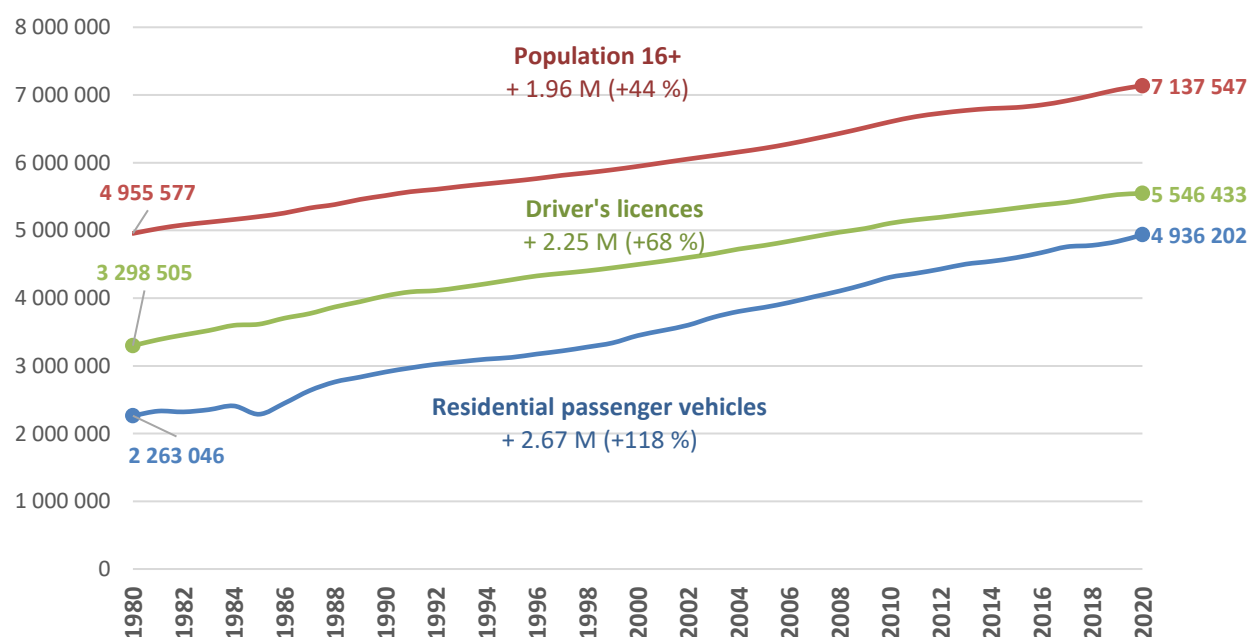


Figure 2.1 Evolution of the adult population, drivers' licences, and registered residential passenger vehicles between 1980 and 2020. Province of Québec.

The figure shows a sustained growth in the last 40 years in the number of residential passenger vehicles (+118 %), which exceeds the increase in the number of drivers' licences (+ 68 %), which

in turn exceeds the growth in the adult population (+ 44 %). In other words, vehicles have been growing twice as fast as the driving-age population.

Car ownership rates and driver's licensing

To provide further insight into that 40-year trend, Figure 2.2 shows the evolution in car ownership and licensing rates among adults (16+ years old) for men and women. Average yearly changes in car ownership rates for each decade are also presented. The overall mean year-on-year change between 1980 and 2020 was +1.2 %.

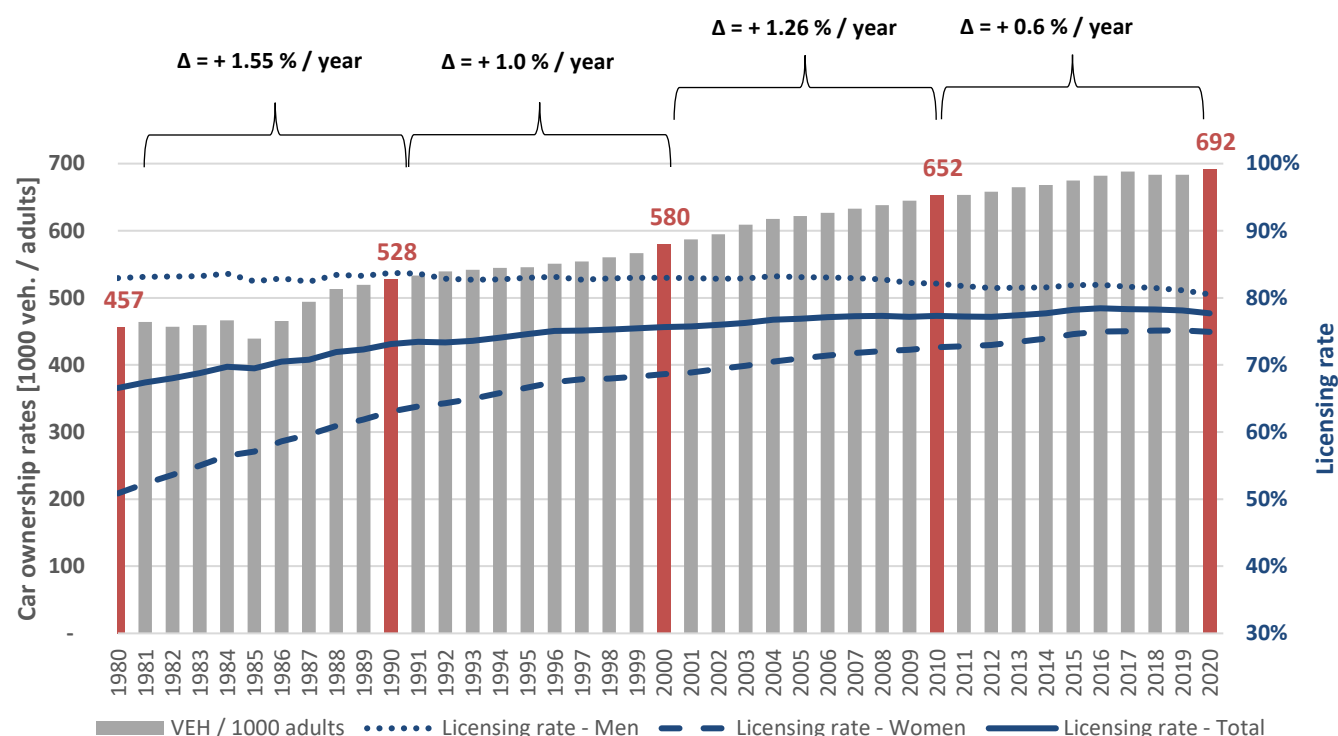


Figure 2.2 Car ownership rates [residential vehicle / 1000 adults], licensing rates for adults (16+ years old). 1980-2020. Province of Québec.

For car ownership rates, the fastest-growing decades were 1980-1990 (+15.5 %) and 2000-2010 (+12.6%). The slower pace between 2010 and 2020 (+6 %) indicates that car ownership rates might be reaching a saturation point. Something referred to as “peak-car” in the scientific literature (e.g., P. Goodwin, 2012; P. Goodwin & Van Dender, 2013). One possible explanation for this growth in car ownership at the provincial level is women’s increased access to cars. Driver’s licensing for women went from 48 % in 1980 to 75 % in 2020. Between 1980 and 1990, that rate increased by

over 1 % per year before slowing down since. It seems to have reached a plateau around 2015-2016, wobbling around 75 % ever since. The rate for men was 82.3 % in 1980, a gap of 34.3 % with women. It peaked at 83.7 % in 1990 and has been slowly declining since reaching its lowest value in 2020 at 80.5 %, reducing the gender gap to only 5.6 %.

Vehicles per household

Figure 2.3 illustrates the number of vehicles per household and the average household size for the census years from 1981 through 2016. To provide further context, the change in household composition over the same period is presented in Figure 2.4.

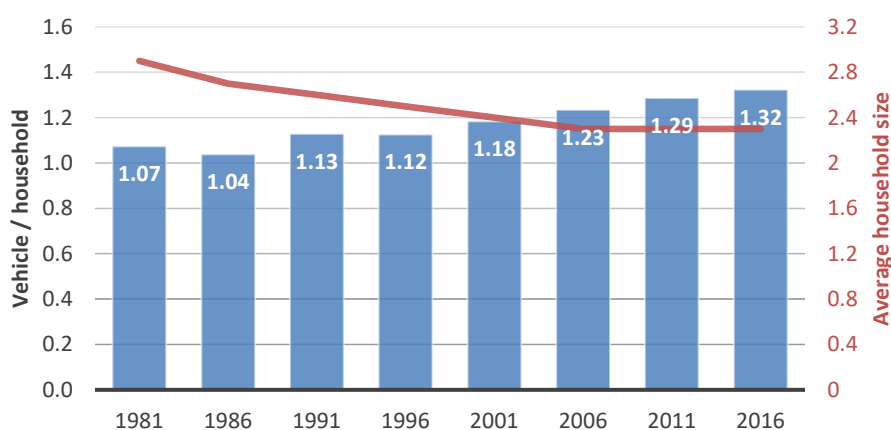


Figure 2.3 Evolution of the number of vehicles per household and average household size. 1981-2016. Province of Québec.

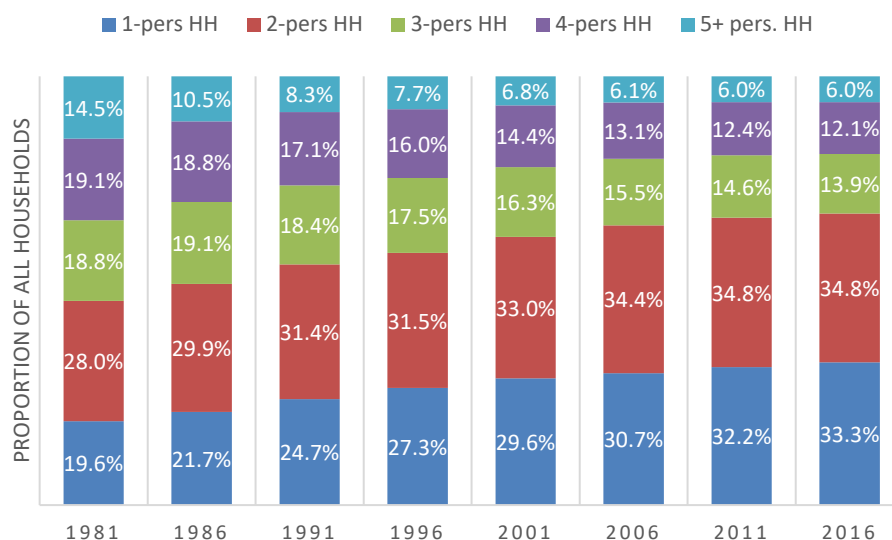


Figure 2.4 Change in household composition. Census years. 1981 to 2016. Province of Québec.

The aggregate number of vehicles per household went from 1.07 in 1981 to 1.32 in 2016. During the same period, the average household size decreased from 2.9 to 2.3. In addition, the proportion of people living alone increased sharply from 19.6 % to 33.3 % over the same period, and the proportion of households with three or more people decreased from 52.4 % to 31.9 %. This decrease in household size has not been accompanied by a reduction in the average number of vehicles per household. As demonstrated by Delbosc (2013), the likelihood of car saturation (at least one vehicle per adult) decreases with household size when more adults can share a car. With smaller households, the possibility of intra-household vehicle sharing decreases.

2.4 Canadian and American comparison

The first comparison is between Canadian provinces. Figure 2.5 shows the car ownership rates measured in vehicles per 1000 adults in 1999 (left values) and 2019 (right values), as well as the percentage change during those 20 years.

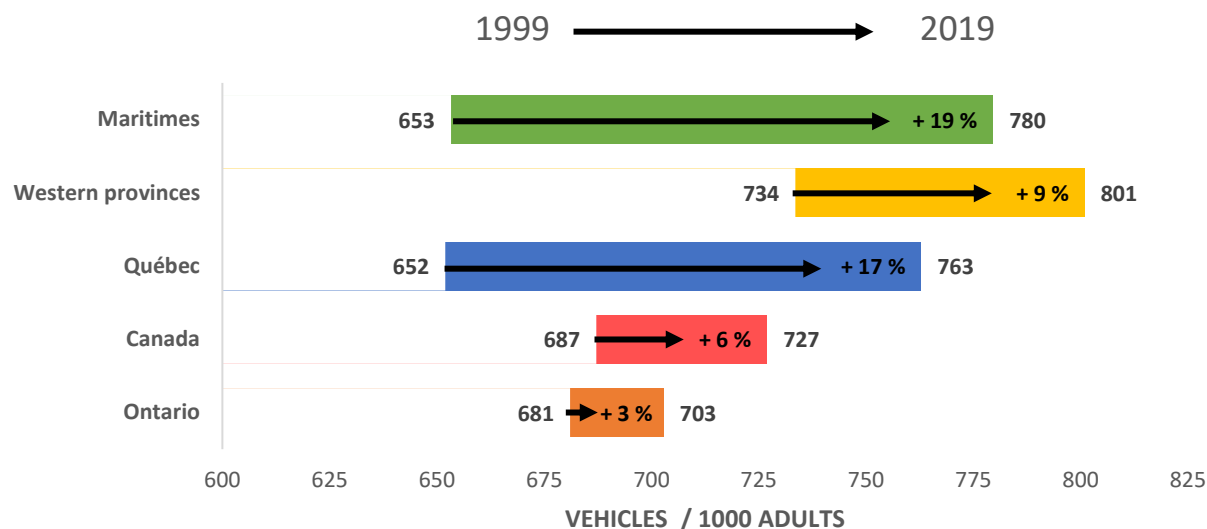


Figure 2.5 Changes in car ownership rates [VEH / 1000 adults] in Canadian provinces between 1999 (left) and 2019 (right). Light-duty vehicles only (< 4500 kg).

In 1999, Québec had the third-lowest rate of car ownership in Canada (after Newfoundland and Labrador (1st) and Manitoba (2nd)). Since then, it has caught up, growing faster than Ontario and the western provinces. This growth has brought Québec to a rate higher than the Canadian average. Only the Maritime Provinces show a more significant increase in their motorization rate. Ontario's car ownership rates stayed very stable over those 20 years.

While each country has a unique transportation context, an international comparison can help to determine if Canada and Québec are trending similarly to other wealthy nations. Optimally, the comparison would be made with G7 countries. However, finding a reliable database that compiles data from those countries is not trivial. One possible source is the OECD online statistical database (OECD, 2022). However, the values for Canada (in vehicles per 1000 people) seem to be incorrect before 2009 (compared to the values from Statistics Canada). The data for the United States seems to be completely off when compared to S. C. Davis and Boundy (2019)'s data. The OECD reports that the US car ownership rate is lower than Canada's, which is very unlikely. Other researchers have reported that the OECD's transportation indicators (including motor vehicle registration) are not plausible (Robertson, 2020). For this reason, the series data comparison is limited to the US as it is the other advanced economy in North America and for which reliable data could be found.

Car ownership rates (in vehicles per 1000 inhabitants) for Québec, Canada and the United States are presented in Figure 2.6. The comparison is not perfect because the United States data source is unclear on what types of vehicles are included. Even with the correct information, it is unlikely that the US and Canada classify and count registered vehicles the same way. Nevertheless, the figure illustrates two points 1) the rate of motorization is much higher in the United States than in Canada and Québec and 2) the 2008 Economic crisis did not have the same impact on both countries' vehicle fleets. The US saw an apparent decrease in car ownership between 2008 and 2010 before its rate rose again in 2013. Between 1999 and 2019, car ownership rates have increased by 21 % in Québec, 9 % in Ontario, 13.6 % in Canada and 6.6 % in the United States.

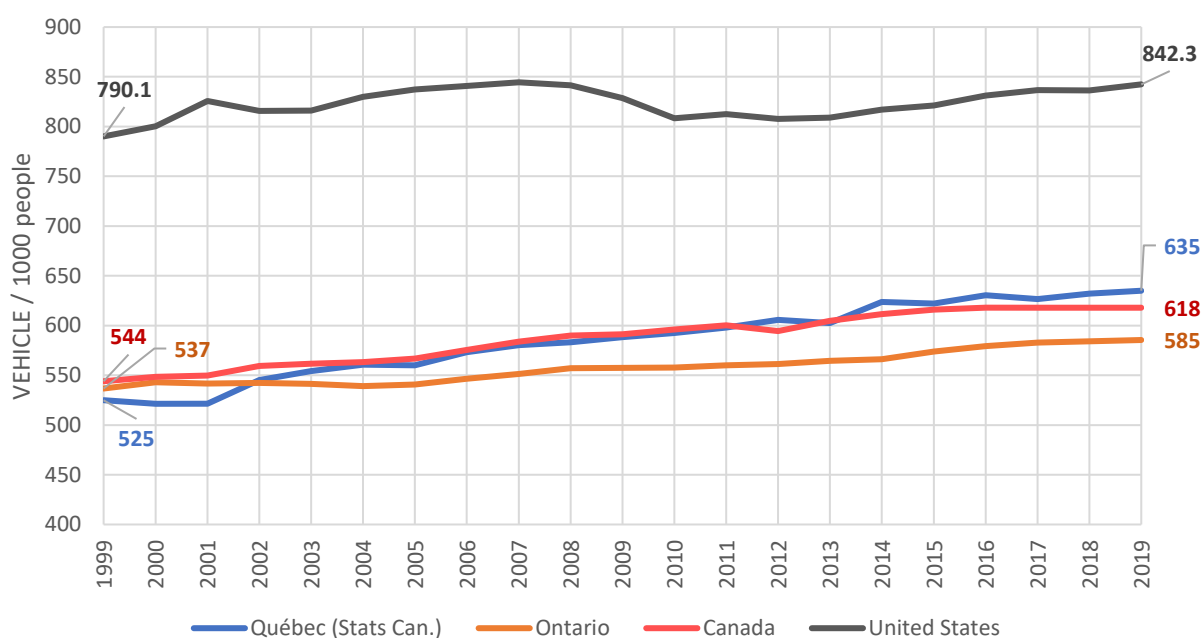


Figure 2.6 Car ownership rates (vehicles / 1000 people). Québec, Ontario, Canada, and the United States. 1999-2019.

Data could be found on the passenger car ownership rate in Europe for the years 2005 and 2017 from the European Environment Agency (EEA, 2019), allowing a comparison of the values and changes between those two years. The statistics are reported in Table 2.1.

Table 2.1 Vehicle ownership rate in Canada, the US, European Union and selected European countries

Vehicle ownership rates (VEHICLES / 1000 people)			
	2005	2017	% change
Québec	560	626	11.8%
Canada	567	618	9.0%
US	837	836	-0.1%
EU28	456	516	13.0%
France	486	492	1.2%
Germany	550	555	0.9%
Italy	599	635	6.1%
Netherlands	435	490	12.7%
Spain	468	505	8.0%
Sweden	461	485	5.2%
UK	461	479	3.9%

In terms of evolution, Québec and Canada are closer to the EU28's average change between 2005 and 2017. Most of the growth in the EU is driven by the Eastern countries (e.g., + 85 % in Poland, + 35 % in Czech Republic) while most Western countries have lower growth rate, except for the Netherlands.

2.5 Summary

For the last 40 years, car ownership rate has been increasing year after year in the province of Québec. The number of registered residential (non-commercial) vehicles has increased 2.6 times faster than the adult population and 1.7 times faster than the number of licensed drivers. However, in the last decade, growth in car ownership rates has been slowing down and might be reaching a saturation point where every driver has access to a vehicle. In 1980, the province had 0.68 passenger vehicles for every driver; 40 years later, that number is at 0.89.

Two major demographic shifts have also been happening during that period that might explain some of that growth in car ownership. The first is the rapid increase in the licensing rates among women who have been catching up with men's rate. The gender gap went from 34 % in 1980 to less than 5.6 % in 2020. This tightening gap is also partially explained by a slight decrease in the licensing rate among men. The second shift is happening within households. The proportion of

single-person and two-person households has been steadily growing over that period, the latter less so than the former. This means larger households are also becoming less common. While the number of children was not included in the analysis, the significant increase in the proportion of single-person households could explain some of the growth in motorization. Multiple-adult households provide more opportunities for within-household car sharing than when people are living alone.

Finally, twenty years ago, Québec had lower average vehicle ownership than the average in Canada, but it now has a higher rate than the national average. One hypothesis is growth in income and wealth, where Québec's median income has been catching up with Ontario since 2000. Maritime provinces have also experienced a boost in car ownership along with a growth in income in the last 20 years (Statistics Canada, 2022a). Overall, car ownership in Canada remains far below what is observed in the United States and slightly above the European Union. However, it seems more robust to economic downturns as it did not decrease after the 2008 financial crisis, unlike the US. Finally, while the US seems to have reached a saturation point with barely any growth in car ownership rates over the last two decades, Québec and Canada have observed upward trends similar to the European Union's average, but higher than most of the wealthier European countries. Having established that car ownership continues to grow in absolute numbers and per capita in Québec (and Canada), the next chapter will examine the literature on factors influencing car ownership, both at the aggregate and household levels.

CHAPTER 3 LITERATURE REVIEW

This chapter reviews many aspects of the published scientific literature relevant to this thesis's general and specific objectives. The chapter starts with a brief overview of the concept of *car dependency* and the *system of automobility* (section 3.1). To understand *why* car ownership is important, section 3.2 reviews how it affects various aspects of travel behaviour (3.2.1, 3.2.2), residential choice (3.2.3) and travel-related attitudes (3.2.4). Then, section 3.3 explores *how* car ownership was studied by reviewing a wide range of methodologies used to model car ownership at the aggregate level (3.3.1), the disaggregate level using traditional models (3.3.2) and, more recently, using machine learning algorithms (0). Section 3.4 contributes directly to the general objective of this thesis by reviewing *what factors* were used to model car ownership and their effects on aggregate car ownership levels (3.4.1) and household car ownership decisions (3.4.2). To widen the scope of car ownership modelling, section 3.5 reviews the concept of mobility tools and how these were modelled. Finally, section 3.6 examines the impacts of shared mobility (bikesharing, carsharing) on household car ownership decisions. Each section contains a summary of the most relevant findings.

3.1 Concepts of car dependency

An early mention of the concept of automobile dependence in the scientific literature comes from Australian researchers Newman and Kenworthy (1989) in their book *Cities and Automobile Dependence - An International Sourcebook*, in which they compare the transport systems, energy expenditures of these systems, urban form, and economic characteristics of 32 cities in North America, Australia, Europe, and Asia. Their goal was to understand better how these different characteristics define the significant variations in automobile dependence among the cities studied. For these researchers, the degree of car dependence in a city is based on car ownership rates, the level of car use (in annual vehicle-kilometres/person) and the degree of use of public transport systems (Kenworthy & Laube, 1999). In their second book, *Sustainability and Cities: Overcoming Automobile Dependence*, Newman and Kenworthy (1999) make several key findings about what influences automobile dependence (as reported in their companion journal article Kenworthy & Laube, 1999). Three of their results include:

1. A city's dependence on the automobile is only weakly related to its level of wealth, whereas European and Asian cities, with levels of wealth similar to that of large American cities, are much less dependent on the automobile. With this conclusion, the authors refute the idea that increasing car dependence is an inevitable consequence of increasing a region's wealth.
2. Urban form, using density as an indicator, would be very strongly correlated with the level of car dependence.
3. A city's dependence on the automobile would not lead to a gain in its economic performance. A more car-dependent transportation system would even have higher total operating costs (as a % of gross regional product). Thus, European and Asian cities would be more efficient in terms of cost and the sustainability (social, economic and environmental aspects) of their transportation systems.

In sum, Newman and Kenworthy's explore the economic and structural factors that are correlated with the variables that characterize, in their view, car dependence (car ownership and use) in some 30 different cities on four continents for a specific selected period (1990-91). The relationship of individuals to the automobile and the cultural and sociological aspects of this dependence and its resilience are not explored.

Criticizing the lack of clarity on what the concept of "car addiction" means, Gabriel Dupuy (1999) published the book *La Dépendance automobile: Symptômes, analyses, diagnostic, traitement* [Car dependency: symptoms, analysis, diagnostic and treatment] in France. As reported by Gallez (2018), Dupuy questions to whom this addiction applies: to individuals, to society, to places?

According to Gabriel Dupuy (1999), car dependency is not just a matter of individual attachment to the car or dependency on its use. Dependence is also structural and societal. It is based primarily on the "car club effect". Thus, the more car users, the more advantages in terms of infrastructure, dedicated services, and access to destinations, adding a kind of collective bonus that increases the personal benefits of car use. In this analogy, Gabriel Dupuy (1999) refers to the development of a social norm related to car use, indicating that "C'est par le comportement des autres que nous sommes incités à utiliser l'automobile et que nous en sommes, par là même, dépendants" [It is

through the behaviour of others that we are encouraged to use the automobile and that we are thereby dependent on it]² (Gabriel Dupuy, 1999, p. 14).

Moreover, according to him, automobile dependence goes beyond the mobility system alone and encompasses a system of organization of our society, from supply chains to the organization of individuals' activities according to their access to the automobile. Something also explained in the English sociological literature by Urry (2004). The significant growth of this system, despite the benefits to individuals and companies in the system, generates increasing negative externalities on public health, society, the environment, the economy and public finances. Moreover, according to Dupuy, it is the individuals excluded from the system - those without a car or worse, without a driver's license - who suffer most from the consequences.

Urry (2004) defines the *system of automobility* as made from six interlinked components that ascertain the domination of that system and maintain the conditions for self-expansion:

1. The car itself has a manufactured object by global companies since the beginning of the 20th century;
2. The car as the second most important item of individual consumption after housing and its associated cultural and symbolic values;
3. An “extraordinarily powerful complex” of interlinked industries (car manufacturing, car maintenance, car sales, petroleum, road building and maintenance, advertising and marketing, the planning and urban design to accommodate its use, and so on;
4. The main global form of “quasi-private” mobility that “subordinates” all other forms of mobility;
5. The dominant “culture” and lifestyle of what constitutes success and the “good life”;
6. The system as the single most important source of material resources and environmental degradation.

Another striking feature of this car-centric mobility system, also known as automobility, is its slow and gradual rise in most Western countries, following the principle that can be described today as

² Free translation by the first author.

the vicious circle of the automobile (Gabriel Dupuy, 2011; Vivre en ville, 2013). The development of low-density suburban areas around highways, where types of land use and activities are segregated, essentially makes it inevitable to use the automobile for most daily trips. In these areas, alternatives (public transit and active modes) are only marginally competitive in terms of time and accessibility. As a result of these developments, roads quickly reach saturation, first during peak periods, and then during off-peak periods on certain critical segments. Unfortunately, to "solve" these congestion problems, investments are made mainly in the development of new roads to "relieve" the pressure on existing roads. It is quickly becoming apparent that wherever this approach has been used, including in Québec, an increase in travel demand by automobile has resulted. In the short and medium term, this increase follows a rebalancing after a reduction in the cost (in time) of travel. In the longer term, urban sprawl beyond existing boundaries brings more motorists onto newly constructed roads, making congestion even worse. This fundamental transportation principle, called "induced demand," completes the vicious circle of car dependence.

At the individual level, the integration of a growing share of the population into an ever more car-centred system has taken place slowly but surely over the decades, encouraged by strong advertising and marketing of the automobile and its associated lifestyle. Such marketing, playing on the utilitarian and practical functions of the car but also largely on the positive emotions it provides and the symbolism and lifestyle it represents, would have contributed to making the car irresistible (Stokes & Hallett, 1992). After decades of favourable marketing, the car has a cultural and normative aspect that is difficult to ignore.

Nowadays, the automobile is perceived as an essential tool for participation in social and economic life for most of the North American population, with the possible exception of residents of dense urban cores. Moreover, even in these urban areas, where activity locations are less dispersed, and alternatives are multiple and generally efficient, the car, supported by this marketing, is widely perceived as an essential need. This leads to the idea that the structural dimension of collective car dependence, combined with its normative and cultural dimensions, may also lead to psychological dependence of the individual. This concept was first explored empirically by Dutch researchers Tertoolen, Van Kreveld, and Verstraten (1998). In their experiment, participants who were informed of the consequences of their car use on the environment and on their personal finances tended to alter their attitudes toward the car or the environment rather than change their behaviour to avoid cognitive dissonance. Tertoolen et al. (1998, p. 181) concluded that

"The car is too strongly linked to feelings of independence and convenience for that to happen. Drivers hold several positive attitudes linked to various immediate individual advantages of car use, whereas there are only limited negative attitudes linked to the later collective disadvantages of car use."

They thus confirm a form of psychological dependence on car use that leads to significant resistance to change, even in the presence of effective alternatives.

In short, when car use becomes the default method for meeting various human needs (physiological and psychological), guided by a favourable territorial context, sustained marketing and advertising, and the perception that the behaviour is the norm (i.e., that most people do this), a form of dependence follows that leads individuals to rationalize, defend, and persist in their behaviour to the point that they no longer perceive alternatives as viable. For example, the car is perceived by many as the only means of fulfilling the "need" for independence (from time, space, others, etc.), something highly valued in Western societies. Jensen (1999) raises the following paradox: by perceiving the car as the only way to fulfill this desire for independence, the individual develops a form of dependence on it.

3.2 Impacts of car ownership on travel behaviour and other related decisions

It is generally accepted that car ownership considerably impacts household travel behaviour. It is relevant to understand which specific aspects of mobility behaviour are affected and how. Indeed, these impacts represent an important rationale behind the continued research interest in modelling car ownership. If the level of car ownership encourages car use, all else being equal, an increase in car ownership can lead to an overall increase in car use and its numerous externalities. The assessment of these impacts depends on the modelling methods used.

3.2.1 Impacts on car use

The first question is: how does car ownership influence car use? To measure "car use", several variables can be evaluated: the distance travelled (daily, weekly, annually or for specific trip purposes), the number of trips made by car, and modal choice (propensity to choose the car over other modes). In a descriptive analysis of data from the UK National Travel Survey, Lucas and Jones (2009) found several critical insights into the relationship between car ownership and car

use. The first is that even people in households without a car may use a vehicle regularly, with 40 percent driving at least once a week. This statistic increases to 90% for members of a one-car household and 95% for households with two or more cars. Second, the number of trips made annually (all modes combined) increases significantly with car ownership, as does the distance travelled per year. However, this is likely confounded by other variables, notably income. These statistics are reported in Figure 3.1 with permission from the authors.

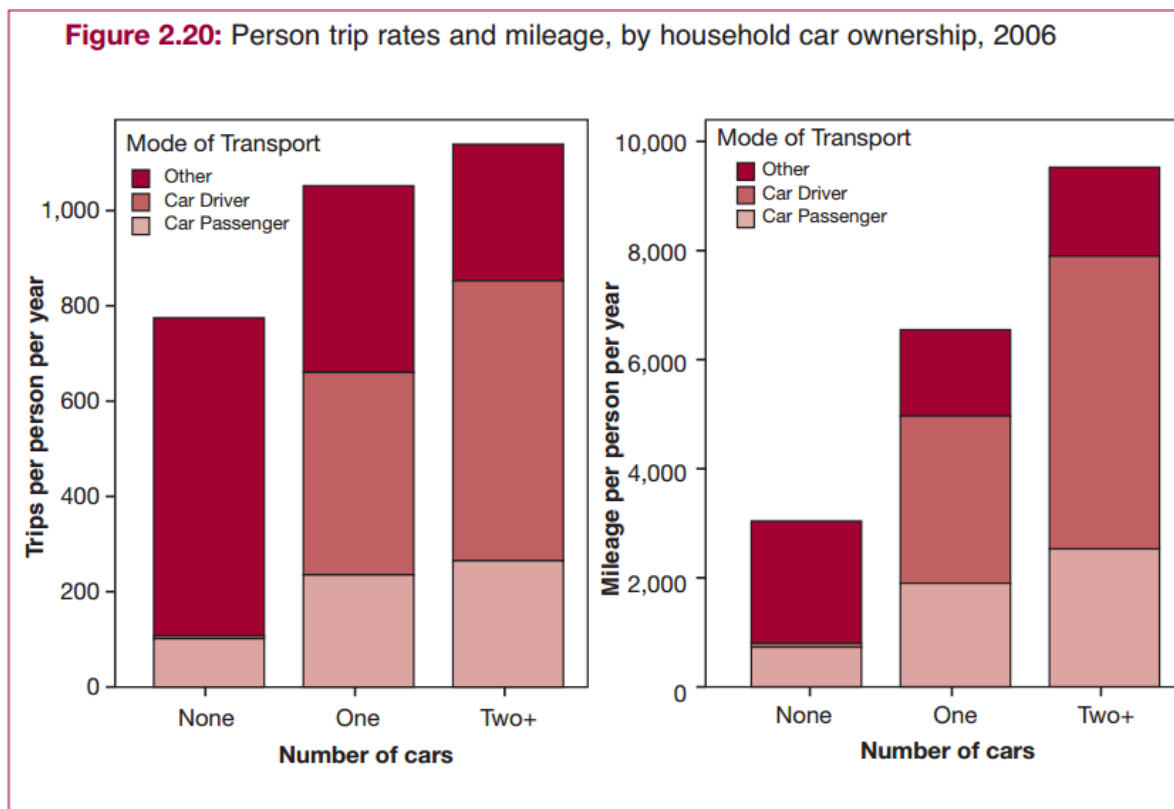


Figure 3.1 Number of trips and distance travelled per person per year as a function of household car ownership in the United Kingdom. Reproduced with permission from Lucas and Jones (2009, p. 47).

Additionally, Lucas and Jones (2009) further exemplify that households with cars tend to use them when looking at the primary mode of transportation for grocery shopping. Thus, grocery shopping is primarily done by car for 22 percent of households without a car, 90 percent for households with one car, and 96 percent by car for households with two or more cars. Unfortunately, the authors only compared the effects of residential location and transit accessibility for households without a

car and not for households with a car. It would have been interesting to know to what extent urban households with cars choose to go grocery shopping via other modes.

Pucher and Renne (2003) found similar patterns in the United States using the 2001 National Household Travel Survey. Analyzing only urban households, zero-car households made 34 % of their trips (all purposes) by private car (either as a driver or passenger) versus 82 % for one-car households, 89 % for two-car households and 90.5 % for 3+ cars households, with a consequential decline in transit and non-motorized mode use. Their results are summarized in Figure 3.2 using data from Table 7 of their paper (Pucher & Renne, 2003, p. 57).

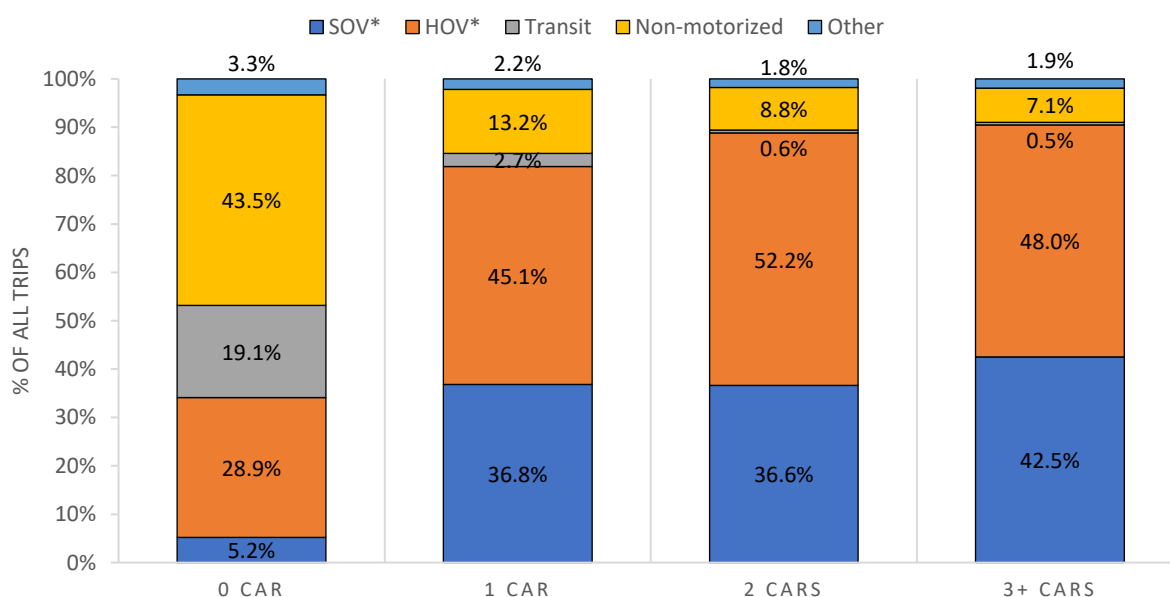


Figure 3.2 Impacts of car ownership on mode choice for US Urban households (2001 NHTS). Based on the numbers presented in Table 7 (p. 57) of Pucher and Renne (2003). *SOV: Single-occupancy vehicle; HOV: High occupancy vehicle.

However, those British and American relationships between car ownership and car use are simply descriptive analyses and not modelling. It gives us an indication that car ownership is associated with car use. Still, the association might be spurious because it is not possible to control for the effects of various sociodemographic and built environment characteristics.

de Jong et al. (2004) report that when car ownership is used as an exogenous variable in activity or modal choice models, it is a significant predictor of car use. For example, Dieleman, Dijst, and Burghouwt (2002) results indicate that household car ownership is by far the most important

variable explaining mode choice. It is positively associated with a higher probability of choosing the car for various trip purposes (and therefore, reduced use of transit, walking and cycling) and positively associated with total distance travelled. However, their study conducted in the Netherlands did account for the *number of cars*. Investigating this question, Caulfield (2011) illustrates, using logistic models that control for built environment characteristics, that households with more vehicles (two and three or more) were less likely to walk, bike, or take public transit and conversely, more likely to drive, than households without cars, but also than households with only one car.

More recent studies criticized this simplistic view of car ownership as a mere exogenous variable (e.g., Xinyu Cao, Mokhtarian, & Handy, 2007b; Kitamura, 2009; Van Acker & Witlox, 2010), stating that the decision is endogenous to other travel-related decisions such as residential location and daily mobility. As theorized decades ago by Ben-Akiva and Atherton (1977), car ownership decisions are part of a hierarchy of choices. It can be considered a medium-term decision that is influenced by long-term decisions of residential and employment location and that, in turn, affects short-term decisions such as daily car use. Researchers have thus suggested that it would be more accurate to consider car ownership as a variable that *mediates* the relationship between the built environment and travel behaviour, specifically car use. This mediating role is confirmed using structural equation modelling (SEM) (e.g., Xinyu Cao et al., 2007b; Van Acker & Witlox, 2010). Van Acker and Witlox (2010) report that not considering this mediating role of car ownership can lead to a misspecification of the effect of the built environment on car use. They also report a direct effect of car ownership on car use (measured in as having made at least one trip by car, as a driver or passenger, on the surveyed day) and that urban planning policies should not only focus on reducing car use but also reducing car ownership. In their quasi-longitudinal approach, Xinyu Cao et al. (2007b) shows that an increase in car ownership leads to an increase in driving and that changes to the built environment (for example, by moving to a more suburban area) lead to an increase in driving indirectly through an increase in car ownership. Interestingly, their results indicate that changes in car ownership do not lead to changes in walking behaviour.

3.2.2 Impacts on activity travel patterns

Does car ownership influence the *frequency* of out-of-home activities? The *location* of those activities and the *duration* of those activities? If so, this has important implications for policies

aiming to curb car use. As the car provides, in most contexts, greater accessibility to opportunities than other modes, if someone owns a car, that person might choose a location for regular activities (e.g., gym, kid's dance lessons, etc.) located further away from home and harder to reach by other modes than someone without a car would choose. The same can apply for shopping trips: the car might allow a family to go grocery shopping at a discount grocery store located further away from home, even if closer stores exist. Encouraging households to reduce car use for those “locked-in” trips might be arduous.

Waygood, Sun, and Schmöcker (2019) used an analysis of variance (ANOVA) with data from Japan to analyze the number of trips and the average trip duration by car ownership levels, types of built environment and lifecycle stages. The first finding is that the number of household trips increases with the number of cars owned and that the difference between car ownership levels was more pronounced in less urbanized areas. The second finding is that households without cars have the lowest average trip duration. For car-owning households, the average trip duration decreases with the number of cars. However, that pattern did not apply to the most car-centric type of built environment where average trip duration kept increasing with the number of cars in the household.

Anowar, Eluru, et al. (2014), citing Bunch and Chen (2007) and Eluru, Pinjari, Pendyala, and Bhat (2010), mention that car ownership influences different aspects of travel behaviour, including frequency, duration, and location of activities as well as mode choice. A closer look at the results of the activity model developed by Eluru, Pinjari, et al. (2010) only suggests that higher household car ownership is associated with fewer at-home activities and is negatively associated with the use of other modes for work and non-work trips.

3.2.3 Car ownership and residential location choice

Residential location choice can be based on economic considerations, household characteristics, and location preferences that arise from lifestyle attitudes and aspirations (Handy, Cao, & Mokhtarian, 2005). In the travel behaviour literature, “the tendency that people intentionally choose residential locations to meet their travel needs and preferences” (Mokhtarian & Cao, 2008, p. 205) is known as *residential self-selection* (RSS) and has been the subject of many debates in the transportation research community over the last two decades (Xinyu Cao, Mokhtarian, & Handy, 2009; Ewing, Hamidi, & Grace, 2015; Guan, Wang, & Jason Cao, 2020; Lin, Wang, & Guan, 2017; Mokhtarian & Cao, 2008; van Wee, 2009; van Wee & Cao, 2022). As van Wee (2009)

discussed, there is an array of other “self-selection” effects in all sorts of decisions that likely affect travel behaviour. Still, residential self-selection has been the most studied.

The reason is simple: researchers have been trying to determine if the built environment (upon which transportation and land-use policy have leverage) really affects travel behaviour or if the observed correlations are due to prior residential location choice of households in neighbourhoods that are consistent with their travel preference (e.g., a household with a preference for walking and transit could self-select itself in a neighbourhood that allows its members to walk and take transit for their daily travel). RSS raises the following questions: if the built environment has a true impact on travel behaviour, how large is that impact and how to accurately measure it?

The literature focuses on two main sources of residential self-selection: 1) sociodemographic and 2) travel attitudes and neighbourhood preferences (Mokhtarian & Cao, 2008). The first is recognized as less of an issue because it arises from generally observed characteristics (income, household size, age group, ethnicity, etc.) and thus can be controlled easily by including those variables in the modelling framework. The second source is more problematic because attitudes and preferences are often missing from large-scale travel surveys used in regional travel demand forecasting models. For this reason, their effects on travel behaviour and residential choice are much less understood. Furthermore, even when attitudes are included, they contain measurement errors. It also remains hard to determine if the included attitudes explain all the previously unobserved influence on travel behaviour or if other unobserved attitudes might still be at play (Mokhtarian & Cao, 2008). Most reviews of residential self-selection focus on this second source: attitudes (Xinyu Cao et al., 2009; Guan et al., 2020; Mokhtarian & Cao, 2008; van Wee & Cao, 2022).

These questions, evidently, also apply to car ownership decisions. Many researchers have attempted to control for attitude-based residential self-selection when modelling car ownership using various methods described by Mokhtarian and Cao (2008) (e.g., Bhat & Guo, 2007; Xinyu Cao, Mokhtarian, & Handy, 2007a; Xinyu Cao et al., 2007b; Pinjari, Pendyala, Bhat, & Waddell, 2011; Salon, 2009; Senbil, Kitamura, & Mohamad, 2009; Van Acker, Mokhtarian, & Witlox, 2014; Van Acker & Witlox, 2010). When summarizing which built environment factors influence car ownership decisions in the section 3.4.1.2, a special care is given to studies controlling for attitude-induced RSS.

If residential location choice affects car ownership decisions (i.e., following a move, a household might want to adjust its car ownership level up or down in a way that maximizes its utility in its new environment), **the present section focuses on the reverse causation hypothesis: can present car ownership level influence where a household will decide to reside?** This is a form of self-selection discussed by van Wee (2009).

One way this could happen is through attitudes about the car. Suppose a household has positive attitudes toward the car and a preference for car ownership; it might possess multiple vehicles and could choose to relocate to a neighbourhood that facilitates car travel and multiple car ownership by offering, for example, more accessible parking. An opposite example would be a household without a car and who would like to remain that way will likely try to relocate to a neighbourhood suitable for car-free living. However, in both cases, the *attitudes toward the car* or the ability to drive would be what influences residential choice and not the ownership of cars itself. In the absence of attitudes, car ownership could be a proxy for car preferences. However, positive attitudes toward the car might stem from car ownership itself. Owning and using a car might lead to a greater appreciation of it which might, in turn, prompt a move toward a neighbourhood that would be more conducive to car use and facilitate ownership. This is further discussed in the next section (3.2.4).

Not discussed by van Wee (2009) is how constraint or ease of parking could be a mechanism through which current car ownership levels might influence relocation in a house with off-street parking, which might only be available in some neighbourhoods (or a car-free household could be more attracted toward a house with no off-street parking). This might be independent of attitudes if, for example, the present car ownership level is the result of constraints that forces car ownership such as job schedule (night shift), job location that might only be reachable by car, job type (working on the road) or walking disabilities.

Overall, the evidence on whether car ownership itself influences residential location is rather thin because discerning the true causal mechanism and its magnitude might prove to be very difficult. For example, by modelling residential choice and car ownership jointly while controlling for unobserved factors, Bhat and Guo (2007)'s results indicate that car ownership preferences seem to influence residential location choice (i.e., statistically significant association). However, their method cannot confirm the direction of the causal relationship (i.e., from car ownership to

residential choice or from residential to car ownership). Because attitudes were not included, it cannot confirm whether the relationship flows *through* attitudes as described above. de Abreu e Silva, Morency, and Goulias (2012), in a structural equation modelling of land-use characteristics at work and home locations (i.e., residential and work location choices), commute distance, car ownership and short-term travel behaviour, show that car ownership negatively influences the choice to live in a “mixed area well served by freeway”. In other words, those having fewer cars prefer to live in those areas. Xinyu Cao et al. (2007b)’s results from a quasi-longitudinal structural equation modelling of recent movers indicate that those having a **stronger positive appreciation of the car’s safety** were more likely to move to low-accessibility areas.

Self-selection can lead to a chain of causal and self-reinforcing effects. The choice of residential location can, in turn, affect car ownership and mobility behaviour. Thus, a form of influence loop can be observed: current residential location can affect mobility experiences and travel behaviour ($BE \rightarrow TB$) which can influence mobility attitudes ($TB \rightarrow ATT$) which can affect future residential location choice ($ATT \rightarrow BE$), which will then affect future mobility behaviours ($BE \rightarrow TB$ at $t + 1$). An example of this complex chain of interactions is the conceptual model of Van Acker et al. (2014), reproduced in Figure 3.3 with permission from the authors.

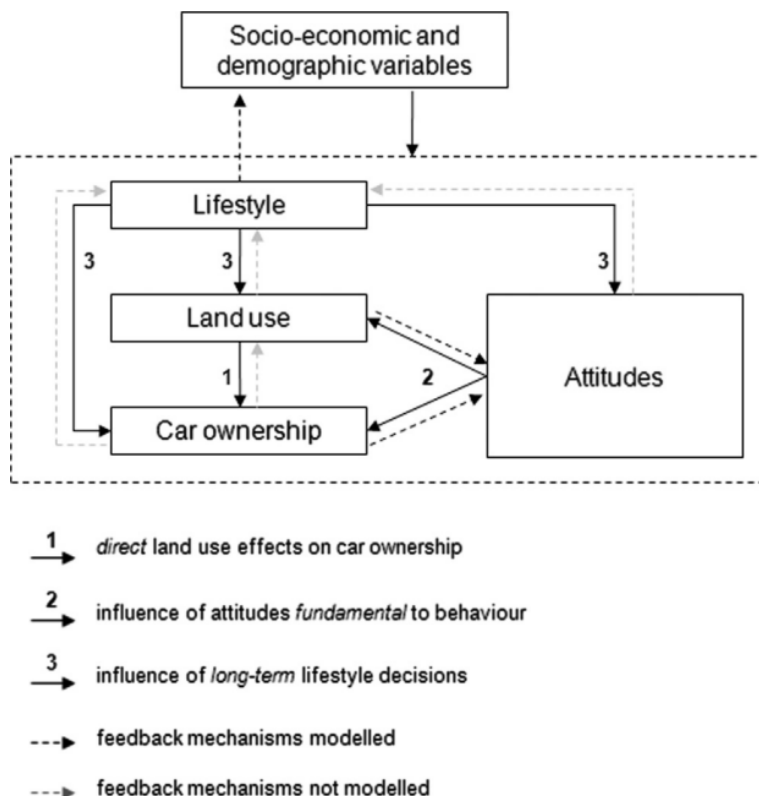


Fig. 1. Conceptual model of car ownership.

Figure 3.3 Conceptual model proposed and tested by Van Acker et al. (2014, p. 89)

3.2.4 Impacts of car ownership on travel-related attitudes

In the residential self-selection hypothesis, travel-related attitudes influence the choice of a neighbourhood that facilitates travel by the preferred modes of transport. There is also a large body of literature, coming mainly from social psychology, where attitudes are modelled as a direct influence to travel behaviour and to behavioural *intention* (see reviews by Chng, Abraham, White, Hoffmann, & Skippon, 2018; Donald, Cooper, & Conchie, 2014; Gardner & Abraham, 2008). Those studies, however, rarely control for built environment characteristics. Nonetheless, this suggests that positive attitudes toward the car might increase the intention to use it for daily trips in various built environment contexts. Similarly, positive attitudes toward the car are likely to encourage car ownership (either directly or indirectly through a choice of a residential neighbourhood that requires or facilitates car ownership). An example of those unidirectional influences flowing from car-related attitudes is given in Figure 3.4 (A). The direction of influence from attitude to car ownership is further discussed in section 3.4.2.4.

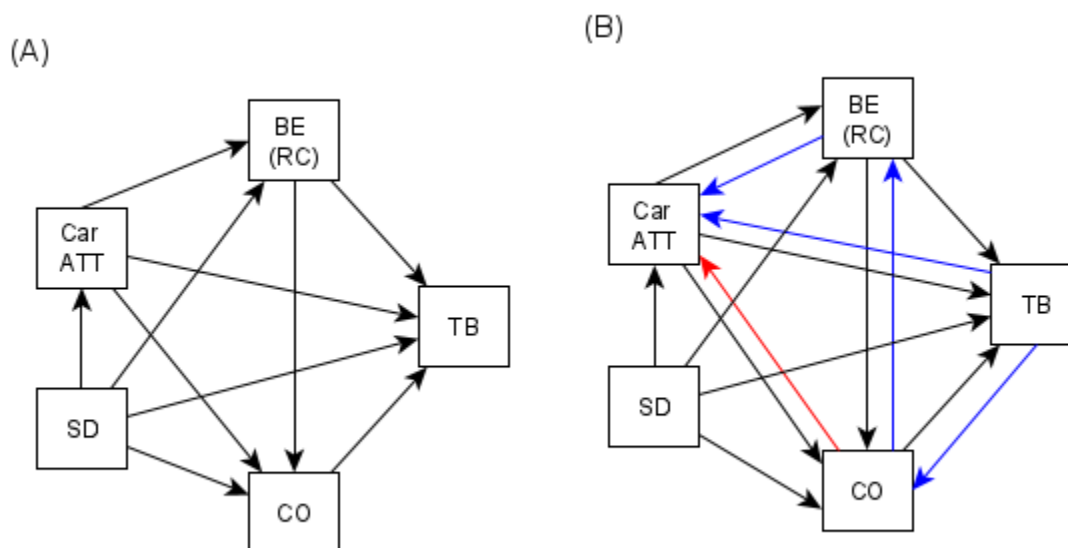


Figure 3.4 Possible direction of relationships between sociodemographic (SD), car-related attitudes (car ATT), built environment (BE), Car ownership (CO) and Travel Behaviour (TB). In (A), relationships are unidirectional. In (B), some relationships are bidirectional.

However, is there a reverse causation hypothesis? Can a (new) behaviour lead to a change in attitudes toward that behaviour? This is discussed in the psychological literature on behavioural theories (see Bohte, Maat, & van Wee, 2009) and increasingly in the travel behaviour literature (e.g., Ewing et al., 2015; Kroesen, 2019). Applied to car ownership, the question is: **can car ownership lead to a change in attitude toward the car** (red arrow in Figure 3.4 (B))?

A possible causal mechanism could work as follows: someone who does not own a car and has neutral attitudes toward it gets a new job that requires them to acquire a vehicle. The person starts using the car to commute to work. The use but also the ownership itself and the possibilities it opens to them leads to a change in attitudes from neutral to positive³. This, in turn, leads to further

³ Based on studies, for example, by Steg (2005) this could be the results of increased utilitarian appreciation of the car: increased feeling of safety, freedom, convenience, but also affective: increased pleasure of driving and even symbolism: increased desire to express herself, her identity through her car after receiving positive comments about her new car.

increases in car use, for example, by using it for other trips and by choosing activity locations more accessible by car than by public transport or active travel (e.g., leaving the city on weekends for outdoor activities). The causal chain could continue further: they might want to relocate to a neighbourhood (e.g., more suburban) that facilitates car travel and car ownership (she's tired of the hassle of having to find on-street parking). The move could further increase their use and reliance on the car, driving up her yearly vehicle-kilometres travelled. This feedback loop is problematic for any society looking to curb car use when car ownership rates are rising, as is the case in the province of Québec, as described in section Chapter 2. The increase in car ownership following the pandemic of COVID-19 could also be a cause for concern. **Is there any evidence of such a causal mechanism?**

Van Acker et al. (2014) used a cross-sectional structural equation approach (SEM) to model the multiple directions of causality in the relationships between lifestyles, built environment (residential choice), car ownership and attitudes, as illustrated in Figure 3.3. In their model, car ownership is modelled as “car availability”, the outcome of a factor analysis of four variables: permanent car availability, possession of a driver's licence, number of household cars and ownership of a transit pass. They show that specific car attitudes influence car availability (positive car attitudes lead to higher car availability, $ATT \rightarrow CO$) but that the *reverse relationship seems stronger*: car availability leads to positive attitudes toward the car ($CO \rightarrow ATT$), but also negative attitudes toward public transport, cycling and walking. Their model does not show if this relationship flows through daily modal choice: does higher car availability lead to increased car use, which, in turn, leads to more positive attitudes toward the car? Nonetheless, such results have far-reaching consequences for transportation planning policies: it would indicate that higher car ownership could potentially explain opposition to projects that aim to improve public transit, walking and cycling. Van Acker et al. (2014)'s model also seems to indicate that neighbourhood choice is more influenced by car-specific attitudes than by attitudes measuring neighbourhood preferences.

In a recent study, Moody and Zhao (2019) found opposing results. They developed a reliable and validated “car pride” scale as one form of car-related attitude. They define *car pride* as “the attribution of social status and personal image to driving and owning a vehicle” (p. 343). Using structural equation modelling with instrumental variables to investigate the bidirectional influence of attitudes and car ownership, they show that car pride strongly influences car ownership

(ATT $\rightarrow$ CO) but that the *reverse* relationship where car ownership influences car pride (CO $\rightarrow$ ATT) is not significant. Going further, they show that the magnitude of influence of attitudes (car pride) on car ownership is considerably superior to car ownership reinforcing attitudes. In short, Moody and Zhao (2019)'s study confirms that for one type of car-related attitude (car pride) and car ownership, the well-known Theory of Planned Behaviour (Ajzen, 1985, 1991) is valid. However, in her doctoral thesis, Moody (2019) goes one step further and shows a possible reverse causation that this effect is indirect and happens through increased car use (CO $\rightarrow$ CU $\rightarrow$ ATT).

3.2.5 Summary

In short, this brief overview indicates that car ownership can affect a whole range of long-term (i.e., residential location) and short-term decisions (i.e., mode choice, distance travelled, destination choices) related to mobility. Many of those might be happening through changes in attitudes. This suggests that, at the individual level, increased car ownership might be self-reinforcing: increased car ownership leads to increased car use, increased appreciation of the car, and choosing locations that facilitate car travel which might further increase car ownership and car use. Can those feedback loops be altered or reversed?

3.3 Car ownership modelling methods

The modelling of car ownership is a much-studied field of research in transportation, mainly because car ownership is an important variable for travel demand forecasting. Car ownership modelling is not one of the four steps in the classical sequential procedure. However, it complements the classical approach by producing outputs (i.e., the number of cars owned by households) which are then used as essential input variables in modal choice and generation models (De Jong et al., 2004). Beyond use in regional transport forecasting, certain types of models, such as aggregate models, are relevant for understanding and forecasting general mobility patterns, pollutant emissions and energy demand at the regional or national level. These models can be used to guide public policy with respect to passenger transportation. Alternatively, disaggregate models, where the modelling unit is the household or the individual, can provide insightful knowledge on the behavioural mechanism shaping car ownership decisions.

The following three sections present an overview of three categories of models: aggregate models (section 3.3.1), traditional disaggregate models (e.g., discrete choice models) of vehicle ownership (section 3.3.2), and recent machine learning disaggregate models of vehicle ownership (section 0). It draws from existing literature reviews (Anowar, Eluru, et al., 2014; de Jong et al., 2004; Potoglou & Susilo, 2008) and is supplemented, when necessary, with more details about specific models that are only briefly covered in those existing reviews. Due to the vastness of the car ownership modelling literature, two types of models described by de Jong and Kitamura (2009) are not covered because they are less relevant to the present thesis: dynamic vehicle holdings models where the fleet composition of a household (including vehicle types) is modelled at some point in time and vehicle transaction models where the change in vehicle ownership status is modelled (e.g., disposal, replacement, and acquisition of vehicles). Variables commonly used to model car ownership are presented in section 3.4.

3.3.1 Aggregate models

de Jong et al. (2004) classified aggregate models into three categories: 1) aggregate time series models, 2) aggregate cohort models, and 3) aggregate car market models. **Aggregate time series models** model the evolution of car ownership over time at the city, region, or country level using income level or gross domestic product (GDP) as the primary input, using sigmoidal functions. This function is generally used to model the achievement of saturation in the number of vehicles per person. For example, J. Dargay and Gately (1999) model the evolution of car ownership rates from 1960 to 2015 using GDP and the number of vehicles per capita data for about 30 countries. An update of their model in 2007 allows for observing car ownership saturation at different levels of wealth in countries according to their urbanization level and population density, thus refining their projection of motorization to 2030 (J. Dargay et al., 2007). Contemporary to de Jong's review, Xiaoshu Cao and Huang (2013) modelled car ownership at a citywide level for 235 cities in China using fixed and random effect clustered panel data models. While providing insights on national and global motorization trends, these models are not considered for the objectives of the present thesis. **The aggregate cohort models** rely on segmenting the population into 5-year age groups and moving them into the future. Each cohort's motorization level is determined by changes in driver's license ownership rates and growth in their income level. This type of model has many limitations, as it does not consider changes in cohort preferences, changes in driving costs, or

potential changes in public policy and technology adoption. Finally, **aggregate car market models** bring vehicle fleets to life by estimating the number of vehicles sold (new vehicles), the number of vehicles retired, and, of course, the existing fleet, which can be broken down by type, age, and fuel type. Examples given by de Jong et al. (2004) are the British TRIMOVE model and the Danish ALTRANS model. These models aim, among other things, to estimate greenhouse gas and pollutant emissions from passenger transport.

3.3.1.1 Spatially aggregated models

Another type of aggregate model is not mentioned by de Jong et al. (2004), namely **static or dynamic models aggregated by geographical division** (e.g., spatial models). Only a few examples of these models are found in the recent literature. This is likely due to the preference for disaggregate models, which provide a more realistic behavioural representation of household car ownership decisions. Their review is nonetheless essential because these models are considered in the first contribution of this thesis to explore the relationship between car ownership rates and various neighbourhood characteristics using administrative data of all registered vehicles within a region. The approach also aims to control and explore various sources of spatial dependence.

A first example is the work by Holtzclaw, Clear, Dittmar, Goldstein, and Haas (2002), who used a series of univariate and multivariate regressions to model car ownership rates (average number of vehicles per household) and vehicle-miles travelled (VMT) per vehicle aggregated by Transit Analysis Zone (TAZ) for Chicago, Los Angeles and San Francisco metropolitan areas. Their results show a significant influence of built environment characteristics (density, walkability, transit supply) on aggregate car ownership rates and VMT, even after controlling for average household size and income. However, their models do not control for spatial autocorrelation, a measure of spatial dependence where spatial zones next to each other display similar values of the investigated variables (Haining, 2001). Failing to control for sources of spatial autocorrelation can lead to correlated error terms violating the assumption of independence of observations. As explained by Haining (2001), this can lead to incorrect tests of significance of explanatory variables, biased coefficient estimates, and inflation of goodness-of-fit measures like the coefficient of multiple determination (R^2).

In the United Kingdom, census data contains information about household car ownership. Using the census dataset covering England and Wales at the level of the Electoral wards (8800 zones),

S. Clark (2007) first modelled average car ownership rates (in vehicles per household) within electoral wards as a function of mean net household income and population density using an ordinary least square regression. Spatial analysis of the model's residual confirmed the presence of spatial correlation from unobserved effects. To correct the correlated residuals, S. Clark (2007) tested two alternative models: a *spatial error model*, which includes a spatial autoregressive coefficient in the error term to account for the residuals' spatial correlation and a *geographically weighted regression* (GWR) which works differently. In a GWR, each modelled geographical unit has its own unique set of coefficients estimated using geographically weighted information from neighbouring areas. The weights can be based on a distance decay function, for example. While both models adequately reduce residual spatial correlation, the author preferred the GWR approach as it provides local estimates of the elasticity between income and car ownership instead of a corrected global elasticity for the spatial error model. It also provides a better fit to the data, moving the R^2 from 0.75 for the global linear model to 0.90 for the GWR.

In a subsequent study, S. Clark and Finley (2009) aggregated the electoral wards into a smaller number of more homogenous zones in terms of population (1138 “tracts” across England and Wales with a population between 30,000 and 62,000). Having the same objective as Clark's previous study of providing accurate elasticity of car ownership with respect to income, S. Clark and Finley (2009) tested four models: a simple linear regression model, a spatial error model, a GWR and a Hierarchical Bayesian Spatial Model. Again, the authors only included two explanatory variables, average net household income and population density, on the basis that other variables would be correlated with either or both variables when modelling car ownership. Their analysis confirms the importance of controlling for spatial autocorrelation when modelling car ownership within contiguous spatial units. Their results indicate that the Bayesian model leaves less residual spatial dependence than the other spatial models (indicated by a lower Moran's I statistic). The authors conclude that the three spatial models provide more realistic elasticities for car ownership with respect to income (η_{co} close to 1) than the non-spatial linear regression ($\eta_{co} = 0.56$).

Using data from Sydney, Australia, Trendle (2019) investigated the relationship between income and car ownership rates measured within statistical zones with an average population of 10,000 people (Statistical Area Level 2 (SA2), 400 zones within the greater Sydney metropolitan area). Car ownership (average vehicles/household) is modelled using an ordinary least square regression

(OLS), a *spatial error model* and a spatial error model with *spatial regimes*. Spatial regimes are similar to latent segmentation methods in discrete choice models. The regimes allow for a spatially heterogeneous relationship between the outcome variable and explanatory variables to be modelled (Anselin, 1990). Each regime has its own set of coefficient estimates (and can even have its own functional form). Trendle (2019) used the natural breaks (“Jenks”) in the percentage of workers commuting to work by public transit in each SA2 area to define three spatial regimes across the modelled region. The models included more explanatory variables than S. Clark (2007)’s model: average household income, average household size, population density, percentage aged 65 or above, percentage of non-English speakers, and percentage of people aged 20 and over with a bachelor’s degree.

Another example of a spatially aggregated car ownership model is reported in an exploratory study conducted for Transport for London by Whelan et al. (2010). They tested a range of model formulations (linear, log-linear, s-shaped functions such as logistic or Gompertz and GWR) to model the number of cars per adult for the London metropolitan area at the lower layer super output area (LSOA) level, a UK statistical unit with an average population of 1,500. Unlike Clark’s studies, they included several sociodemographic explanatory variables (income, household structure, dwelling tenure, nationality) along with three transport policy-relevant variables: accessibility by public transport, on-street parking permit cost and coverage, and a measure of local walking and cycling accessibility to amenities. They concluded that all four built environment variables had the expected sign (negative impact on car ownership rates) and magnitude. Despite the additional variable, their GWR model obtained a similar R^2 (0.90) than was obtained by S. Clark (2007)’s GWR. Except for the GWR formulation, the other models Whelan et al. (2010) tested did not account for spatial autocorrelation. Despite lower model fit ($R^2 = 0.85$), the authors argued that the S-shaped logistic and Gompertz formulations can, however, account for saturation in the relationship between car ownership and income. Such a relationship is presented as more realistic than a linear relationship.

Gao, Mokhtarian, and Johnston (2008) used data at the census tract level from Sacramento County in California to model the endogenous relationship between job accessibility, employment, income, and car ownership using structural equation modelling (SEM). A total of 276 census tracts are modelled, and car ownership is measured as the number of cars per capita for the year 2000. Other sociodemographic characteristics (education, median rent, household composition,

household size, proportion of rented households) measured within the census tract are treated as exogenous to one or more of the four core endogenous variables. It is the only aggregate model of car ownership found in the literature that treats those four variables endogenously to explore their bidirectional relationships. The approach, however, does not control for spatial autocorrelation between adjacent statistical units.

Klincevicus, Morency, and Trépanier (2014) tested an aggregate and disaggregate approach to examine the influence of carsharing on car ownership. For the aggregate model, they aggregated large-scale Origin-Destination survey data from Montréal at the Census Tract level to model the average number of vehicles per household within tracts. They used a simple linear regression model and did not control for spatial dependence.

Lansley (2016) conducted a canonical correlation analysis of 10 car segments in the UK with neighbourhood socio-economic characteristics measured at the lower super output area (LSOA, a UK statistical unit with an average population of 1600 people).

S. Clark and Rey (2017) investigated if the *evolution* of car ownership rates within neighbourhoods is spatially influenced by changes in car ownership within neighbouring regions. The transition between various car ownership levels in Great Britain (England, Scotland, and Wales) between 1971 and 2011 is modelled using spatial discrete Markov chains at the Middle Layer Super Output Area level, a UK statistical unit of about 2500-3000 people (8500 units modelled). Comparing the results with a classic non-spatial Markov chain confirms neighbourhood influence on the *evolution* of car ownership rates. S. Clark and Rey (2017)'s method, however, only modelled the passage of time and neighbourhood effect and did not control for any changes to sociodemographic and built environment characteristics that might explain changes in car ownership rates.

3.3.1.2 Summary of aggregate modelling methods

Table 3.1 presents a summary of recent zonal aggregate models of car ownership. In sum, aggregate models have several advantages: they are generally simple and are based on more readily available datasets (e.g., census and administrative registration data). These datasets are usually collected for purposes other than analyzing car ownership and are thus much cheaper than expensive travel surveys. Census data, if it contains car ownership information, or otherwise combined with administrative registration data, covers entire countries, states, or provinces. In

other words, they account for all registered vehicles, not only a surveyed sample. For this reason, it can provide a complete picture of a region and help investigate the spatial distribution of car ownership and its spatial relationship with several neighbourhood-level sociodemographic and built environment characteristics. The review indicates that advanced spatial modelling methods that simultaneously incorporate *contextual effects* (influence of explanatory variables from neighbouring zones), *endogenous effects* (influence of the outcome variable from adjacent zones) and unobserved spatial effects (influence of unmeasured variables from neighbouring zones) have not been used. These potential models are further discussed in the literature review of Chapter 6 (first contribution). The present review also indicates that the smallest aggregate modelling unit used so far is the UK's Lower Layer Super Output Area (LSOA) with a population between 1600 and 13000. Using even smaller zones might provide more insights into sources and patterns of spatial correlation of car ownership rates.

Of course, aggregate models suffer from several limitations, including data aggregation bias (loss of information), collinearity issues forcing the use of a limited number of variables, and the impossibility of capturing the decision-making processes related to household car ownership choices. Given these limitations, it is not surprising that researchers are most interested in disaggregated models where car ownership is modelled at the household or individual level, despite the higher cost of data acquisition.

Table 3.1 Summary of zonal aggregate models of car ownership

Studies	Data source	Modelling method	Outcome	Modelling unit	Explanatory variables	
					SD	BE
Holtzclaw et al. (2002)	US Census data for Chicago, Los Angeles and San Francisco Metro areas	Series of single-IV bounded Power fits models	VEH / HH	TAZ, n = 314 (CHI), 1459 (LA), 1047 (SF)	HH income, HH size	Pop. density, transit levels, transit accessibility to jobs, local shopping opp., pedestrian/cycling friendliness, proximity to jobs
S. Clark (2007)	UK census data for England and Wales	OLS Regression, Spatial error model and GWR	VEH / HH	UK Electoral wards, n = 8837	Net HH income	Pop. density
Gao et al. (2008)	US census, Sacramento, CA	Structural equation modelling	VEH / person	US Census tract, n = 206	Income, education, HH size, % workers, median rent	% rental housing, job accessibility
S. Clark and Finley (2009)	UK census data for England and Wales	OLS Regression, Spatial error model, GWR & Hierarchical Bayesian Spatial Model (MCMC)	VEH / HH	"Aggregated Tracts", n = 1138	Net HH Income	Pop. Density
Whelan et al. (2010)	UK census data for Greater London	S-Shaped Logistic and Gompertz Regression, GWR	VEH / adults	LSOA, n = 5300	Net adult Income, HH composition, race, HH tenure, Age	Pop. density, public transit accessibility, walking accessibility, on-street parking permit cost and coverage
M. K. Adjemian et al. (2010)	US census in SF Bay Area	OLS, spatial error model, spatial lag model	VEH TYPES	US census tract	Median income, education, age, HH size, gender, Marital status, race	Pop. density and median year of HH constructions
Klincevicus et al. (2014)	MTL OD Surveys	OLS Regression	VEH / HH	CAN Census tract	Avg. HH income	Dist. to CBD, carsharing stations, pop. density
S. Clark and Rey (2017)	UK census data	Spatial and non-spatial Markov Chain	VEH / HH	UK MSOA, n = 8800	-	-
Trendle (2019)	Australian census data for Greater Sydney	OLS regression, SEM, SEM with spatial regimes	VEH / HH	AUS SA2, n = 402	HH income, HH size, age, language, education	% commuting by transit

3.3.2 Disaggregate models

Anowar, Eluru, et al. (2014) conducted an extensive review of disaggregate modelling methods of car ownership. At the date of submitting the present thesis, no new review had been published on the subject. Anowar, Eluru, et al. (2014) suggest a four categories classification based on the type of car ownership representation. Their classification can be summarized in a two-by-two matrix presented in Table 3.2 and is used to structure the present section. Only the modelling methods are discussed in the current section. Outcomes from the models are presented in section 3.4.

Table 3.2 Suggested classification of disaggregated car ownership models by Anowar, Eluru, et al. (2014)

Exogenous static	Exogenous dynamic
Endogenous static	Endogenous dynamic

3.3.2.1 Exogenous static models

Exogenous static models are the simplest of the four modelling methodologies. They attempt to model car ownership as a decision independent of other decisions (e.g., residential location choice, levels of vehicle use) at a single point in time. Car ownership is often modelled as the *number of cars* owned and sometimes as individual access to the automobile (i.e., vehicles per driver within households). Many studies also focus on modelling the composition of household fleets in terms of types of cars (various categorizations are used). Because the type of cars is not available in the Montréal datasets used for this thesis, the present review focuses only on modelling methodologies used to model the number of vehicles.

Ordered response models

The simplest car ownership representation involves using a binary logistic regression to model whether households own at least one vehicle. Alternatively, Delbosc (2013) used this type of model to model household car saturation (less than one vehicle per adult vs. one or more vehicles per adult). However, in most cases, it is much more interesting to try to understand what explains the *number* of vehicles owned by households. In such an approach, due to diminishing occurrences of a high number of vehicles, the last category generally groups together “X or more vehicles”

where X varies from two to four based on the local distribution. In the US context, X is often three, sometimes four. In Europe, Asia and elsewhere, X is usually two and sometimes three.

To account for the fact that some households, for a range of unobserved reasons, are constrained to only some car ownership levels (e.g., 0 or 1 car while the complete set of alternatives modelled is 0, 1, 2, 3+). Whelan (2007) used hierarchical binary dogit models, which include saturation terms by area and household types. In the first model, the alternatives are zero car or 1+ cars. In the second, the choice is 2+ cars vs 1, conditional on ownership of 1+ car and the third choice is 3+ cars vs 2, conditional on owning 2+ cars. No other application of this type of model was found.

Since this number of cars is considered a discrete ordinal variable, ordered logit or probit models have been used extensively, for example, by Potoglou and Kanaroglou (2008) and by Xinyu Cao et al. (2007a) for their cross-sectional model (see Anowar, Eluru, et al. (2014)'s Table 1, p. 445-446 for a complete list up to 2013). Ordered response models work by modelling a *continuous latent variable* representing the propensity to own vehicles, and that latent variable is mapped to the observed number of vehicles.

In an innovative study, Goetzke and Weinberger (2012) used a binary probit model of car ownership with instrumental variable and a two-stage conditional maximum-likelihood estimation procedure to measure the effect of neighbourhood contextual (observed sociodemographic characteristics) and neighbourhood endogenous effects (average car ownership behaviour) on household car ownership decisions. In the first stage, the endogenous variable (percentage of households with at least one car in the census tract) is regressed on a set of tract-level built environment characteristics, sociodemographic characteristics, and a set of instrumental variables (i.e., variables that can predict the average neighbourhood car ownership but are not correlated with the household-level car ownership). The predicted value and its residuals are used in the second stage: the binary probit model of household car ownership. The probit model also includes direct effects (household-level sociodemographic and neighbourhood-level built environment) and contextual effects (neighbourhood-level average sociodemographic).

More recently, Ding and Cao (2019) used a Bayesian cross-classified multilevel ordered probit model to control for spatial dependence issues arising from built environment characteristics measured within zonal units at multiple locations (home and work). That is, all observed households in a survey residing in the same zones or working in the same zones used for spatial

aggregation of built environment features will have the exact same values for those features, leading to spatial dependence (i.e., these observations are not independent). This could underestimate standard errors of coefficients and thus wrongly demonstrate that some variables are significant while others might not. According to Ding and Cao (2019), if zonal aggregates are used at multiple locations for the same households (home and workplace), then standard multilevel models cannot be used, and special models such as cross-classified multilevel methods are needed.

Unordered response models

The other widely used modelling approach for exogenous static models is to ignore the natural ordering of the number of cars by using unordered models such as the multinomial logistic model (MNL; McFadden, 1974). The first formulation of this type of model for car ownership was reportedly done by Ben-Akiva and Lerman (1975) and has been regularly employed in recent years, with 11 studies reported between 1998 and 2013 by Anowar, Eluru, et al. (2014). MNL is based on the random utility maximization (RUM) principle, which means that households operate rationally and associate a certain level of utility with each level of car ownership. The idea is that households will decide on the optimal number of cars (and types) that maximizes the utility of their fleet. A limitation is that the decision is assumed to be instantaneous. Recent applications of this modelling method have been done by Caulfield (2012) in Dublin, Ireland, Zegras (2010) in Santiago de Chile and by Potoglou and Kanaroglou (2008) in Hamilton, Ontario.

Ordered or unordered?

One crucial question is: which of those two representations (ordered versus unordered structure) of household car ownership more accurately represents the true underlying choice process? The importance of this question lies in the use of car ownership models to accurately predict changes in car ownership as a result of changes in sociodemographic and built environment conditions. The first comparison was made by Bhat and Pulugurta (1998), who weighted both methods' theoretical and practical implications and compared them empirically using several datasets. An important argument the authors brought forth in favour of the unordered structure is that if the true underlying process is the ordered structure (e.g., the ordered-response logit model), then using the unordered model (e.g., MNL) can still obtain valid results, but with a loss in estimation efficiency (i.e., an efficient estimator requires fewer observations to obtain the smallest possible deviance and the

“true” value). In the opposite case, where the true mechanism is based on the utility maximization principle of the unordered structure, but the ordered response model is used, this could lead to probability estimations biases. Comparing several fit indices between both models using four datasets from the United States and the Netherlands, Bhat and Pulugurta (1998) concluded that the MNL is consistently superior to the ordered-logit and that aggregate level elasticities of the latter are inaccurate. Their results are confirmed by Potoglou and Susilo (2008). They added the ordered probit to the comparison and concluded that the MNL was superior on theoretical and empirical grounds to both ordered-response models. Finally, in a more recent analysis, Anowar, Yasmin, Eluru, and Miranda-Moreno (2014) compared the ordered logit with the MNL in their traditional form and their more advanced structure with latent classes. The latent class discrete choice model allows for heterogeneity in the population (represented by discrete “classes”) on the effects of explanatory variables on the outcome variable. They concluded that the latent-class models offer superior model fit and that the unordered mechanism (MNL and LC-MNL) performed better than the ordered mechanism (ordered-logit).

An alternative unordered formulation is the Multinomial probit model (MNP). Paleti et al. (2013) developed an MNP formulation incorporating spatial spillover effects from observed and unobserved factors to model vehicle type choice. Incorporating spatial interaction from observed and unobserved effects in a discrete choice model is highly complicated. The formulation requires estimating complex multidimensional integrals that are intractable by traditional simulation or Bayesian estimation procedures. Paleti et al. (2013) used Bhat’s maximum approximate composite marginal likelihood (MACML) inference method to overcome this. However, the complexity of this estimation procedure likely explains why it remains, to this day, along with the endogenous model of Goetzke and Weinberger (2012) and M. K. Adjemian et al. (2010), one of the rare disaggregate models of car ownership controlling for spatial interactions effects. Spatial interaction effects on car ownership are discussed in the section 3.4.2.5.

Relaxing the IIA assumption

In short, the MNL has been very popular because of its superiority to ordered response models, ease of interpretation and estimation (it has a closed-form expression, and the estimation can be achieved by maximum likelihood) and its wide availability in statistical software. However, it relies on the assumption of Independence of Irrelevant alternatives (IIA-Property), which,

according to some, can be quite restrictive. Croissant (2020) argues that, in practice, this is an unrealistic assumption that is often violated, notably if important explanatory variables affecting the utility of the alternatives are missing (Train, 2009). The property means that the ratio of probabilities between two alternatives depends on the attribute of those two alternatives and nothing else. This also leads to proportional substitutions, where improvement to one alternative will increase the probability of this alternative while decreasing the probabilities of all other alternatives by the same proportion. Train (2009, p. 52, ch. 3) gives a good example with vehicle type choice. If three types of vehicles are available: small gasoline cars, large gasoline cars and small electric vehicles (EV), and the government wants to model the effect of subsidizing the purchase of small EVs. What will affect the market share of all three vehicle types? Proportional shifting means that a 10 % increase in the market share of small EVs would come from a 10 % decrease in the market share of both small and large gasoline cars. However, people who prefer small cars might be more likely to switch to an EV than those who prefer large vehicles. In such a case, the MNL would overestimate the reduction in the share of large gasoline cars, which could, in turn, overestimate the expected reduction in greenhouse gas emissions from the EV subsidy.

The nested logit (NL), part of the Generalized Extreme Value (GEV) class of models, has been proposed as a good generalization to relax this assumption (Train, 2009). It allows the set of alternatives to be grouped into subsets (“nests”) so that the IIA-Property holds within each nest but not between alternatives in different nests. To extend the vehicle type example: if it’s expected that subsidizing small EVs would draw more from small cars than from large cars, the NL could be used where the first level would be car size and the second level, fuel type. Small gasoline and small electric would be in the “small cars” nest, and the “large cars” nest would have only gasoline cars.

Z. Guo (2013a) used the nested logit in an interesting way to control for endogeneity bias between the type of parking households have access to (on-street or off-street) and car ownership decisions. The first level models the kind of parking, and the second level models car ownership levels (0, 1, 2, 3+ cars for the off-street parking nest and 0, 1, 2+ cars for the on-street parking only nest). The assumption behind this approach was that households with similar parking types have unobservable preferences that explain why they selected a house with or without off-street parking. In other applications, the nested logit was used to model at the first level the household’s decision to dispose of or acquire a new vehicle and at the second level to model the type or model of the

vehicle (e.g., Mohammadian & Miller, 2003) or for various combinations of vehicle types (e.g., Xinyu Cao, Mokhtarian, & Handy, 2006). The challenge of nested-logit models is to identify the specification of nests that best represents the underlying choice process (Anowar, Eluru, et al., 2014). In other words: which alternative goes in which nest?

Integrating heterogeneity

Another limitation of the MNL is its inability to handle unobserved heterogeneity (or “taste”) in the population with respect to the choice to be modelled. It can only control for systematic variation arising from observed sociodemographic (e.g., a low-income household might be more influenced by the cost of cars than higher-income households). Generalizations have been proposed to accommodate taste heterogeneity. The most common are the latent-class discrete choice framework and the mixed-logit model.

In a latent-class discrete choice model, heterogeneity is accommodated by having the population segmented into k number of classes. The segmentation is endogenous to the choice process as it is estimated simultaneously, and each class has its own set of parameters for the choice model. Furthermore, covariates can be used to improve the class-allocation model and allow some of the heterogeneity between classes to be a function of the observed attributes of the decision-makers.

Anowar, Yasmin, et al. (2014) used the latent-segmentation discrete choice framework to model car ownership in Québec City using unordered and ordered structures in the choice models. For both structures, they concluded that using two latent classes was superior in terms of relative model fit to the traditional version of the models, despite doubling the number of parameters. The segmentation was based on a combination of sociodemographic and built environment variables. In a more recent study, S. H. Kim and Mokhtarian (2018) used a latent-class MNL model to investigate how attitudes can moderate the effect of sociodemographic and built environment influences on household car ownership decisions. In other words, they tried to understand how attitudes induce systematic heterogeneity within the population related to the number of vehicles owned. Only attitudes were included in the class allocation model while sociodemographic and built environment variables were included as explanatory variables of the choice model for the number of vehicles owned by households. Their results suggest that the LC model was better than the simple MNL by enhancing the behavioural understanding of the choice process. It shows, for example, that the "auto-oriented" households were quicker to add cars with increased income and

household size, while those in the "urbanite" class were more sensitive to built environment features. The latent-class framework has also been used to accommodate preferences for vehicle types (e.g., Beck, Rose, & Hensher, 2013; J. Zhang, Kuwano, Lee, & Fujiwara, 2009).

Another approach to incorporate heterogeneity in the choice process is the highly flexible mixed-logit approach. The method allows for random taste variation, has no restrictions on substitution patterns, and, in the case of panel data, can allow for the correlation of unobserved factors over time (Train, 2009). In a mixed-logit model, the parameters β are continuously distributed across individuals based on a pre-defined distribution (Hess, Ben-Akiva, Gopinath, & Walker, 2011). This can be the normal, log-normal, or any other distribution chosen by the analyst. This is where lies one of the drawbacks of this approach: it falls on the analyst to make assumptions about the most likely distribution that best represents the unobserved heterogeneity in the studied population. Additionally, the integral to solve to obtain the unconditional probabilities is intractable and, thus, requires simulations. Like the segmentation model of the latent class discrete choice framework, the parameters of the chosen random distribution can be a function of selected covariates (e.g., sociodemographic characteristics) (Greene & Hensher, 2003). The standard logit model and the latent-class logit model are special cases of the mixed-logit where the value of β is constrained to a single value for all individuals or k discrete values.

Which method should be preferred to accommodate heterogeneity when modelling car ownership? Mixed-logit or latent-class? One advantage of the latent-segmentation approach over the mixed-logit model is that it does not require making specific assumptions about the distribution of parameters across decision-makers (Greene & Hensher, 2003). Additionally, both Greene and Hensher (2003) and Shen (2009) concluded that the LC-MNL offers a superior model fit than the mixed-logit when tested on their datasets, while both being careful not to suggest that their results are evidence that this is always the case. And finally, the use of a latent class framework facilitates interpretation by making it more intuitive to understand the role of heterogeneity in the choice process. It has been recommended for transportation applications by Hess et al. (2011). Anowar, Eluru, et al. (2014) also recommend the latent-class discrete choice model as the best modelling option for accommodating heterogeneity in exogenous static models. This does not mean the mixed logit should not be used. Its highly flexible nature can make it appealing to the experts, but it might not be as straightforward for applied work.

Among other approaches for static exogenous modelling, Anowar, Eluru, et al. (2014, pp. 456-457) describe some lesser-used models such as the standard Poisson regression model (Shay & Khattak, 2012), the linear regression (Flamm, 2009; Klinevicius et al., 2014) or early applications of machine learning algorithms such as artificial neural networks (Mohammadian & Miller, 2002). According to Anowar, Eluru, et al. (2014), all of these models would have several limitations that would make them less recommendable than the ordered and unordered response models presented above.

Summary

In sum, based on these previous works and based on Anowar, Eluru, et al. (2014)'s recommendations, the latent-class discrete choice model is suggested as one of the simplest, most intuitive ways to model car ownership as an exogenous decision while allowing for heterogeneity in the influence of various variables on car ownership decisions. As for the vehicle representation, the unordered structure should be preferred. This approach is considered for the third contribution (Chapter 8) of the present thesis.

3.3.2.2 Endogenous static

For this category of models, the goal is to jointly model one or more decisions considered endogenous to car ownership decisions. These decisions can be up or down the hierarchy of travel-related decisions suggested by Ben-Akiva and Atherton (1977). Modelling those choices endogenously can be complex, and a wide range of methods have been applied. Without repeating the description of Anowar, Eluru, et al. (2014), it is worth mentioning a few methods that have been used to model some important joint decisions.

As mentioned in the section 3.2.3, residential self-selection is a critical aspect to control for when evaluating the effect of built environment variables on travel behaviour, including car ownership decisions. Because some underlying and unobserved attitudes might affect both the choice of a residential neighbourhood and the number of cars to own, both decisions cannot be assumed to be exogenous.

Modelling all possible combinations

The simplest method consists in modelling all the possible combinations of car ownership status and residential location using the MNL, as done by Salon (2009). A major downside is that,

depending on the number of alternatives included for each choice, this can rapidly lead to an unmanageable number of alternatives to model and parameters to estimate. Because Salon also added mode choice to the joint decisions, her final choice set had 180 alternatives. This is also the approach taken by Weinberger and Goetzke (2010), but with a drastically reduced set of alternatives. Using micro-census data for households that have recently moved to five large metropolitan areas of the US, they jointly model the decision to choose a central city location or not (dummy) and the number of cars (0, 1, 2+). The six combined choices are modelled using a Multinomial Probit model. Like the MNL, it is based on the random-utility maximization principle, but the assumption of IIA is relaxed to ensure unbiased estimates in the (likely) correlations between some alternatives. As only recent movers are modelled, this allows them to test if people's previous residential location influences their joint residential / car ownership choice.

Simultaneous equation systems

Bhat and Guo (2007) developed a simultaneous discrete choice structure to jointly model residential location choice and household car ownership. The residential choice is modelled through an unordered structure and car ownership as an ordered logit, with both equations joined together with common error terms and estimated simultaneously. Pinjari et al. (2011) extended the approach to model the entire hierarchy of choice decisions: long-term residential location choice, medium-term car ownership and bicycle ownership decisions and short-term mode choice. Their results indicate that none of the choice dimensions are exogenous to one another and that unobserved characteristics simultaneously impact several choice decisions.

This mixed multidimensional modelling framework has also been used to simultaneously model ownership of multiple mobility tools (e.g., car ownership, carsharing membership, bicycle ownership, transit pass ownership). Details about those applications are presented in the section 3.5.2 on mobility tool ownership modelling methods.

To model household fleet composition in terms of vehicle types and each vehicle's use, the multiple discrete-continuous extreme value model (MDCEV) developed by Bhat (2005, 2008) has been proposed. The method makes it possible to endogenously model multiple discrete decisions (e.g., vehicle types) along with continuous variables such as the use of each vehicle owned (Bhat

& Sen, 2006). The methodology has also been expanded to incorporate a nested-logit structure (Bhat, Sen, & Eluru, 2009).

Two-stages instrumental variable models

Another approach has been to use two-stage instrumental variable models where the first stage models the first choice in the sequence of choice, and the second stage uses the predicted value from the first stage as an explanatory variable. The model relies on identifying instrumental variables (or “instruments”) that are correlated with the first choice but not the second. Zegras (2010) modelled the number of vehicles using a MNL model in the first stage. They used the predicted number of cars in a linear regression model of total driving distance on the surveyed day. Jiang, Gu, Chen, He, and Mao (2017) used a similar approach but with a double-hurdle model to predict VKT. The first “hurdle” was the decision to use the car, and the second “hurdle”, conditional on the first, was the distance travelled.

Structural equation modelling

The other relevant approach to endogenously model several choice dimensions is structural equation modelling (SEM). SEM refers to a family of models which combines a *measurement model* linking observed variables (indicators) to latent variables and a *structural model* defining the directional relationship between observed and latent variables. SEM can identify three types of effects: direct, indirect, and total effects. The direct effect is the change in an endogenous variable due to a direct change in a ‘cause’ variable. The indirect effect is the change to that endogenous variable from changes in the ‘cause’ variable but going through another endogenous variable. The total effect is the sum of both. A simple illustration of a path model that includes only measured variables is presented in Figure 3.5. The model tests the direct effect of BE on car use and the indirect effect through car ownership. In such a model, car ownership is said to mediate the effect of BE on car use.

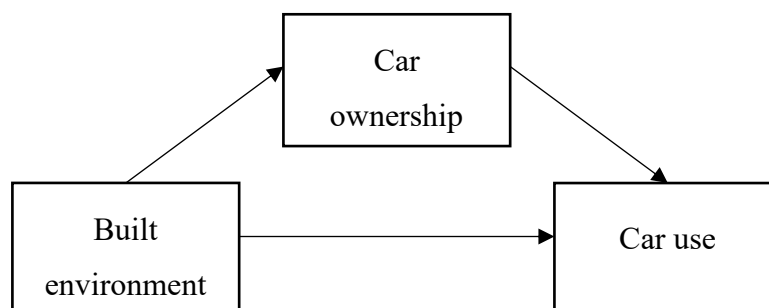


Figure 3.5 Structural model of the effect of the built environment on car ownership and car use

As described in section 3.2.1, this method has been used to explore how car ownership mediates the effect of the built environment on travel behaviour (de Abreu e Silva et al., 2012; Van Acker & Witlox, 2010). In a subsequent study, Van Acker et al. (2014) used SEM to test multiple directions of causality between lifestyles, attitudes (residential, travel and mode-specific), built environment at home location and car ownership (effectively modelled as a composite factor named “car availability”).

However, traditional SEM can easily accommodate binomial and continuous outcomes but not discrete multinomial variables such as the number of cars owned by a household. This is why for example, Van Acker and Witlox (2010) and de Abreu e Silva et al. (2012) treated the variable “number of cars” as continuous and why car ownership was modelled as “car availability” by using continuous factor scores obtained from a factor analysis of four variables (permanent car availability, possession of a driver’s licence, number of cars in the household and possession of a public transit pass) by Van Acker et al. (2014).

More recently, Moody and Zhao (2019) used SEM to test the bidirectional influence of a measure of car pride (12-item reliable and validated scale) on car ownership while controlling for individual and household sociodemographic characteristics. Car ownership is modelled as a dichotomous outcome (no car versus car ownership). Because car pride and car ownership are assumed endogenous, the method of instrumental variable is used to establish the magnitude and significance of both directions of influence (car pride → car ownership and car ownership → car pride). “Instruments” are variables that influence the explanatory variable (i.e., car pride) but do not correlate with the error term of the outcome variable (i.e., car ownership). The instruments are

then used to predict the explanatory variable, thus leading to a “purged” version with no endogeneity bias with the modelled outcome. The instrumental variables also need to be free from influence from both the outcome and other explanatory variables in the model. The difficulty in such a method is always to find the right instrument that respects those criteria.

As an (imperfect) instrument for car pride, Moody and Zhao (2019) used a measure of “general authentic pride” regarding people’s life and achievement that is measured without any reference to the car. For household car ownership, the instrument is the average car ownership level within the census block group of each household. Again, this is an imperfect instrument, as Goetzke and Weinberger (2012) demonstrated because individual behaviour aggregates to neighbourhood behaviour. See section 3.4.2.5 for details about Goetzke and Weinberger (2012)’s results. The conceptual framework tested by Moody and Zhao (2019) did not include any measure of the built environment beyond a dummy variable for New York City versus Houston, Texas (the two cities surveyed).

Summary

Several methods of various levels of complexity have been proposed to jointly model car ownership with other decisions considered endogenous (e.g., residential location, car use). The simplest methods bundle the different alternatives together (e.g., central neighbourhoods and one car, suburban neighbourhoods and two cars, and so on) and model them using multinomial probit or logit models. More complex methods used joint equation systems, structural equation modelling or two-step instrumental variable models.

3.3.2.3 Exogenous dynamic

In this third category, the evolution of car ownership over time is modelled. The section focuses only on the modelling of car ownership, considering other decisions as exogenous. The next section (3.3.2.4) covers the endogenous dynamic models. The methods are further categorized according to the type of data that is used: true panel data, pseudo-panel approach (repeated cross-section surveys) and quasi-panel approach (data measured at one point in time but with retrospective questioning to gather information about a previous date). The type of data also dictates how car ownership is modelled. True panel data is sometimes used to model the *changes* in car ownership when the focus is on a subset of households having changed the number of cars they own. The pseudo-panel approach, however, does not model *changes* in car ownership, but the

number of cars owned. Finally, the objective of quasi-longitudinal methods is to focus on the observed changes in car ownership (adding / removing cars from the fleet), but that change can be null (no change).

True panel data: discrete choice model

The most robust methodology to investigate the evolution of car ownership decisions relies on panel data where the same households are surveyed at multiple points in time. This type of analysis can explore, for example, the influence of household life stages on car ownership.

One such dataset is the Dutch National Mobility Panel survey. Pendyala, Kostyniuk, and Goulias (1995) used a selected sample of 485 individuals measured for six waves of this panel from 1984 to 1989 to analyze the changing relationship between household income and car ownership. However, while the data was longitudinal, the approach was repeated cross-sectional, where an ordered Probit structure was used to model the number of cars owned at each point in time and then to compare income elasticity between waves for various household types.

As explained by Anowar, Eluru, et al. (2014), an issue when using true panel data is the temporal correlation between repeated observations of the same household that might arise due to two types of unobserved effects: 1) “spurious state dependence” which is the effect of unobserved preferences (heterogeneity due, for example, to lifestyles) that are assumed invariant over time and can affect intra-temporal correlations between alternatives and 2) “true state dependence” which is the result of time-dependent unobserved factors such as transaction cost of changing vehicle. The first effect can make some car ownership alternatives closer than others, thus violating the IIA Property of the MNL (Nobile, Bhat, & Pas, 1997). The second leads to the persistence of car ownership over time. Failure to account for them can lead to biased results and wrong policy recommendations. One solution is to extend traditional discrete choice models with either random or mixed-effect models. Nobile, Bhat, and Pas (1997) applied a random-effect multinomial Probit model to the Dutch National Mobility Panel dataset. *True state dependence* (intratemporal correlation) is accommodated by allowing a general form for the error term covariance matrix. *Spurious state dependence* is accommodated by allowing heterogeneity in household response to some factors (random effect) due to unobserved households’ preferences.

Similarly, J. Dargay and Hanly (2007) applied a random-effect ordered Probit model to 11 years of data from the British Household Panel Survey, and A. Nolan (2010) used a random-effect binary Probit on six years of the Living in Ireland survey. Their models work by including a lagged dependent variable (i.e., the number of cars owned the year before) to accommodate for *true state dependence* and the introduction of household-specific error components in the error term that are time-invariant to account for unobserved household preferences (assumed constant in time) to control for any *spurious state dependence*. Train (2009, ch. 6) illustrates that including lagged dependent variables in a mixed-logit model is more accessible than in the Probit formulation as it does not require adjustment to the probability formula or simulation method.

More recently, Klein and Smart (2017) tested two models on eight waves (from 1999 to 2013) of the Panel Study of Income Dynamics in the US (~9000 representative households): a fixed-effect and a random-effect Poisson regression model of the number of cars per adult in the household. The goal was to investigate what factors could explain Millennials' observed car ownership levels compared to older generations. Results are discussed in the section 3.4.3.3.

In a subsequent study, Klein and Smart (2019) used the same panel data with six waves from 2003 to 2013 to specifically investigate how life events and changes to the built environment affect the likelihood of households to increase or decrease their number of cars. They use a population-averaged autoregressive binary logit model of changes. This type of model allows controlling for serial correlation and heteroscedasticity associated with panel data. The increase and decrease in car ownership are assessed in two separate models where the outcome takes a value of one if the household added one or more cars or shed one or more cars to its fleet between two waves (2 years apart). In the increase model, all households are considered. In the decrease model, only households with at least one car in the previous wave are modelled.

Beyond their rarity and prohibitive cost, an important limitation of panel data is the attrition issue between waves and the self-selection of respondents. Those who choose to respond wave after wave often exhibit different observed and unobserved attributes from those who dropped out.

True panel data: hazard-duration models

A second dynamic modelling approach that uses true panel data is to consider the evolution of a household's vehicle fleet over time (in type and number of vehicles) by modelling, for example,

decisions related to the purchase, sale, and duration of ownership of cars. This can be achieved using a hazard-based duration framework that models the probability that an event will happen at a specific point in time. An example is the work by Mohammadian and Rashidi (2007), who modelled three types of vehicle transaction: replacement, acquisition and disposal, using both independent and competing hazard models with random-effect to control for heterogeneity using a Toronto car ownership dataset covering eight years of data for 900 households. Yamamoto (2008) used competing-risk duration models to represent the type of transaction (replacement, acquisition, or disposal) of a vehicle and the duration until the next transaction on a large French panel survey (Parc-Auto) covering 15 years. The goal was to analyze the effect of life-course events such as childbirth, residential relocation, household composition change, and change in income resulting from employment change.

Pseudo-panel approach

If multi-wave panel data are the gold standard for dynamic modelling of car ownership, they remain rare and costly to collect. One alternative used by researchers is the construction of *pseudo-panels*. In this approach, “synthetic households” are followed over time using data from several successive waves of surveys. These “synthetic households” can be based, for example, on cohorts defined by the year of birth of the household head (e.g., Cornut, 2016; J. Dargay & Vythoulkas, 1999; Matas & Raymond, 2008). A recent example is the work by Cornut (2016), who applied the pseudo-panel approach using five iterations of the large-scale *Enquête Globale Transport* of the Paris Metropolitan region between 1976 and 2010 to examine changing elasticities of car ownership with respect to income and fuel price. He applied a fixed-effect semi-log model to estimate the number of cars per household and 3-year cohorts based on the respondent’s birth year.

A critique of this methodology resides in the variable used for grouping together “synthetic households”. Using a single variable, like the household head’s birth year, is very limiting to investigate car ownership variation over time. In a more recent application of the pseudo-panel method to investigate car ownership in Singapore, Song, Diao, and Feng (2021) added residential location as a grouping variable, subdividing the city-state into 13 regions for which five cohorts of 10 years-of-birth intervals were constructed. Car ownership was modelled as a continuous variable as it represented the mean value of car ownership for each region-cohort. The dynamic fixed-effect model is estimated using the General Method of Moment (GMM) approach.

Anowar, Eluru, and Miranda-Moreno (2016) and Papu Carrone and Rich (2021) did not use the concept of synthetic household. Instead, they pooled together data from multiple years of large-scale travel surveys. Anowar et al. (2016) used the 1998, 2003 and 2008 Origin-Destination surveys for the Montréal region. To account for the passage of time, they included a “time-elapsed” variable since the first time point (1998). Papu Carrone and Rich (2021) pooled together ten years (2007-2018) of the Danish National Travel Survey that included scale parameters for each survey year. Longitudinal effects were captured by allowing the coefficients for the alternative-specific constants and the age-cohort variables to vary over time. Specifically, the coefficient at time t consisted of two parts: a time-constant and a time-varying part, with the latter following a logarithmic functional form.

In terms of car ownership representation in those pseudo-panel models, Anowar, Eluru, et al. (2014) report that various discrete choice models have been used. Matas and Raymond (2008) compared an ordered Probit with the MNL, Papu Carrone and Rich (2021) used a MNL, while Anowar et al. (2016) used a generalized version of the ordered logit model (GOL) with random-coefficient (mixed) where the coefficients of the predictors are allowed to vary between the levels of car ownership modelled while maintaining the ordinal nature of car ownership levels (a shortcoming of traditional ordered models).

Quasi-panel approach

The fourth approach to dynamic modelling of car ownership that Anowar, Eluru, et al. (2014) do not cover uses “quasi-panel” data. The quasi-panel method collects data at one point in time but asks retrospective questions to collect information on household characteristics at a previous date in time. The idea is to collect data from recent movers and non-movers (control group) to observe the effect of changes in built environment characteristics on a travel behaviour outcome variable (e.g., car ownership) and thus identify the “true” causal effect of BE on travel behaviour.

Xinyu Cao et al. (2007a) employed this method using a specific survey collected in Northern California in 2003. They employed a static-core model to analyze the changes in car ownership for movers while incorporating the influence of the lagged car ownership value (the recalled number of cars before the move), current and prior values of some explanatory variables, as well as the change for some of them. To avoid multicollinearity issues, only two of the three values (prior, current and change) for each explanatory variable could be used. Changes in car ownership

are approximated as a quasi-continuous variable and modelled using ordinary least squares regression. Their model also controls for attitude-induced residential self-selection by including neighbourhood and travel attitudes. J. Cao and Cao (2014) also used a quasi-panel survey of movers to investigate the effect of a new light-rail line on household car ownership in Minneapolis, controlling for attitude-induced self-selection. They modelled the change in car ownership from before and after the move for residents of the light-rail corridor and residents from four “control” corridors using an ordered logit structure. Xinyu Cao, Næss, and Wolday (2019) used the same method to analyze the effect of changes in built environment characteristics on change in car ownership for households who moved closer or farther from the centre of two urban regions in Norway. Change in car ownership (shedding, no change, acquiring) was modelled using an ordered-logit model controlling for changes in household size and controlling for residential self-selection through the inclusion of neighbourhood attitudes. Finally, X. Huang, Cao, Yin, and Cao (2017) used a mixed-process ordered Probit model to jointly model changes in mobility tool ownership (car, motorcycle, bike and e-bike) of movers in Beijing. The paper is further discussed in section 3.5.2 on mobility tool ownership modelling methods.

Unlike panel data and pseudo-panel data, which often rely on large-scale government-funded surveys, quasi-panel data is usually collected using ad hoc surveys by researchers with smaller sample size and may lack representativeness. Furthermore, because respondents are asked to recall information from a previous time point, this might lead to bias and incorrect reporting due to memory issues (Becker et al., 2017).

Summary

In summary, various types of datasets (panel, pseudo-panel, and quasi-panel) have been used to investigate changes in household vehicle ownership over time. Different methodologies, adapted to each approach, were employed with no clear indication of which method should be preferred. The use of *true panel* data allows for a robust investigation of how changes in household structure, income, and life events can influence the number of cars owned by households. It can also investigate the effect of time-evolving variables such as fuel price. This type of data remains rare and often does not contain information on past built environment characteristics making it harder to assess if their evolution over time could affect car ownership (for example, Klein and Smart

(2017) included a measure of accessibility by transit at the census tract level, *but not the change* in transit accessibility over the 14 years they studied).

The *quasi-panel* approach appears like a robust methodology to circumvent this shortfall and investigate how changes in built environment characteristics impact car ownership while also controlling for residential self-selection through the specific collection of attitude variables. Before-after studies investigating specific changes to transportation supply could provide even more robust evidence and further insights into the complex relationship between the built environment, attitudes and travel-related decisions such as car ownership. They could allow for example the measurements of attitudes at different points in time, something impossible to do with retrospective questioning employed in quasi-panel surveys.

Finally, the *pseudo-panel* approach makes use of widely available large-scale travel surveys but could be improved in two ways. First, when the sample size is large enough, a better characterization of “typical households” could be defined, going beyond the year of birth and region-based cohort. This could be done through a more robust typology of households and individuals (Deschaintres, Morency, & Trépanier, 2021). Second, as this approach relies on data collection that is often five or more years apart, the effect of changes in the built environment should be considered and investigated. Something that was not done in any of the papers summarized here, likely due to the difficulty in acquiring transport supply and land-use data for older years.

3.3.2.4 Endogenous dynamic

The idea behind this last category of models proposed by Anowar, Eluru, et al. (2014) is to model endogenous decisions at several points in time using true panel data or a pseudo-panel approach.

True panel data

Kitamura (2009) used a simultaneous equation system to model the endogenous dynamics of household car ownership decisions, trip generation and modal split. In other words, it simultaneously estimated trip generation and mode split at time t as a function of current car ownership and past trips and mode split decisions, while car ownership itself is influenced by trip and mode choice decisions at $t - 1$. An ordered Probit structure is used to model the number of cars owned by households. The analysis is conducted using four waves of the Dutch National

Mobility Panel. The sample retained for modelling contains only households measured with at least three consecutive time point observations.

In a recent study, McBride, Lee, Lundberg, Davis, and Goulias (2016) used a Longitudinal Mixed Markov Latent Class model to analyze the evolution of car ownership and car use for 230 households across ten waves (1989-2002) of the Puget Sound Travel Panel. The approach creates clusters of travel behaviour called “states” (these states can be viewed as automobility styles) between which households will transition from one wave to the next. Those latent states are based on three observed variables: household car ownership, number of solo car trips and number of shared car trips. Then the probability for households to transition from one “state” to another is modelled as a function of changes in within-household characteristics (e.g., newborn, changes in the number of workers, etc.) and changes in land-use happening between t and $t - 1$ and t and $t + 1$. This allows the analysis of changes in mobility styles in reaction to or in anticipation of household demographics or land-use changes. Observed sociodemographic in the first year of observation are used as explanatory variables for the initial “state”. Furthermore, analysis of household behavioural change dynamics between the four “states” over the ten-wave period reveals three “classes” of households (hidden Markov chains). In other words, these classes represent latent longitudinal heterogeneity in how households *adapt* their automobility styles in response to demographics and land-use changes. Finally, McBride et al. (2016) analyzed correlations between those latent classes and a range of observed attitudes toward travel and specific modes declared by the household spokesperson.

Pseudo-panel

An example given by Anowar, Eluru, et al. (2014) to “mimic” the dynamic nature of household fleet decisions is the work by Eluru, Bhat, Pendyala, and Konduri (2010) who used a joint discrete-continuous copula based framework to model residential location choice, along with vehicle type ownership decisions and vehicle-miles travelled. The approach uses a cross-sectional dataset where the order of acquisition of each vehicle in the household fleet is known. And thus, unlike the application of the MDCEV described in the Endogenous static section, which assumes that the decision of the entire household vehicle fleet is instantaneous, the approach taken here models “synthetic” repeated choices of vehicle acquisition and type (“no vehicle” is one of the

alternatives). The number of repeated choices modelled depends on the number of adults in the household, and the choice can incorporate the impact of the vehicle types already owned.

Sun, Susilo, Waygood, and Wang (2014) used a form of “pseudo-panel” approach to examine if changes in automobility (car ownership, car travel time and proportion of trips by car) between 1970 and 2000 in Osaka, Japan, due to changes in demographics and life-cycle stages or changes in the built environment. The three components are estimated endogenously using a simultaneous equation system but separately for the two time points using the large-scale mobility surveys for each year. Coefficients and explanatory variables from each year-model are then used to predict changes in automobility characteristics of the other year and therefore analyze the stability of the relationships between variables.

Quasi-panel

In a step-up from their car ownership-only model (Xinyu Cao et al., 2007a), Xinyu Cao et al. (2007b) used the same quasi-panel datasets of movers from Northern California to explore the causal relationship between *changes in the built environment*, *changes in car ownership* and *changes in walking and driving behaviour*. They used structural equation modelling (SEM) to model the various paths of causality while controlling for residential self-selection by including latent residential preferences and travel attitudes.

Summary

Overall, studies investigating the multiple endogenous travel-related decisions (residential location, car ownership, daily travels) remain very rare, likely due to data availability and the complexity associated with modelling those decisions jointly over time. Nonetheless, they are the most advanced approach able to provide a complete picture of household travel-related long-, medium- and short-term decisions.

3.3.2.5 Summary of disaggregate discrete choice modelling methods

Table 3.3 presents a summary of all methods reported in the present section.

Table 3.3 Summary table of car ownership modelling methods

Category	Type of data	Modelling method	Examples
<i>Exogenous static</i>			
Continuous response	Cross-sectional	Linear regression	Flamm (2009) Klincevicus et al. (2014)
Binomial response	Cross-sectional	Binary Logit Binary Dogit Binary Probit	Delbosc (2013) Whelan (2007) Goetzke and Weinberger (2012)
Ordered response	Cross-sectional	Ordered logit Ordered Probit Multilevel ordered Probit	Bhat and Pulugurta (1998) Potoglou and Susilo (2008) Xinyu Cao et al. (2007a) Ding and Cao (2019)
Unordered response	Cross-sectional	MNL MNP	Potoglou and Kanaroglou (2008), Zegras (2010) Paleti et al. (2013)
Relation of IID	Cross-sectional	Nested-Logit	Mohammadian and Miller (2003), Z. Guo (2013a)
Integrating heterogeneity	Cross-sectional	Latent-class MNL; Latent-class ordered Logit	S. H. Kim and Mokhtarian (2018), Anowar, Yasmin, et al. (2014)
<i>Endogenous static</i>			
Bundling the choices	Cross-sectional	MNL MNP	Salon (2009) Weinberger and Goetzke (2010)
Joint modelling	Cross-sectional	Simultaneous equation system MDCEV	Bhat and Guo (2007) Bhat and Sen (2006), Bhat et al. (2009)
Two-stages instrumental variable	Cross-sectional	MNL in first stage for CO	Zegras (2010), Jiang et al. (2017)
Structural equation modelling (SEM)	Cross-sectional	SEM	Moody and Zhao (2019), Van Acker et al. (2014); Van Acker and Witlox (2010), de Abreu e Silva et al. (2012)

Note: MNL=Multinomial Logit; MNP = Multinomial Probit; RE = Random-effect

Table 3.3 Summary table of car ownership modelling methods (continued)

Category	Type of data	Modelling method	Examples
<i>Exogenous dynamic</i>			
Discrete choice response	True panel	Probit RE Binary probit RE Ordered probit RE MNP RE Poisson	Pendyala, Kostyniuk, and Goulias (1995); Nolan (2010); Dargay and Hanly (2007) Nobile et al. (1997) Klein and Smart (2017)
Probability of event occurrence (“timing” models)	True panel	Competing hazard-base models Binary logit autoregressive model	Mohammadian and Rashidi (2007), Yamamoto (2008) Klein and Smart (2019)
Pseudo-panel: synthetic households	Repeated cross-sectional	Fixed-effect semi-log Dynamic fixed-effect regression MNL with RE	Cornut (2016) Song et al. (2021) Papu Carrone and Rich (2021), Matas and Raymond (2008)
Pseudo-panel: pooled datasets	Repeated cross-sectional	Generalized ordered Logit with RE	Anowar et al. (2016)
Quasi-panel	Quasi-longitudinal	Static-core model Ordered-Logit	Xinyu Cao et al. (2007a) Xinyu Cao et al. (2019)
<i>Endogenous dynamic</i>			
Joint modelling	True panel	Simultaneous equation systems	Sun et al. (2014)
Longitudinal latent class	True panel	Longitudinal Mixed Markov Latent Class	McBride et al. (2016) J. H. Lee and Goulias (2018)
Simultaneous equation systems	Cross-sectional with historical info.	Joint discrete-continuous copula based	Eluru, Bhat, et al. (2010)
Quasi-panel	Quasi-longitudinal	SEM	Xinyu Cao et al. (2007b)

Note: MNL=Multinomial Logit; MNP = Multinomial Probit; RE = Random-effect

3.3.3 Machine learning models of car ownership

When Anowar, Eluru, et al. (2014) published their review, machine learning methods were only starting to be used in travel behaviour research. Indeed, they only report on the work by Mohammadian and Miller (2002), who developed a multilayer perceptron artificial neural network (ANN) to model household vehicle type choices. They compared its performance with a nested-logit model (NL). In terms of predictive power, the ANN performed substantially better,

classifying 70.4 % of the test set correctly compared to 49.2 % for the nested logit. However, the NL performed slightly better in predicting aggregate market share. The authors nonetheless relied on the NL for variable interpretation (elasticities, tests of significance, etc.).

Since Anowar and colleagues' review, the use of machine learning models in transportation research has been vastly expanded. Car ownership has been modelled using neural networks (Basu & Ferreira, 2020), random forest (Sabouri, Brewer, & Ewing, 2020), support vector machines (Paredes, Hemberg, Reilly, & Zegras, 2017) and gradient-boosting decision trees (W. Zhang, Zhao, Cao, Lu, & Chai, 2020). Paredes et al. (2017) compared MNL to five machine learning methods (gradient boosting decision trees, decision tree classifiers, support vector machines (SVM) and random forest) on the same dataset. They concluded that MNL offers more theoretical insights and can outperform or equal ML methods in prediction accuracy when the dataset is not preprocessed to take full advantage of the machine learning algorithms. However, when adequate pre-processing of the data for ML methods is done, it leads to accuracy up to 10% better than MNL, but at the cost of losing interpretability. In their comparison, MNL and Gradient Boosting decision trees (*xgboost*) led to the same accuracy when the dataset prepared for MNL was used. Basu and Ferreira (2020) conducted a similar comparison and concluded that Neural Networks outperformed the ordered logit, MNL and other machine learning methods in terms of prediction and generalization capabilities. The author still relied on the MNL to get insight into the effect of the independent variable on household car ownership decisions.

Most of these studies focused on the predictive power of machine learning methods, which, based on this short review, offers similar or superior performance. However, most machine learning models can be perceived as “black boxes” and do not provide much insight into the effect and significance of explanatory variables. We note, however, that for all those studies, the authors did not use interpretability tools available to some machine learning methods, such as computing the *relative influence of explanatory variables* and producing *partial dependence plots*. One exception is W. Zhang et al. (2020), who used both tools. The former allows them to rank the most influential sociodemographic and built environment variable in predicting the number of household cars in Beijing. The latter is used to investigate the non-linear influence of built environment attributes on car ownership.

The relative influence works by computing, for each explanatory variable used in an ensemble of decision trees, the squared improvement resulting from its use at each split of a tree, averaged over all trees in the ensemble. Partial dependence plots (PDP) show the average change in the outcome variable (or in the log-odds of the response variable in the case of a binary response) when changing the value of the inspected explanatory variable, holding every other variable constant at their mean. They can be calculated from many machine learning models that use the concept of an ensemble of decision trees such as Random Forest, gradient boosting machine, or Generalized Additive Modelling. Partial dependence plots (PDP) have been increasingly used in travel behaviour research to investigate the potential non-linear effect of built environment characteristics.

As walking, cycling, and active travel are generally more sensitive to subtle changes in built environment characteristics, many papers investigated non-linear effects specifically on those behaviours for various subpopulations or trip purposes. This has been done by analyzing partial dependence plots produced from gradient-boosting decision trees (GBDT) (X. Huang, Lu, Yin, & Tan, 2021; Liu, Wang, & Xiao, 2021; Yang et al., 2022), Random Forest (Cheng, De Vos, Zhao, Yang, & Witlox, 2020) or Generalized Additive Modelling (GAM) (Wali, Frank, Chapman, & Fox, 2021; Wu et al., 2021). Partial dependence plots produced specifically from GBDT have been used to investigate the non-linear and threshold effects of built environment characteristics on car mode choice or VKT (Ding, Cao, & Næss, 2018; Ding, Cao, & Wang, 2018; K. Wang & Wang, 2021) (Ding, Cao, & Wang, 2018) as well as transit ridership at metro stations (Ding, Cao, & Liu, 2019).

In summary, machine learning methods are no longer confined to the sole purpose of prediction. With the development of tools such as partial dependence plots, they can provide a helpful interpretation of the association between explanatory variables, notably their non-linear relationship with the outcome variable. In the second contribution presented in Chapter 7, Gradient boosting decision trees are developed, and partial dependence plots are produced to visualize non-linear relationships between a host of built environment characteristics and accessibility measures on household car ownership when measured within different buffer sizes. This allows for the investigation of the assumption of a linear-in-parameter relationship between built environment variables and car ownership in traditional discrete choice models.

3.4 Factors influencing car ownership decisions

A wide variety of explanatory variables have been tested and incorporated in car ownership models. At the time of submission of the present thesis, there was no review or meta-analysis of factors influencing car ownership like the studies that can be found for travel behaviour (e.g., Ewing & Cervero, 2001, 2010; Stevens, 2017). The present section is thus an attempt to summarize, without any claim at being exhaustive, what factors have been demonstrated to influence household car ownership decisions.

3.4.1 Explanatory variables of aggregate models

This section summarizes the exogenous variables used in spatially aggregated car ownership models described in section 3.3.1 and summarized Table 3.1. Because of the nature of the modelling methods, these variables are aggregated over geographic areas of various sizes. This is the case both for sociodemographic variables and built environment attributes. Due to the nature of the modelling methods and the type of data used, these models can only inform on correlations between aggregate level statistics. Effects of those variables are described in the next two sections. A summary is presented in Table 3.4 and Table 3.5

3.4.1.1 Sociodemographic characteristics

In aggregate models, sociodemographic characteristics are averaged over the population of the zonal areas used as modelling units. When interpreting the results, care must be given to avoid ecological fallacy. Ecological fallacy refers to making inferences about individual behaviour from aggregated data (Lloyd, 2014). It is a critical issue if relationships found at the aggregate level cannot be observed at the individual level (Dusek, 2004). With this caveat in mind, spatial models can be very useful to study how the relationship between variables varies over space. For example, how do neighbourhood-level characteristics correlate with car ownership rates, and how do spatial interactions influence this relationship?

In this respect, many of the spatial aggregate models of car ownership reviewed are interested in the relationship between income and car ownership rates and how it varies geographically. In two separate studies using UK data, S. Clark (2007) and S. Clark and Finley (2009) tried to obtain accurate estimates of the elasticity of car ownership with respect to income while controlling for

spatial dependence using various methods. S. Clark (2007) obtained an elasticity of 0.61 (a 10 % rise in income would lead to a 6.1 % rise in average vehicle/household) with a global (UK) model not controlling for spatial dependence, a value of 0.83 for a spatial error model and a median value of 0.74 using a Geographically weighted regression (GWR). In the second paper, elasticities ranged from 0.57 to 1.0 (S. Clark & Finley, 2009), with the highest values obtained with a more precise control for spatial dependence. S. Clark (2007)'s GWR model also shows significant spatial heterogeneity for the income parameter. For example, in many areas of London, households have fewer cars for the same income as in rural areas. There is also spatial variation in the elasticity, indicating that in some areas, such as city centres in some parts of the country, car ownership levels are much more sensitive to income than in most rural areas or even some neighbourhoods of London. In both studies, the only other included explanatory variable is population density.

Analyzing the relationship between income and car ownership in Greater Sydney, Australia, Trendle (2019) obtained a car ownership elasticity with respect to income of 0.56 (with a spatial error model), a value lower than the 0.93 obtained by S. Clark and Finley (2009) also with their spatial error model. This difference could be explained by significant structural differences between cities in the United Kingdom and Australia. Using three spatial “regimes” based on the proportion of transit commuters, Trendle (2019) shows that the elasticity of car ownership to income is the *lowest* in the urban core, where transit ridership and income are high, while car ownership is low. The elasticity is the *highest* in the outermost areas of the city, where transit ridership and density are very low.

In the other studies listed in Table 3.4 (i.e., Gao et al., 2008; Holtzclaw et al., 2002; Whelan et al., 2010), average income was less the focus of the investigation but rather a control variable (or an endogenous variable in the structural equation modelling of Gao et al. (2008)) to more precisely capture the influence of built environment variables on car ownership. Overall, as expected, increased in average income is associated with an increase in average car ownership rates, but with important spatial variations.

Other aggregate sociodemographic variables were included in some of the reviewed studies. A larger average household size is associated with higher rates of vehicles per household (Holtzclaw et al., 2002; Trendle, 2019) but lower rates when the dependent variable is measured in vehicles per person (Gao et al., 2008). A higher proportion of seniors (65+) is associated with higher

vehicles per household (Trendle, 2019), while a higher proportion of young adults (17-30) is associated with lower rates of vehicles per adult (Whelan et al., 2010). A higher proportion of single-adult and single-adult households with children is associated with a lower average rate of vehicles per adult in London (Whelan et al., 2010). Finally, education seems to have opposite effects depending on the city. In Sydney, Australia, a higher proportion of adults with a bachelor's diploma is associated with lower average vehicles per household (Trendle, 2019). In Sacramento, California, results of the SEM indicate a positive association with vehicles per person (Gao et al., 2008). The proportion of rental housing units is negatively associated with car ownership rates in both studies (Gao et al., 2008; Trendle, 2019). Finally, Gao et al. (2008) also show that a higher number of workers per capita is positively associated with higher rates of vehicles per person.

3.4.1.2 Built environment characteristics

All reviewed studies included population density as a measure of the built environment, except for Gao et al. (2008). All models in all five studies indicate that a higher density is associated with lower car ownership rates (S. Clark, 2007; S. Clark & Finley, 2009; Holtzclaw et al., 2002; Trendle, 2019; Whelan et al., 2010). Higher transit accessibility and higher active travel friendliness or accessibility are associated with lower car ownership rates (Trendle, 2019; Whelan et al., 2010). Higher job accessibility (by all modes) from a census tract is associated with lower rates of vehicles per person in that tract (Gao et al., 2008).

Due to high multicollinearity issues between built environment characteristics when aggregated within spatial units of various sizes, no other aspect of the built environment (e.g., diversity, design) was included in the reviewed studies.

3.4.1.3 Summary of variables used in spatially aggregated models

Sociodemographic variables used in spatially aggregated models reviewed are summarized in Table 3.4, and built environment variables in Table 3.5. Sociodemographic variables have mixed effects, while built environment variables (based on how they are computed in the reviewed studies) are always negatively associated with car ownership rates.

Table 3.4 Sociodemographic variables used in spatially aggregated models of car ownership

Variables	Correlation with average zonal car ownership rates	
	Negative	Positive
SOCIODEMOGRAPHICS		
Average HH or adult income		(S. Clark, 2007; S. Clark & Finley, 2009; Gao et al., 2008; Holtzclaw et al., 2002; Trendle, 2019; Whelan et al., 2010)
% non-English speaker	(Trendle, 2019)	
% Western European		(Whelan et al., 2010)
% Asian	(Whelan et al., 2010)	
% of adults with a bachelor's degree	(Gao et al., 2008)	(Trendle, 2019)
% aged 65+		(Trendle, 2019)
% aged 17-30	(Whelan et al., 2010)	
HH size	(Gao et al., 2008) ^a	(Holtzclaw et al., 2002; Trendle, 2019)
% of 1-adult HH	(Whelan et al., 2010)	
% of 1-adult HH /w children	(Whelan et al., 2010)	
% of 2-adult HH		(Whelan et al., 2010)
Workers / person		(Gao et al., 2008)
Median rent		(Gao et al., 2008)

Note: HH = Household; ^a negative because car ownership is measured in VEH / PERSON (all ages).

Table 3.5 Built environment variables used in spatially aggregated models of car ownership

Variables	Correlation with average zonal car ownership rates	
	Negative	Positive
BUILT ENVIRONMENT		
Population density	(S. Clark, 2007; S. Clark & Finley, 2009; Holtzclaw et al., 2002; Trendle, 2019; Whelan et al., 2010)	
% workers commuting by Transit	(Trendle, 2019)	
Zonal Transit Density / PT Accessibility	(Holtzclaw et al., 2002; Whelan et al., 2010)	
Active travel friendliness or accessibility	(Holtzclaw et al., 2002; Whelan et al., 2010)	
Job accessibility by car	(Gao et al., 2008)	
% of rental housing units	(Gao et al., 2008; Trendle, 2019)	
Distance to downtown		(Klincevicus et al., 2014)
Nb of carsharing stations within 500 m	(Klincevicus et al., 2014)	

3.4.2 Explanatory variables of static disaggregate models

The variables used in disaggregate models of car ownership are much more varied than in aggregate models and can be classified into four categories:

- 1) sociodemographic characteristics (at the individual and household level)
- 2) built environment characteristics (including accessibility measures)
- 3) attitudes (of the survey respondent)
- 4) Other factors (e.g., vehicle cost, parking, commute variable, contextual effects)

Because of the large number of studies, the present review is restricted to studies having been published in the last 25 years (i.e., since 1997), using data from advanced economy countries or cities and where the focus is on *car ownership levels* (i.e., the number of cars). Studies that model vehicle types (e.g., make, vintage, or models) or vehicle purchase transactions, while informative, are not included. Studies jointly modelling car ownership with other mobility tools are presented in section 3.5.2.

The next four subsections present the *association* between car ownership levels and variables classified into the four categories of factors mentioned above. The last section reports evidence of the *causal* influence of some factors on car ownership as demonstrated by studies using structural equation modelling while controlling for residential self-selection or studies modelling *changes* in car ownership levels following changes in built environment characteristics using longitudinal or quasi-longitudinal datasets.

3.4.2.1 Sociodemographic variables

Sociodemographics (sometimes called socio-economic variables) refer to variables describing the household or the individuals within the household. Because most disaggregate models of car ownership use households as modelling units, almost all models in the literature include household-level attributes to control for household composition and socio-economic status (household size, number of workers, number of children, etc.). However, several studies also include individual-level characteristics such as age, gender, race, driving disability, etc., usually included in the models either for the household head or the respondent. Income is generally measured at the household level in travel surveys and is thus considered a household-level variable.

Most sociodemographic characteristics can be regarded as “pure” exogenous variables because the relationship can only go in one direction: the number of children can influence car ownership decisions, but car ownership itself is unlikely to influence the number of children households decide to have (people do not have more kids just to fill-up the purchased minivan). While this is true for *most* variables of this category, it could be argued that *some* sociodemographic variables might be endogenous to car ownership in specific contexts. The **working status** of household members is an example: the number of workers in a household is usually positively associated with the number of cars. However, in areas with little to no alternatives to driving, the accessibility provided by car ownership itself can facilitate the search for a job as well as maintaining that job over time. The same logic can apply to **income**, where owning a car can provide access to higher-paying jobs and thus allow households to increase their income. A third problematic variable is the **number of licensed drivers in a household** or the **ratio of licensed persons** (the number of licence holders divided by household size). Many studies include it as an exogenous variable (M. Adjemian & Williams, 2009; Anowar et al., 2016; Ding & Cao, 2019), even stating it to be the primary determinant of the number of cars owned (e.g., H. S. Kim & Kim, 2004). Including this variable could lead to endogeneity bias: the same unobserved preferences for car ownership might be correlated with preferences for driver’s licensing within the household. Furthermore, the influence might be bidirectional: the number of licensed drivers in the household can influence the number of cars owned, but the number of vehicles itself can also influence licensing decisions. A young adult living with their parents might be more inclined to obtain their license if their family owns multiple cars than if they own zero or one. The same endogeneity applies to the presence of an immobile person (someone who did not travel on the survey day) in the household, a variable used, for example, by Anowar et al. (2016). No studies reviewed for this thesis modelled those variables as endogenous to car ownership. Some studies employed another approach to incorporate sociodemographic variables in their car ownership models. For example, Van Acker et al. (2014) factor analyzed various household characteristics to obtain “stage of life” variables. In their model, older working families and young families were associated with higher car availability, while students living at home were associated with lower car availability.

Effect of individual-level variables

The **gender** of the respondent (or household head) is often, but not always, significant. Some studies in the US and the UK found that a woman respondent or “head of household” is associated with lower household car ownership levels than if the respondent or household head is a man (e.g., Xinyu Cao et al., 2007a; J. Dargay & Hanly, 2007; Ding & Cao, 2019), while others (Moody & Zhao, 2019; Van Acker & Witlox, 2010) found no statistically significant effect of gender. In W. Zhang et al. (2020) studies, it ranks as the second least influential variable. Anowar et al. (2016), using data from Montréal, captured gender effects by including the number of men in the household, which was significant and positively associated with higher car ownership levels. However, as Xinyu Cao et al. (2007a) explained, because a women respondent in their sample was associated with being lower income, having a smaller number of workers and a smaller number of driving-age members, it is likely capturing some of the effects of those characteristics plus some other unobserved effects.

Age is sometimes included as an individual variable where the value for the respondent (or household head / oldest household member) is included. The variable is often included as a continuous variable which assumes a linear-in-parameter relationship with car ownership in most models. In such cases, it is reported that car ownership either increases with age (e.g., M. Adjemian & Williams, 2009; Ding & Cao, 2019) or decreases (Xinyu Cao et al., 2007a, 2007b; Van Acker & Witlox, 2010). However, this linear-in-parameter assumption is likely invalid due to a life-cycle effect where car ownership level follows a bell-shaped curved where car ownership is highest in midlife (Klein & Smart, 2017; Papu Carrone & Rich, 2021). Thus, those opposite effects when using a continuous age variable might be explained by the year of data collection (and therefore, which generation qualifies as “old”), the country or region surveyed, and the representativeness of the survey sample (Was it a survey primarily of commuters? Was it a representative large-scale travel survey?) To control for that lifecycle effect, some studies also included age squared as an explanatory variable (Macfarlane, Garrow, & Mokhtarian, 2015; Weinberger & Goetzke, 2010).

Several studies reported evidence of this life-cycle effect. W. Zhang et al. (2020), using data from Beijing, report threshold effects of age where car ownership probability increases up to 35 years old, stays high until about 65 years old and then goes down. This is similar to Anowar et al. (2016), who reported that middle-aged households (average age of household members between 30 and

60) had a higher propensity for car ownership compared to younger and older households. Papu Carrone and Rich (2021) in a pool dataset of repeated cross-sectional travel surveys in Denmark with data from 2007 to 2017 defined those aged 48 to 57 as the reference category. For those younger than 48 years old, they report negative correlation for owning 1 and 2+ cars. For those aged 58 to 67 and 68 and above, they have a higher probability of owning one car, but a lower probability of owning two or more cars. Klein and Smart (2017)'s 13 years of panel data analysis confirm that car ownership peaks in midlife (40-60) but also exhibit generational (“**cohort effects**”) trends discussed further below in the section 3.4.3.3. This is also evidenced in true panel data studies (B. Clark, Chatterjee, & Melia, 2016; Klein & Smart, 2019)

Race is sometimes included in modelling conducted with US datasets. White/Caucasian is associated with higher car ownership levels even when income is included (Ding & Cao, 2019; J. Y. Guo & Bhat, 2007; Klein & Smart, 2017; Potoglou & Susilo, 2008). M. Adjemian and Williams (2009) obtained more nuanced results by using specific dummies for African Americans, Hispanic and Asian “heads” of households in an MNL model. Being African American was not significant for all car ownership levels, Asian was negative for three and four or more cars, while Hispanic was negative for two and four or more cars. However, all race dummy variables became not significant when neighbourhood-level variables (% of each race) were included. In Goetzke and Weinberger (2012)'s study, only Asian and Hispanic households were associated with lower car ownership (binary) relative to white households when neighbourhood-level sociodemographic were included.

Education is seldom included. When it is, it can be nonsignificant when income is also controlled for (e.g., Van Acker & Witlox, 2010). B. Clark, Chatterjee, et al. (2016) found that in the UK, higher education was associated with a higher propensity for owning one car but not two or more. In Beijing, however, the variable ranks as the 7th most influential out of 18 in W. Zhang et al. (2020)'s gradient-boosting decision tree model, and has a slight positive association with car ownership. In Norway, when income was included, **higher education** was associated with higher car ownership levels in a medium-sized city (Stavanger) but associated with lower car ownership in a large city (Oslo) (Næss, 2016).

Effects of household-level variables

The importance of income: One of the most important variables influencing household motorization is **income**. Some concluded that it is the most influential variable in their models (e.g., Zegras, 2010). W. Zhang et al. (2020) estimate the relative influence of income at 31.1 % in their gradient-boosting model. Despite its importance, this variable is not always included because of its unavailability in many datasets (e.g., Anowar, Yasmin, et al., 2014; Caulfield, 2012; Yamamoto, 2009). Its omission violates the assumption that essential variables are present, calling into question the validity of all other variable coefficients obtained without its presence. Even when income is measured, it tends to have a large proportion of non-responses. If that proportion is not excessive, one method is to remove all observations without income (e.g., Zegras, 2010). However, this approach is valid only when data is missing completely at random (MCAR) since it can otherwise bias regression and correlation coefficient estimates (van Buuren, 2018). Income is unlikely to be missing completely at random. If income is treated as categorical, an alternative is to create an “unknown” income category. This approach was used, for example, by Potoglou and Kanaroglou (2008), who had 40 % of non-response for income. A more sophisticated method is to use multiple imputations to fill in the missing responses, as Becker et al. (2017) did with a Swiss dataset. Any analysis of car ownership using income as an explanatory variable should be considered suspicious if the treatment of missing values is not detailed.

In the absence of income, some authors used the neighbourhood’s income level. This is the method used by Anowar et al. (2016), lacking access to the income variable from the Montréal Origin-Destination Surveys (1998, 2003, 2008), who used the median income of census tracts (CTs) according to an arbitrary three-level classification (low = < \$40,000/year, medium = \$40,000 to \$80,000/year, and high = >\$80,000/year). Such a strategy comes with a significant loss of information and could be problematic if the areal units used for aggregation have considerable income disparities. Recognizing that such a technique is common in epidemiology studies, M. Adjemian and Williams (2009) specifically tested the validity of using census aggregate variables when household-level variables are missing for car ownership modelling. The variable tested were income, household size, age, race composition and unemployment. They concluded that for income, household size and age, census data proxies aggregated at the smallest possible unit tested (i.e., the block group of the American census) offer reasonable approximation for household-level parameters in terms of sign and significance. It even performs better in terms of predictive power than the model using survey data only, which might be explained by the presence of neighbourhood

(or “contextual”) effects. Indeed, in a first MNL model containing *both* census proxies and household-level variables, income was the only variable with significant coefficients for all car ownership levels (0 (Ref), 1, 2, 3, 4+) for both the block-group median income and individual household income. As individual and neighbourhood income increases, so does the likelihood of owning more cars. Contextual neighbourhood effects on household car ownership are specifically investigated by Goetzke and Weinberger (2012) and Paleti et al. (2013) and discussed further below.

In short, M. Adjemian and Williams (2009)’s results suggest two things: 1) neighbourhood effects on car ownership should be further investigated (contribution 1 of this thesis) and using census-level data as a proxy for income is acceptable (contribution 3 of this thesis) if the variable is in the same unit (e.g., ‘000 \$ / year). Care in interpreting the results is nonetheless recommended.

Effect of income: All else being equal, higher income is associated with a higher number of vehicles owned by households (M. Adjemian & Williams, 2009; de Abreu e Silva et al., 2012; Z. Guo, 2013a; H. S. Kim & Kim, 2004; S. H. Kim & Mokhtarian, 2018; Macfarlane et al., 2015; Moody & Zhao, 2019; Paleti et al., 2013; Potoglou & Susilo, 2008; Zegras, 2010). However, many studies show that the relationship is not linear. Whelan (2007)’s results from his third dogit model indicate that income is not significant when choosing between three or more cars and two cars for households having two or more cars. Interactions between income and household types show that income influences the probability of having a third car only for households with 3+ adults. Whelan’s results are based on data from the United Kingdom. In the US, Bhat and Pulugurta (1998)’s MNL results indicate that income was significant only for owning 2+ cars but not one (ref = 0). This suggests that car ownership is a necessity for most, even the lowest-income households. Using data from Hamilton, Canada and separating income levels into arbitrary categories (low, middle, high), Potoglou and Kanaroglou (2008) show that medium income increases the likelihood of owning one car relative to low income and that high income increases the likelihood of owning two vehicles, but not one and not three (not significant). Their “unknown income” category had no significant effect relative to low income. The likely explanation behind Whelan (2007) and Potoglou and Kanaroglou (2008)’ results is that wealthier households would buy more expensive vehicles, not more vehicles (e.g., the gain in utility, for a high-income couple, of adding a third or fourth vehicle is marginal). Results from the US, where car ownership rates are higher, might be different.

Income as moderator of built environment variables: When tested in interactions with built environment variables, some found that it can **moderate** their effect on car ownership. This was already demonstrated using aggregate modelling methods (e.g., S. Clark, 2007; S. Clark & Finley, 2009; Trendle, 2019). Disaggregate models can provide further insight on which specific variables are moderated by income. For example, Bhat and Guo (2007) found that low-income households located in high-employment areas are much more likely to be car-free than wealthier households.

Wealth was only found to be included in Klein and Smart (2017, 2019)'s studies. It had an independent effect from income. All households above the lower quintile (20%) had higher levels of car ownership (cars / adult), but the relationship was not linear. Going up the quintile ladder (from 2nd to 3rd and so on), the difference diminished. This suggests a similar effect as income: at some point, there simply is a saturation in car ownership, and additional wealth beyond a certain threshold does not have as strong an effect on the number of cars owned.

In almost all studies where it is included, **household size** positively influences car ownership (e.g., M. Adjemian & Williams, 2009; Xinyu Cao et al., 2007a; H. S. Kim & Kim, 2004; Moody & Zhao, 2019), but sometimes only for the probability of owning a second car, not the first (Z. Guo, 2013a). However, household size appears insignificant when other variables capturing the number of specific household members are included, such as the number of part-time and full-time workers, suggesting that the number of children would have little influence on car ownership (Bhat & Pulugurta, 1998). In addition, larger households, if they own more vehicles, would have a lower probability of being saturated (at least one vehicle per adult), as they allow for greater sharing of vehicles among members, thus reducing the need for a vehicle for each adult (Delbosc, 2013).

The **presence** or the **number of children** seems to have no effect or ambiguous effects depending on which other household composition variables were included. Some found positive effect (J. Dargay & Hanly, 2007; Jiang et al., 2017; Macfarlane et al., 2015; Papu Carrone & Rich, 2021). However, Bhat and Pulugurta (1998) concluded that the presence of non-adult in the household was not significant when the number of working and non-working adults were included. H. S. Kim and Kim (2004) and Potoglou and Kanaroglou (2008) also found that the presence of children was not significant both for single parents and two-parent households. Zegras (2010) found variable effect depending on the number of children. Having one to three children increased the likelihood of owning one car compared to none, was not significant for owning two cars and decrease the

probability of owning three or more cars. Having four or more children increased the probability of owning two cars. Anowar, Yasmin, et al. (2014) found consistent negative effects of the number of children on car ownership across their four tested models (traditional OL and MNL, Latent-class OL and Latent-class MNL). Curiously, the variable was negative even for the probability of having one car instead of none in their MNL models. The explanation provided is that raising children is expensive and reduces the available income left for more cars. In a subsequent study using Montréal large-scale OD survey data, Anowar et al. (2016) tested the presence of children of various ages. Children between 5 and 14 years old had positive influence on the propensity for car ownership while the presence of teenagers (15-19) had no statistically significant effect. With slight differences in the age range, B. Clark, Chatterjee, et al. (2016) found that young children increased the propensity to have one car versus zero or none but having teenagers had not statistical significance on owning one versus no car. The number of young children (≤ 6 years old) ranks as the least influential variable out of 18 in W. Zhang et al. (2020)'s model.

Household composition often refers to the life-cycle stage of the household. The household typology used to express composition varies widely between studies. The categories are often based on the number of adults, presence of children (Potoglou & Kanaroglou, 2008; Whelan, 2007) and sometimes include the status of household members (retirees or workers) (H. S. Kim & Kim, 2004; Zegras, 2010). Beyond the obvious results that single-person households (with or without children) generally have fewer cars than larger households, other results are more divergent.

The **status of household members** is commonly used (number of full-time workers, part-time workers, number of students, etc.). The effect of the **number of full-time workers** is usually as expected: it increases the propensity for higher car ownership (Bhat & Guo, 2007; H. S. Kim & Kim, 2004). When a multinomial logistic model is used, results indicate that the variable influences the probability of owning two or more cars versus none but has no impact on owning one versus no car (Anowar et al., 2016; Bhat & Pulugurta, 1998; Potoglou & Kanaroglou, 2008). Encouragingly, Anowar et al. (2016) found that the impact diminishes over time (between 1998 and 2008). An exception is Van Acker and Witlox (2010), who found no effect of full-time employment on their individual-level car availability factor. M. Adjemian and Williams (2009) found no statistically significant effect of having one household member unemployed on owning one or two cars versus none and a negative effect on three or four car ownership probabilities.

The influence of the number of **part-time workers** is more ambiguous. Some found that the probability of having 1 or 2 vehicles versus none decreases with the number of part-time workers (Anowar, Yasmin, et al., 2014; Potoglou & Kanaroglou, 2008), while Anowar et al. (2016) and Bhat and Pulugurta (1998) obtained the opposite effect (i.e., positive association with car ownership).

Summary

In summary, sociodemographic variables are often considered the most important category of factors influencing car ownership. Their presence in models is crucial to understand the behavioural mechanism shaping household decisions. For this reason, they are often considered as “control” variables to ensure they do not confound the relationship between built environment characteristics and car ownership. Failure to control for their effect in car ownership models could lead to seriously biased estimates for built environment characteristics. One rare exception is Caulfield (2012), who estimated two separate MNL models: one with sociodemographic variables only and the other with built environment variables only.

In terms of **effect size** or **relative influence**, many studies concluded that sociodemographic attributes play a more important role than built environment features in explaining household car ownership levels (e.g., Bhat & Guo, 2007). Using Gradient-boosting decision trees which can estimate the relative importance of explanatory variables, W. Zhang et al. (2020) concluded that sociodemographic variables have a combined relative influence of 62.4 % while built environment variables collectively explain 37.6 % of household car ownership decisions. The relative influence refers to the variable’s capacity to reduce the loss function relative to the other variables in the model. It is usually normalized to sum to 100 % for all included variables.

3.4.2.2 Built environment and accessibility variables

Built environment characteristics at home location

A common and “crude” way to account for the built environment is to include dummies that define the type of environment (urban, suburban, rural). Unfortunately, there is often no information provided on the characteristics of each type of environment (e.g., Bhat & Pulugurta, 1998; Potoglou & Susilo, 2008) or only density (Whelan, 2007) or population threshold values (B. Clark, Chatterjee, et al., 2016). Furthermore, when nationwide datasets are used, researchers often include

dummy variables indicating if the household lives in a large metropolitan area (B. Clark, Chatterjee, et al., 2016; H. S. Kim & Kim, 2004; Papu Carrone & Rich, 2021; Weinberger & Goetzke, 2010; Whelan, 2007). With exceptions for some large car-oriented US metropolitan areas (e.g., Dallas, Los Angeles, Atlanta) in H. S. Kim and Kim (2004)'s analysis, dummy variables for metropolitan areas are always associated with lower car ownership propensities, even when other built environment variables are controlled for. Neighbourhood dummies have also been included, for example, by Anowar et al. (2016) in Montréal, to capture potential unobserved effects (e.g., higher environmental consciousness).

Otherwise, most studies included one or more of the five “D” variables of the built environment as described by Ewing and Cervero (2010): **density** (population and employment), **diversity** (of land-use or business types), **design** (street network), **destination accessibility** (local accessibility to nearby opportunities, regional accessibility captured as distance to central business district or number of accessibility reachable by various modes) and **distance to transit** (distance to the nearest bus or rail stop, or density of stops within zones). The impact of the D's and their numerous variants are further discussed.

Population or household density is the most common variable “D” by far. Its impact is almost always as expected: higher density is associated with lower car ownership levels (e.g., M. Adjemian & Williams, 2009; Anowar, Yasmin, et al., 2014; Ding & Cao, 2019; Potoglou & Susilo, 2008; Zegras, 2010). However, its impact can be marginally significant on car ownership when some other built environment variables are included, as demonstrated by Bhat and Guo (2007). A finding similar to Ewing and Cervero (2010)'s meta-analysis results for travel behaviour. The reason is simple: density is usually highly correlated with many other built environment variables. Van Acker and Witlox (2010) used a “built-up index” (% of the built-up surface within the census tract) as a proxy for density. They found it was negatively associated with their individual-level car availability factor. Population density was also found not to be significant when spatial dependence is controlled for (Goetzke & Weinberger, 2012).

Employment density is not as common as residential density but is nonetheless impactful on car ownership when included. Higher employment density at home location is associated with a lower propensity for car ownership (Ding & Cao, 2019; W. Zhang et al., 2020). In Bhat and Guo (2007)'s results, it is marginally associated with lower car ownership levels but also displays important

heterogeneity in its effect on car ownership due to unobserved factors. Potoglou and Kanaroglou (2008) report that a **mixed density index** of employment and population density performed better than the two types of density included individually in their model. Higher mixed density is associated with a lower probability of owning two or three plus cars but has no effect on owning one car versus zero.

Various indices of **land-use diversity** are used. While the type of input land-use categories and computation methods vary, a higher value means more diversity and is associated with lower levels of car ownership (Anowar, Yasmin, et al., 2014; Ding & Cao, 2019; Potoglou & Kanaroglou, 2008; Zegras, 2010). Potoglou and Kanaroglou (2008) found it was only significant with lower probabilities of two and three and more cars, but not one. As an alternative and less common way of measuring density, Xinyu Cao et al. (2007a) used the number of different types within a 400 m radius around each household which was negatively associated with the propensity for car ownership. Anowar et al. (2016) used the surface area of commercial land-use and institutional land use (separately), with their results suggesting that both are negatively associated with car ownership. Jiang et al. (2017) found it was not significant when attitudes were included in the model.

Design variables appear to be the least commonly used in car ownership modelling despite evidence from travel behaviour research that it has the second-highest association with vehicle-kilometres travelled (Ewing & Cervero, 2010). Among the tested design variables, we note that higher **street-block density** (Bhat & Guo, 2007) or **smaller block size** (Ding & Cao, 2019) are correlated with a lower car ownership propensity, while higher **4-way intersection density** reduces the likelihood of owning two or more cars (Zegras, 2010). M. Adjemian and Williams (2009) used the mean age of homes in the census tract or block group. While it is not a street network design *per se*, the variable is likely correlated with the street layout. Newer homes were associated with higher car ownership levels.

Transit accessibility and availability: In most models, higher access to transit have a statistically significant and negative influence on car ownership propensity. Many variables with disparate levels of precision in capturing the effect of transit on car ownership have been used.

Specifically, as the **distance to the nearest bus stops** increases (Bhat & Guo, 2007; H. S. Kim & Kim, 2004) or the **distance to the nearest rail station** (Van Acker & Witlox, 2010), so does car

ownership propensity. According to W. Zhang et al. (2020), car ownership probability increases quickly beyond a distance of 0.4 km from a bus stop and 1.2 km from a Metro station. A caveat in the results is that their study did not include precise household coordinates but instead used the local neighbourhood centroid to compute those distances. In New York City, (Z. Guo, 2013a) found that distance to rail only increased the probability of car ownership for households with access to off-street parking. Surprisingly, for those with only on-street parking, the variable was found not significant.

The presence of a **metro station** in the Transport Analysis Zone (Ding & Cao, 2019) or the length of metro lines in the Euclidean buffer (Anowar et al., 2016) is also associated with reduced propensity for car ownership. However, in Zegras (2010)'s analysis, metro station availability in the zone only decreases the probability of owning two or more cars but was not significant for the first car. The **number or density of bus stops** within the zone or buffer also decreases the propensity for car ownership (Anowar et al., 2016; Ding & Cao, 2019) while Potoglou and Kanaroglou (2008) in Hamilton, Canada, found only a negative influence on owning three or more cars and S. H. Kim and Mokhtarian (2018) found it only affected the second car.

A **transit accessibility index**, which included access distance and level-of-service, was used by Anowar, Yasmin, et al. (2014) in Québec City as segmenting variable in their Latent-class choice models. The variable was associated with higher probabilities of belonging to the “transit-friendly” segment, which owned fewer cars than the “transit independent” segment. In Goetzke and Weinberger (2012)'s study, the transit accessibility measure became not significant when contextual and endogenous spatial effects were included in the models.

Zegras (2010)'s model also included a **car-to-bus accessibility ratio**. The higher the ratio, the higher the probability of car ownership. Papu Carrone and Rich (2021)'s results indicate that **accessibility by car** has no statistical association with car ownership, but **accessibility by public transit** was associated with a lower car ownership propensity. Those results suggest that what really matters is how competitive public transit is in accessing destinations relative to the car.

Regional accessibility is often simplistically measured as the distance to the central business district (CBD) or second-order centre. In Europe, regional accessibility is reported to play a critical role in car ownership decisions (Xinyu Cao et al., 2019; Van Acker & Witlox, 2010) while W.

Zhang et al. (2020) found that local accessibility measures were more influential than the distance to regional centres of various sizes.

Local accessibility: W. Zhang et al. (2020) used the **density of retail and service facilities** within a 1 km buffer. The variable ranks as the second most influential on car ownership levels after income. It also shows a clear threshold effect: the number of cars owned drops rapidly between 65 and 145 establishments per square kilometre, after which no further effect is observed. B. Clark, Chatterjee, et al. (2016) was the only study found using **accessibility to food stores**. In their model, it was one of the rare included built environment variables to have a statistically significant effect on car ownership. It is associated with an increased probability of living without a car versus owning one or more cars but has no impact on the number of vehicles for car-owning households.

Built environment characteristics at work location

Most exogenous static car ownership models assume that long-term decisions, such as residential choice, precede medium-term decisions about car ownership. The same assumption could be made about work location. However, only a few studies investigated the impact of the built environment at work locations on household car ownership decisions. Intuition would suggest that if someone works in an area that is not easily accessible by other means than the car (e.g., an industrial park located on the edge of town and poorly served by transit), that might play an important role in that person's household decision to own cars even if the residential built environment suggests otherwise. A rare example is a recent analysis by Ding and Cao (2019) using a Bayesian cross-classified multilevel ordered Probit model with data from Washington DC metropolitan area. Their results suggest that built environment characteristics at the home location are more important than those at work locations, but some key attributes of the work location are nonetheless important. Among the work location variables tested, **land use mix**, **average block size (design)**, **metro station availability** and **residential density** were insignificant, while three were significant: **employment density**, **bus stop density** and **distance to CBD** were associated with lower levels of car ownership. The result is intuitive for employment density and bus stop density but counterintuitive for distance to CBD. The author's hypothesis and common intuition were that work locations farther from downtown would be associated with a higher propensity to own more vehicles. Ding and Cao (2019) do not explain this curious finding, suggesting that further studies are needed in different metropolitan areas to shed light on this relationship. An important caveat

of their studies is that while car ownership is modelled at the household level, only the work location characteristics of the respondent are included in their model.

Another example is the work by de Abreu e Silva et al. (2012), which also included some characteristics of the built environment at the work location. In their SEM, a description of the built environment was included as the result of factor analysis of several built environment attributes. In short, working in a “**central, denser and accessible area**” or a “**mixed and compact zone**” negatively influences the number of cars owned.

Summary

This review suggests that most built environment variables can be found significant in at least one study. Some variables are more commonly included (e.g., density, diversity, access to transit) than others (e.g., local commercial accessibility, design, regional accessibility). However, it remains very difficult to draw conclusions about the significance and the sign of the correlation with car ownership due to vast disparities in the way the variables are calculated (within household-specific buffers? Of what size? Within zones? In which context?), what car ownership representation was used (ordered, unordered) and more importantly, what other variables were controlled for? This latter point is a critical issue prohibiting the clear assessment of impacts. Population density will often be found statistically significant on car ownership propensity, but not when more “precise” variables such as accessibility measures are included. A more exhaustive review of the impact of the built environment on car ownership should focus on studies employing robust methodologies that test for a wide variety of variables, controls for key sociodemographic characteristics, notably income, and use large-scale representative travel surveys. Furthermore, most studies reported so far did not control for residential self-selection, which might further confound the results. We turn to those next.

3.4.2.3 Impact of the built environment after controlling for residential self-selection

Does the built environment still impact car ownership decisions once attitude-based residential self-selection is controlled for?

Mokhtarian and Cao (2008) reviewed eight methods for controlling for attitude-based residential self-selection. One is qualitative, five are quantitative cross-sectional analysis, and two are longitudinal. The present section focuses on the evidence from cross-sectional studies controlling

for residential self-selection. The methods employed are only mentioned, and readers can refer to Mokhtarian and Cao's review to understand how they work.

Evidence of how changes to the built environment lead to changes in car ownership obtained from longitudinal or quasi-longitudinal methods are described in section 3.3.2.3.

Evidence from models with direct statistical control

Xinyu Cao et al. (2007a) used two methods to test if BE still influenced car ownership when attitude-induced RSS was controlled for. In the first method, they used direct statistical control by including residential and travel attitude variables (factor scores from a factor analysis) in a cross-sectional ordered probit model of car ownership. In the model without attitudes, the perceived outdoor spaciousness of the neighbourhood and an objective measure of diversity (number of business types within 400 m) were significant and negatively correlated with car ownership. When attitudes were included, both variables became insignificant. The authors argue that from this perspective, RSS explains much of the difference in automobile ownership. However, results from the second method using a quasi-panel approach point toward some effects of BE on car ownership. Details are presented in the section 3.4.3.2. In a subsequent study, J. Cao and Cao (2014) concluded, using a cross-sectional model, that a higher job density remains significant and negatively affects car ownership when RSS is controlled through the inclusion of attitudes in the model.

Evidence from joint discrete-choice models

Bhat and Guo (2007) used a joint modelling of car ownership and residential choice that accommodates heterogeneous sensitivity to the built environment arising from observed and unobserved characteristics to control for residential self-selection. Their results suggest important sociodemographic effects in the residential choice process, with income being the dominant factor. They conclude that failing to control for sociodemographic that also influence residential choice when modelling car ownership can lead to inflated built environment effects. With some caveat, they concluded that there are no statistically significant unobserved correlated effects between both decisions and, thus, that independent models of residential choice and car ownership that control for sociodemographic can be used to estimate the "true" effect of built environment characteristics on car ownership. However, as Mokhtarian and Cao (2008) pointed out, Bhat and Guo's method

is robust in the absence of attitudinal variables. However, there is only so much information that can be squeezed out of survey data without moving unobserved variables to the observed realm. Their model confirms that **population density, employment density, street-block density, availability of transit in the zone** and **shorter distance to bus stops** are negatively associated with car ownership when controlling for RSS using their method.

More recently, Mulalic and Rouwendal (2020) developed a joint model of residential location choice and car ownership to evaluate the impact of built environment characteristics, notably the role of Copenhagen's metro system. Both decisions are treated as simultaneous, and the model is applied to a high-resolution disaggregate administrative dataset with a very large sample size (20 % of the area's population). Using scenarios, the model is then used to assess the impact of a new circular metro line in the city centre (18 stations) that opened in 2019. The model predicts housing prices, neighbourhood sociodemographic composition and car ownership. Under the fixed supply and variable price housing scenario, the number of cars within the entire modelled region would be reduced by 2.6 %, with a higher reduction coming from two-car households reducing to one (3.1 %) than from one-car households reducing to zero (-2.3 %). In short, the model does not only account for changes in car ownership of those already living near the metro but also of people moving into the catchment area and reducing their car ownership. Those metropolitan-level aggregate results that control for residential choice thus confirm an important negative effect on household car ownership of a critical built environment characteristic: **access to a city's metro network**.

Evidence from cross-sectional structural equation modelling

Modelling the structural relationships between lifestyles, neighbourhood characteristics and car availability, Van Acker et al. (2014) concluded that built environment characteristics such as density, good local accessibility and proximity to regional centres still lead to lower car availability when attitudes and lifestyles were controlled for. They also point to the importance of controlling for residential self-selection through residential and travel and mode-related attitudes because these have important impacts on residential location decisions.

Abreu e Silva et al. (2012) demonstrated using a structural equation model of four categories of endogenous variables: land-use characteristics at home and work location, commuting distance, car ownership and short-term travel behaviour that the type of built environment at both work and

home location had a direct effect on car ownership. Specifically, living and working in dense, mixed-used and accessible areas negatively influenced the number of cars. Their model, however, *did not* control for attitudes in the choice of home and work locations.

3.4.2.4 Impacts of attitudes and other psycho-sociological factors

In social psychology, “attitude” is a psychological construct that represents the evaluation of something (an object, a behaviour, a person, a group, an issue, an idea, etc.) ranging from negative to positive (APA, 2022). They have been increasingly used in transportation research to enhance our understanding of travel behaviour (Kroesen & Chorus, 2018). As described in the section 3.2.4, attitudes toward travel, specific modes, and residential characteristics have been commonly used to control for *residential self-selection* (RSS) when measuring the effect of built environment characteristics on travel behaviour. However, as explained by Bohte et al. (2009), because their use in the field is relatively new, attitudes have varied substantially in their types, in the ways they are measured and in how they are included in modelling frameworks of various travel behaviours. This is unlike the field of social psychology, where their use is much more mature, and measurement methods are standardized. For example, measuring specific attitudes toward a particular behaviour relies on validated scales (e.g., Ajzen, 2002). A “scale” refers to a set of items or statements often measured using Likert scales that, grouped, form a latent construct. A scale is validated when it has been tested independently and presents high internal consistency, i.e., the items are consistent toward one another and measure various aspects of the same underlying construct. Kroesen and Chorus (2018) argue that including and testing for the causal influence of attitudes on behaviour presents a fatal dilemma. If the measured attitudes are too general, they are relatively exogenous to the behaviour of interest but only correlate loosely with it. If the attitudes are too specific to the behaviour, they correlate highly with it but are likely endogenous to the behaviour. In both cases, the causal mechanism might be impossible to demonstrate.

In a subsequent study, Kroesen (2019), echoing previous scholars (Chatman, 2009; Næss, 2009), criticizes the use of attitudes as direct statistical control for residential self-selection. The main issue is that if attitudes influence both residential choice and travel behaviour (including car ownership), it is very likely that both also influence them. In his study, Kroesen (2019) specifically demonstrated using longitudinal data that the built environment causally influences travel-related residential preferences (i.e., the importance people give to accessibility to transit, highways, their

workplace, and local shops when choosing a residential location). However, he concludes that mode-specific attitudes that are *not* reasons for residential location shouldn't have, in theory, this endogeneity bias.

Despite those caveats about their use in travel behaviour, it remains relevant to analyze *which* attitudes have been included in car ownership modelling and *how* these attitudes affect household decisions regarding the number of cars to own.

Residential attitudes

In their SEM model of lifestyle, built environment, car ownership and attitudes, Van Acker et al. (2014) showed that positive **residential attitudes toward open space and quietness** (typically associated with more suburban and rural settings) lead to higher car availability (their outcome variable is a composite measure of household car ownership, driver's licencing, public transit pass and access to the household car) while a positive **desire for higher local accessibility** leads to lower car availability. In Xinyu Cao et al. (2007a)'s cross-sectional model, positive **attitudes toward "outdoor spaciousness"** is associated with a lower propensity for car ownership. In comparison, positive **attitudes toward accessibility** are associated with a lower propensity for car ownership.

In J. Cao and Cao (2014)'s cross-sectional model, having preferences for a **"large backyard"** and a **"lots of off-street parking"** is positively associated with car ownership, while preferences for **"easy access to transit stop/station"** is negatively associated. However, in their quasi-longitudinal model of movers, those neighbourhood preferences were not statistically significant on the change in car ownership following the move.

General travel attitudes

Regarding general travel attitudes, having pro-environmental attitudes about travel was associated with lower car availability. In contrast, those feeling **normative pressure to reduce car** use had a higher car availability score (Van Acker et al., 2014).

Xinyu Cao et al. (2007b) included general travel attitude factors in their quasi-panel SEM of car ownership and use. However, the included general travel attitudes (travel minimizing and accessibility) had no impact on changes in car ownership following a residential relocation. Jiang

et al. (2017) also found no statistical impact of travel-minimizing preferences on the choice of one car and two cars versus zero.

Car and other modes-related attitudes

In terms of specific car-related attitudes, Van Acker et al. (2014) found that perceiving the car as comfortable was associated with higher car availability, but the perception of negative consequences of the car was *not* significantly associated with car availability. Xinyu Cao et al. (2007a) found that the perception of **dependency upon the car for daily activity** and **high safety concerns toward alternative modes** were positively associated with car ownership. Overall, Xinyu Cao et al. (2007a) concluded that residential preferences and travel attitudes collectively play an important role in car ownership decisions, but that observed sociodemographic remain dominant. J. Cao and Cao (2014) showed that, on the one hand, having **pro-driving attitudes** is positively associated with the propensity for car ownership, but the variable is barely significant. On the other hand, having **pro-transit attitudes** negatively affects the propensity for car ownership and is highly significant. However, in their quasi-longitudinal model of movers, both mode-specific attitudes had no effect on the change in car ownership following the move. In their other study using the same dataset, this time in a SEM of car ownership and car use, Xinyu Cao et al. (2007b) show that a latent attitude factor they named **car dependent** had no influence on changes in car ownership following a relocation, only a positive influence the changes in VKT. Jiang et al. (2017) found that those with a **preference for cycling** and **transit** had a lower propensity for owning two cars compared to zero, but the variable had no influence on the first car.

Moody and Zhao (2019) developed a reliable scale of 12 items to measure “car pride” as one component of the symbolic aspects of cars. They define **car pride** as “the attribution of social status and personal image to owning and using a vehicle” (p. 334). Some of their results were already introduced in the section 3.2.4. In short, with a robust method to test the significance of both directions of influence (car pride $\rightarrow$ CO and CO $\rightarrow$ car pride), they show that (1) individual car pride significantly and substantially influences household car ownership, (2) that as previously mentioned, car ownership does not seem to influence car pride directly, (3) that car pride has a larger impact than most included household and individual level sociodemographic, including income and (4), that car pride has a more substantial influence in Houston, Texas than in New

York City. This latter result suggests that the transportation and built environment context is associated with car-related attitudes such as car pride. In Houston, which has a more car-oriented environment than New York City, people seem to derive more symbolic benefits from owning and using a car. However, they did not control for the within-city built environment context.

Flamm (2009) used a linear regression model to assess the impact of **environmental knowledge** (about the consequences of car use, 7-item scale) and **environmental attitudes** (protecting the environment is worth the economic cost of stricter laws and regulations) on car ownership. Their results indicate that knowledge about the environmental impacts of cars was not significant, but **environmental attitudes** were negatively associated with the number of household cars.

Lifestyles

Van Acker et al. (2014) also showed lifestyle influences on car availability. For example, a **more active lifestyle** and a **lifestyle oriented toward friends** and societal trends lead to higher car availability.

Moderating effects of attitudes

S. H. Kim and Mokhtarian (2018) posited that attitude could moderate the effects of sociodemographic and built environment characteristics on household car ownership decisions. Through a latent-segmentation discrete choice framework, they tried to understand how attitudes induce systematic heterogeneity within the population on the number of vehicles owned. They used three attitudinal factor scores obtained from a factor analysis of attitudinal statements (“pro-transit”, “pro-active-travel” and “pro-(high)density”) in the class allocation model, while sociodemographic and built environment variables were included only in the choice model. They showed that a two-class solution (“auto-oriented” and “urbanites”) offered the best model fit and that the latent-class approach enhanced the behavioural understanding of the choice process. In terms of moderating effects, the “auto-oriented” were quicker to add cars with increased income and increase in the number of workers, while “urbanites” were more sensitive to built environment features, notably density. In fact, density had no statistically significant effect on the “car-oriented”. However, job-housing balance and accessibility to transit stops appeared to have a similar effect on both classes’ car ownership decisions: a lower propensity to own two or more cars.

The role of past residential experience

Some researchers investigated if past residential locations (considered general proxies of lifestyle preferences and travel/residential attitudes) could affect the present residential location and car ownership decisions.

A first example is Weinberger and Goetzke (2010). They explored the impact of the *type* of environment a household lived in before relocating to one of five major US cities (Boston, Chicago, Philadelphia, San Francisco and Washington, DC) on the joint choice of residential location (within central neighbourhoods of the city or not) and car ownership (0, 1, 2+ cars). They used a series of dummy variables to determine if the previous location (in the past 2 to 5 years) was rural, from a metropolitan area or from six “transit-rich” US metropolitan areas (e.g., New York, Boston, Chicago, etc.). Their results revealed that households living in those transit-rich areas before relocating were more likely to choose a central neighbourhood location and less likely to own cars. They were also less likely to own cars even if they selected a location outside the central neighbourhoods. Coming from the central neighbourhoods of those transit-rich cities had an additional negative effect on car ownership. They controlled for a range of sociodemographic characteristics, including income, but not specific built environment attributes nor previous car ownership levels. Nonetheless, this indicates how much previous transport experiences affect car ownership decisions. Specifically, they concluded that “car-free” living is a learned experience, something that people from transit-poor US cities or rural areas might never have learned.

The findings were corroborated by Macfarlane et al. (2015) using a similar method but with more objective metrics to characterize prior residential locations. Instead of coarse dummies for specific types of US metropolitan areas and inner city or outer city living, they used population density and the proportion of workers not commuting by car within the previous ZIP codes in which the household head has lived. Furthermore, unlike Weinberger and Goetzke (2010), they used up to nine previous residential locations in a weighted calculation of “previous exposure”. However, they did not jointly model present residential choice and ownership but focused only on the current number of cars owned (1, 2 and 3+) and only considered car-owning households (the vehicle ownership data came from Georgia’s Department of Motor Vehicle). Macfarlane et al. (2015)’s results indicate that, yes, past residential exposure to density and non-automobile modes both

influence present car ownership. However, they conclude that the effect of past exposure is marginal at the individual level and on the aggregate using various scenarios. This is contrary to Weinberger and Goetzke (2010)'s finding, who observed a substantial marginal effect of past exposure. But again, households without cars were not considered in Macfarlane et al. (2015), which might explain the differential findings.

While no study has ever looked into this, anecdotal evidence suggests that immigrants moving to Montréal from Europe or other countries known to be less dependent on the automobile might also have a lower propensity for car-free/car-light living and a higher tendency to choose central locations conducive to such a lifestyle.

3.4.2.5 Other variables

Commute variables

Based on the assumption that the employment location is exogenous to residential choice and car ownership decisions, Bhat and Guo (2007) included the average commute driving time (minutes) and **commute driving cost (\$)** for all working household members. They show that both variables are important determinants of residential choice and that commute driving time is positively associated with a higher propensity for car ownership and higher driving costs are associated with a lower propensity for car ownership. A result backed by Anowar et al. (2016) in Montréal, who also stated that the effect of the variable has been increasing over time. Considering car ownership and **commuting distance** as endogenous variables, de Abreu e Silva et al. (2012) showed that the greater the commuting distance, the greater the number of cars owned.

The provision of a **company car** (common in Great Britain) was tested by Whelan (2007). Results indicate that for those already having one or more cars, it increases the probability of having 2+ or 3+ cars. This was contrary to his assumption that company cars would replace personal vehicles.

The provision of **free parking at the workplace** was tested and found to be significant and positively associated with car ownership by Ding and Cao (2019). They also found that employees who were provided **van pooling or transit subsidies** were less likely to own cars.

Parking

The influence of residential (off-street) and on-street parking on car ownership is rarely studied. Z. Guo (2013a) reports that only five studies before his have specifically included parking when modelling car ownership. The first reason for this under-investigation is the lack of residential off-street parking data in travel surveys often used to model car ownership. The other difficulty stems from the endogenous relationship between parking supply and car ownership: it is likely that households choose a home that accommodates their (current or desired) level of car ownership. Unobserved preferences for car ownership might also be correlated with unobserved preferences for specific types of homes that usually come with parking or not (e.g., single-family homes versus multi-apartment buildings). This means that the association between car ownership and parking is not too hard to demonstrate but demonstrating that parking supply has a *causal effect* on car ownership is much trickier.

As for the impact of **on-street parking**, population density, street-block density, and the average age of homes can be considered proxies for on-street parking supply. However, Z. Guo (2013a) argues that aggregate or proxy measures of on-street parking supply near the home may lead to an underestimation of the effect of parking on car ownership and the inability to draw policy recommendations. Indeed, because on-street parking is affected by a wide variety of regulations (time limits, street cleaning, parking permits cost and other factors), it remains difficult to estimate with precision the level of constraints or easiness in finding parking nearby.

To address those issues, Z. Guo (2013a) used a random sample of about 770 households from the large-scale New York Metropolitan Transportation council survey of 1998. Using precise surveyed household addresses, off-street (garage and driveway) and on-street parking were assessed for each observed household using Google Street View and Google Bing Maps Satellite images.

Causality was assessed using a nested-logit structure. The first level is the decision of having a home with or without off-street parking. The second level is a multinomial logistic model of the number of cars controlling for sociodemographic and built environment characteristics. Z. Guo (2013a) argues that this method controls for the endogeneity issue by treating the unobserved preferences affecting both car ownership and parking as fixed within each parking subgroup.

What were the main findings? 1) Z. Guo (2013a)'s method suggests evidence of a causal relationship for both off-street and on-street parking supplies. 2) For households with off-street

parking, both **garage** and **driveways** increase the likelihood of owning more cars for all car ownership levels, the latter being more important. Interestingly, they are also *less likely* to own more cars as on-street **parking crowdedness** increases and as the **number of street cleaning days** increases despite their off-street parking access. 3) For households with on-street parking only, the relationships are not as clear-cut, suggesting the measures used to capture on-street parking availability are poor proxies. **On-street parking crowdedness** decreases the probability of owning one car versus none but is not significant for 2+ cars, and the **number of days of street cleaning** has no effect. 4) For households with off-street parking, the parking supply variables (off- and on-street) have more influence than sociodemographic and built environment variables, including income. In a parallel study using only the subsample with off-street parking, Z. Guo (2013b) concludes that free residential on-street parking increases car ownership by 9 %. Finally, those results from New York City might only be generalizable to cities with similar dense urban neighbourhoods and a general shortage of parking (like Montréal). As Z. Guo (2013a) concludes, these findings might not apply to suburban areas or post-War car-oriented cities like Phoenix or Las Vegas.

Using a subsample of urban dwellers from the large-scale Norwegian National Travel Survey (2013/2014) who answered a parking-specific add-on survey, Christiansen, Fearnley, Hanssen, and Skollerud (2017) provide some correlational evidence to support Guo's finding. Using a simple binomial logistic regression of car ownership controlling for sociodemographic (including income) and transit level-of-service, their results cannot determine causation but shows that those with a **reserved parking spot** are three times more likely to be car owners than those without. Papu Carrone and Rich (2021), using several years of the large-scale Danish National Travel Survey, also show that parking availability at home was positively associated with the likelihood of owning one and two or more cars compared to none.

One aspect that could not be tested by Z. Guo (2013a, 2013b), because they did not exist in New York in 2010, is the effect of **resident on-street parking permit, their cost** and the **potential waiting list** to obtain the permit. This was investigated by Groote, Ommeren, and Koster (2016) in Amsterdam's city centre (a high-density, mixed-used, pre-automobile-built area with excellent active travel and public transit accessibility). In that context, off and on-street parking is extremely scarce. Off-street parking costs are extremely prohibitive (estimated at 3500 Euros/year), specific on-street parking (dedicated spots) permits cost 12 000 Euros per year, while general residential

parking permits (allowing permit holders to park anywhere in the district) cost on average 400 Euros annually, with variation by districts. In other words, general residential parking permits are *heavily subsidized*. Waiting-list time for such permits can be up to four years, with an average of one year. To be on the list, one needs to live in the district, own a car, and thus have to pay the full price for off-street or on-street parking (or park in free parking lots outside the city) during the waiting period. Groote et al. (2016)'s model controls for various sociodemographic and built environment variables and residential self-selection through a boundary-discontinuity design⁴, but can only test for the effect of the wait-list duration. **In such a context, how does this affect car ownership?** Their results suggest that car ownership is reduced by 2 % per year of waiting-list duration. The second finding is that this subsidized parking permit policy is income-regressive because high-income households (≥ 100 k Euros/year) are five times more likely than the poorest category (< 18 k Euros/year) to have those subsidized permits.

Dwelling type as a proxy for parking

Because of the rare availability of off-street parking information in travel surveys, some researchers used a dummy for single-family homes as an explicit “proxy” for off-street parking availability (Potoglou & Kanaroglou, 2008; Potoglou & Susilo, 2008). Other studies also used a single-family home dummy without mentioning it as a proxy for parking (e.g., Bhat & Guo, 2007; Bhat & Pulugurta, 1998; Goetzke & Weinberger, 2012). In those five studies, the single-family home dummy is always statistically significant and positively associated with higher a car ownership propensity. It remains curious, however, that none of these studies mention the endogeneity bias between single-family homes and car ownership, where the same unobserved preferences for car ownership might also influence the choice of a single-family home.

Secondary home or cabin: In regions such as Canada, owning a secondary home in the countryside is common. How does this affect car ownership, notably for urban dwellers? Unfortunately, no clear evidence could be found on the subject. In a mobility tools ownership model of cars, local transit pass and nationwide transit pass in Switzerland, Loder (2016) did include a dummy variable for owning a secondary home. Without much explanation, the variable

⁴ See the paper for how that method works.

was only included in the equation of the nationwide transit pass ownership...and not in the car ownership model. Further investigations are thus needed. In an analysis of the rebound effect of urban living in Scandinavian countries with low mobility costs, Næss (2016) suggests, based on qualitative interviews, that some urban dwellers might own a car for the sole purpose of reaching their secondary or vacation home in the countryside. More research and evidence are needed on the relationship between secondary home ownership and car ownership and the implication for annual VKT, notably of urban residents with otherwise low car use in their daily travels.

Pet ownership and car ownership

The *Société de Transport de Montréal* launched in fall 2022 a pilot project to allow dogs in the Metro network outside of peak hours (STM, 2022). Dogs are still prohibited in buses.

This means that until very recently, dog owners were not allowed to travel with their dogs on the Metro. In such a context, could **dog ownership** influence car ownership? Sehatzadeh, Noland, and Weiner (2011) used a two-stage least-square ordered Probit model to investigate the role of pets and the built environment on walking frequency while considering car ownership as a mediating variable. The first stage was the car ownership model (number of household cars treated as a truncated continuous variable), which shows a statistically significant and positive association between the number of vehicles owned by the household and dog ownership. The results for other pets, such as cats, were not tested and could be different.

Spatial dependence effects on household car ownership

At an aggregate level, all studies testing for spatial dependence effects on aggregate car ownership rates between nearby neighbourhoods confirmed its presence (e.g., S. Clark, 2007; S. Clark & Finley, 2009; Trendle, 2019). However, as previously explained (section 3.3.2.1), testing for such an effect is much trickier for discrete choice models. In a rare study integrating distance-based spatial dependence effects in a discrete choice car ownership model, Paleti et al. (2013) show that, yes, spatial interaction effects do influence household car ownership decisions (specifically, vehicle type choice). The spatial parameter is significant, and the model with the spatial parameter fits the data better. First, it confirms the presence of spatial interaction effects arising from observed and unobserved characteristics. Second, the influence of those interactions diminishes with increased distance between households. Their study, however, does not test specifically what

mechanism causes those spatial interaction effects. Two explanations are proposed: 1) spatial interaction effects are caused by social interactions between nearby households and thus influencing vehicle type decisions, or 2) the effect of attitude-based residential selection where households with similar vehicle type preferences cluster in the same neighbourhoods. The next question is whether spatial interaction effects matter from a policy perspective. Computing aggregate elasticities from the models with and without spatial interactions, Paleti et al. (2013) show that while the signs of the variables are the same, the *magnitudes* of the effects are consistently higher for both sociodemographic characteristics and accessibility measures, sometimes considerably so when spatial dependence is considered. This suggests compounding effects due to spatial spillover that cannot be ignored when forecasting the effect of transport policies.

Are social influence and peer effects a source of spatial dependence?

Is it possible that a household's car ownership decision is influenced by its social group? The work by Dittmar (1992) on the symbolic function of material possessions and its role on their owner's personal and social identity suggests this might be the case. Furthermore, for most households, the car is their most expensive good (apart from housing if owned). One that is highly "showable" (why park your new car in your garage if you can leave it in the driveway to exhibit to all your neighbours?). Indeed, as demonstrated notably by Steg (2005), the car serves a strong symbolic function in addition to its utilitarian function.

Based on the hypothesis that the neighbourhood is a valid reference social group, Goetzke and Weinberger (2012) investigated the presence of two types of social interaction effects on household car ownership decisions in New York City: *contextual* effects and *endogenous* effects. According to Manski (2000), the former refers to the behaviour of an agent (household or individual) being influenced by the *characteristics* of their peers, while the latter refers to the agent's behaviour being influenced by the *behaviour* of that social group. Contextual effects flow in one direction: from the group to the individual, while endogenous effects are bidirectional, i.e., the group's behaviour influences individual behaviour and individuals aggregate to the group behaviour. As previously mentioned, M. Adjemian and Williams (2009) observed when testing for the validity of using census zonal aggregate variables as proxies for individual characteristics that contextual effects (e.g., race, age, income) are likely influencing car ownership decisions.

Goetzke and Weinberger (2012) only tested the effect of *observed* contextual effects such as sociodemographic characteristics within the neighbourhood (i.e., census tract). The endogenous effect is measured as the percentage of households with at least one car within the census tract. Their modelling methodology is described in section 3.3.2.1. First, they show that both contextual *and* endogenous effects significantly impact household car ownership decisions. Specifically, when both effects are included, the **average car ownership level of the neighbourhood** (the behaviour of others) positively impacts household car ownership. As for contextual effects, their results appear counterintuitive at first: the proportion of bachelor's degrees and the average household size are *not* significant, but the **proportion of graduate's degrees** has a *negative* effect, while the **proportion of poor households** has a *positive* effect. However, both variables have the expected sign on the first stage estimation of the neighbourhood car ownership level (the proportion of graduate degrees is positive, and the proportion of poor households has a negative effect). The authors conclude that all else being equal, those living in a census tract with a higher proportion of graduate degrees are *less likely* to own a car than would normally be expected without social spillover effects. While poor household living in tracts with a high proportion of poor households are *more likely* to own cars than would normally be expected without controlling for social spillover. In other words, they acknowledged that those observed contextual effects likely act as proxies for unobserved effects such as social norms and attitudes. For highly educated households in New York City, the social norm might be not to own cars. In contrast, for poor households living among other poor households, there might be a stronger symbolic status associated with car ownership, thus increasing ownership likelihood more than would normally be expected.

Summary of other factors

The influence of parking (residential and on-street), commute-related variables, spatial dependence effects, pet ownership and secondary home ownership on household car ownership decisions have all been tested, albeit in only a few studies. Those few studies suggest statistically significant effects of sometimes substantial magnitude (notably for parking and spatial influence) on car ownership. When included, they can eclipse the effects of other variables, and when they are not, coefficients obtained for other variables can be substantially different. These results

indicate that more research should investigate their role on car ownership and their interactions with other levels of decisions (residential location and travel behaviour).

3.4.3 Explanatory variables of dynamic disaggregate models: what *causes* changes in car ownership?

The data analysis presented in Chapter 2 for the province of Québec and Canada indicates that car ownership rates are increasing over time, which is consistent with data from other countries such as the US (S. C. Davis & Boundy, 2019) and Denmark (Papu Carrone & Rich, 2021). The more important question is: which factors are behind those upward trends in car ownership? For example, if overall household income increases after controlling for inflation, does this lead to higher car ownership? If a new metro line opens, can this lead to a reduction in car ownership for neighbouring households? For the overall region? Are there cohort effects where, for example, highly motorized generations retain high car ownership levels as they age?

This section aims to answer the following three questions:

- 1) How do change in household sociodemographic characteristics and life events influence changes in car ownership?
- 2) Do changes in the built environment *cause* changes in car ownership?
- 3) Have *preferences* for car ownership been changing over time?

3.4.3.1 Effect of sociodemographic changes

The literature shows that life events are major triggers for car ownership level changes. Klein and Smart (2019) indicate that life events have a more substantial effect than context (BE) change. More important is identifying which specific changes lead to an upward or downward adjustment in car ownership. Are households quicker in adding cars or removing cars from their fleet? Are those changes happening *after* a specific life event (e.g., the birth of a child, a new job) or *before*, in anticipation of this life event (McBride et al., 2016; Oakil, Ettema, Arentze, & Timmermans, 2014)? Are those life events leading to *relative* changes in household car ownership (a change in the number of cars happens because a driver joins or leaves the household) or absolute (the number of drivers remains constant)? This is a crucial difference introduced by J. Dargay, Hanly, Madre, Hivert, and Chlond (2003).

To investigate those questions, quantitative (true panel and quasi-panel) and qualitative methods have been used. Insights obtained from qualitative surveys and interviews are not covered here (see B. Clark, Lyons, & Chatterjee, 2016 for an example). Still, some of those findings were recently summarized in a literature review that focused explicitly on factors leading to household-level car ownership reduction (Aguilera & Cacciari, 2020).

In a descriptive analysis using panel data from Germany, France, and the UK, J. Dargay et al. (2003) show that between two consecutive years, the proportion of households increasing their number of cars is respectively 0.9, 0.2 and 1.3 percentage points higher than the proportion of households shedding at least one car (4 %, 5.2 % and 7 %). The data is not recent, but those household-level changes explain the aggregate upward trend in car ownership. As illustrated in Chapter 2, the year-on-year average increase in vehicles per 1000 adults in Québec between 1980 and 2020 was 1.2 %. However, B. Clark, Chatterjee, et al. (2016) observed using large-scale panel data from the UK that between 2009 and 2011, slightly more households relinquished a car (9.1 %) than added a car (8.9 %). The global financial crisis of 2008 is hypothesized to explain that trend for that specific period.

The stickiness of car ownership

This relates to the persistence of car ownership over time by households (“resistance to change”) due, for example, to imperfect information, search time, habits, learning process, inertia, etc. This is associated with an asymmetry in adjusting car ownership following upward or downward changes (of equal absolute values) in explanatory variables Kitamura and Bunch (1990). In other words, the magnitude of the coefficient might be different following a reduction or increase in one explanatory variable, a concept called “hysteresis”.⁵

This asymmetry of car ownership in relation to income has been observed by Pendyala et al. (1995) and statistically confirmed by J. M. Dargay (2001). Dargay showed, using modelling of pseudo-panel cohort data, that households are quicker in adding cars (larger elasticity) following an increase in income than shedding cars following a reduction in income (smaller elasticity).

⁵ The concept seems to have been introduced to travel behaviour by P. B. Goodwin (1977) when discussing mode choice and is discussed for car ownership, for example, by Kitamura and Bunch (1990) and J. M. Dargay (2001).

Furthermore, the response is not instantaneous and happens slowly, over time. Acquiring a vehicle can be seen as a luxury at first, but once the habit of using it is installed and its perceived convenience is experienced, it becomes perceived as a necessity.

However, B. Clark, Chatterjee, et al. (2016), also using panel data from the UK (albeit more recent), found the opposite: shedding a car following an income reduction was more likely than increasing car ownership following an equivalent income raise. However, they admit that this might have been confounded by the economic conditions after the 2008 recession. Except for B. Clark, Chatterjee, et al. (2016)'s results, most studies found that the elasticity of car ownership in relation to income is not symmetrical. This issue is a serious barrier to reducing car dependency.

Concurrently, in their quasi-panel model of movers, Xinyu Cao et al. (2007a)'s results indicate that past ownership level was the strongest determinant of change in the number of cars owned after the move. Specifically, households with a higher number of cars before the move were more likely to *reduce* the number of cars after moving to a new location than households with a lower number of vehicles, even when controlling for changes in income, in the number of adults and in some built environment features.

Another aspect of stickiness relates to *who* is more likely to acquire or dispose of a car. Both Oakil et al. (2014) and B. Clark, Chatterjee, et al. (2016) found that **older households (60+)** were less likely to change their level of car ownership than younger households. B. Clark, Chatterjee, et al. (2016)'s results suggest that the **younger households** (oldest members aged 16 to 24) were the quickest to reduce car ownership. In other words, car ownership volatility is higher when younger and lower when older. There is also more volatility in disposing of the second or third car than the first one (B. Clark, Chatterjee, et al., 2016; J. Dargay & Hanly, 2007).

Quasi-panel evidence

Xinyu Cao et al. (2007b) and J. Cao and Cao (2014) included two sociodemographic changes in their quasi-panel model: **income** and **the number of adult household members**. An increase in both variables leads to a rise in car ownership. However, for Xinyu Cao et al. (2007b), an increase in the **number of children under five years old** did not lead to changes in car ownership in their model. In the Netherlands, Oakil et al. (2014), using a retrospective survey with questions covering the past 20 years, found that the **birth of a child** was associated with a higher probability of adding

a car. That acquisition was often made in *anticipation* of the event (before the birth). This could explain Xinyu Cao et al. (2007b)'s results. When children become adults and leave the family home, Oakil et al. (2014) found no statistical impact on car ownership. This result might be explained by the Netherlands' context, where adult children still at home do not necessarily have their own car, which they would take with them when leaving the family nest. **Retirement** was associated with an increased likelihood of disposing of a vehicle, but the change in car ownership was made in *anticipation* of the event. Finally, Oakil and colleagues also note that a **residential relocation** was associated with an increased probability of adding a car after the event, which could be explained by moving to more suburban/rural areas. But since their model did not investigate changes in a spatial context, this hypothesis cannot be confirmed.

In a subsequent study, Oakil (2016) investigated the gendered differential impact of life events on individual car access. Their results indicate that **divorce, residential relocation, changes in employment and the birth of a first child** significantly impacted the decisions of the respondent to move from no access (no car in the household) or partial access (a car shared by more than one adult) to full access (one car per adult) *only* for female respondent. The only life event found to be significant for men was **moving in with a partner** (also significant for women). However, *none of those events* significantly explained a reduction from full-car access to no or partial car access. Due to the low sample size (rarity of car ownership changes), no changes to the built environment were tested (except through a dummy for relocation) to explain those car access reductions.

True longitudinal panel evidence

A common approach to studying household-level mobility behaviour change is the concept of “mobility biographies” (Aguilera & Cacciari, 2020). The method focuses on key life events that lead to major changes in people's lifestyles, including car ownership changes. Findings from two recent applications of the method, both using large-scale representative longitudinal panel data, are provided here (B. Clark, Chatterjee, et al., 2016; Klein & Smart, 2019). These were selected because they also explicitly account for changes in the built environment, which is not the case for other works (e.g., Oakil, 2016; Oakil et al., 2014). B. Clark, Chatterjee, et al. (2016) used two waves (2009-2011) of the large-scale UK Household Longitudinal Study (n = 19334) to explore the effect of life events on changes in car ownership while controlling for some attributes for the built environment. Their large sample size allows them to distinguish the acquisition of a first car

($0 \rightarrow 1$) from adding a car ($1 \rightarrow 2+$) and the disposal of one car while retaining at least one ($2+ \rightarrow 1$) to moving to no car ($1+ \rightarrow 0$) using separate binary logit models. Klein and Smart (2019) used the mobility biography approach with data from six waves (from 2003 to 2013) of the Panel Study of Income Dynamics in the US ($n = 9000$ representative households) to model changes in car ownership following life events and changes in built environment context (following relocation). Results of both studies are reported together by direction of change (adding or removing cars) and by types of life events. Both studies confirm, unsurprisingly, that most life events (changes in income, wealth, number of adults in the household, college graduation, coupling/ decoupling, the birth of a child, getting a new job, retiring, developing a health condition, etc.) have a statistical influence on both the probability to increase or decrease car ownership. **Changes to household composition** are the strongest determinant of car ownership changes.

What leads to an *increase in car ownership*? B. Clark, Chatterjee, et al. (2016) found that larger, more educated, and higher-income households were more likely to add cars, while the presence of children (at $t = 1$) reduces the odds of adding cars. Klein and Smart (2019) also indicate that lower-income families have a lower probability than affluent families to increase car ownership in response to any of those events, an intuitive result.

As for life events, Klein and Smart (2019) found that the most important factors are, in that order, **forming a new couple, graduating from college** and **the arrival of a child**. Furthermore, the impacts are substantial only for households previously without cars and much more moderate for households with at least one car. B. Clark, Chatterjee, et al. (2016)'s results indicate that having a household member **acquiring a driver's licence, additional adults, and couple formation** significantly and substantially increase the odds of moving from $0 \rightarrow 1$ and $1 \rightarrow 2+$.

Getting employed and an increase in income and wealth all lead to higher odds of adding cars in both studies. B. Clark, Chatterjee, et al. (2016) also found that changing employers significantly and positively influenced the addition of vehicles, but only for households who already have cars ($1 \rightarrow 2+$). However, the authors explain that the causal direction of that influence cannot be tested: it is possible that adding a car allows a household member to change employment or that the car ownership change is made in *anticipation* of employment changes. As discussed in the section 3.4.2.1, this poses the question of endogeneity between employment status, income, and car ownership. Something that was not found to be tested by any study reviewed so far. Residential

relocation was not significant in B. Clark, Chatterjee, et al. (2016)'s study in adding cars ($0 \rightarrow 1$ and $1 \rightarrow 2+$). Having someone in the family develop difficulty walking increases the likelihood of adding cars (Klein & Smart, 2019).

In the other direction (*decrease in car ownership*), the two most impactful events in Klein and Smart (2019)'s study are **relationship dissolution** and **the last of the children leaving the family home** ("nest emptying"). However, to use the term suggested by J. Dargay et al. (2003), these events lead to *relative* changes in car ownership for the household because it is associated with a change in the number of drivers. Events that do not change the number of drivers have less impact. For example, gaining or losing a job, retirement and reduction in income are statistically significant and positively associated with decreasing car ownership compared to the baseline (life events not happening). These events have a more substantial impact on lower-income families. Someone in the household developing health issues (other than mobility related) also increases the odds of shedding a car. B. Clark, Chatterjee, et al. (2016)'s results indicate that residential relocation was not significant for increasing car ownership, but it is significant for both types of car ownership reduction ($2+ \rightarrow 1$ and $1+ \rightarrow 0$). Changes in built environment characteristics following a relocation are discussed below. In their review, Aguilera and Cacciari (2020) also report the results from a few other studies on which life events lead to car ownership reduction. They summarize that a **fall in income**, a **decrease in household size** and **retirement** are associated with a *reduction* in car ownership levels.

3.4.3.2 Effects of changes in the built environment

In their study about household demotorization (defined as the reduction of car ownership at the household level), Aguilera and Cacciari (2020) summarize that moving from an urban to a more suburban location generally leads to an increase in car ownership, while the opposite (from suburban to more urban) can lead to a reduction in the number of cars. As previously discussed, this effect might be confounded by residential self-selection (e.g., Xinyu Cao et al., 2009; Kroesen, 2019; van Wee, 2009). Isolating the true causal effect of the built environment is difficult. Was the move to a more central location motivated by a desire for a more car-light living? Was the relocation motivated by other reasons, but once in the new area, households realized they needed to adjust the number of cars they owned upward or downward? Does it even matter which came first (attitude or BE change)?

As described in section 3.3.2.3, one approach suggested to test the causal effect of the built environment on car ownership is through the quasi-panel method of retrospective questioning of movers. Xinyu Cao et al. (2007a, 2007b) were among the first to use the method. In their first study, they modelled changes in the number of cars after the move using a static-score model. First, unlike their cross-sectional Probit model of present car ownership level, including attitudes directly in the model did not push the included BE variables toward insignificance. This suggests that some built environment characteristics remain significant in car ownership decisions even after controlling for RSS. Their results indicate that **changes to the perceived “spaciousness”** of the neighbourhood lead to positive changes in car ownership. Similarly, J. Cao and Cao (2014) found that those moving to an area perceived to have more off-street parking tended to increase the number of cars they owned. In other words, moving from a place perceived as more suburban leads to an increase in car ownership. This finding was confirmed by their SEM of car ownership and car use using the same dataset in their second study (Xinyu Cao et al., 2007b). Furthermore, **a diverse land use** (number of different business types) at the new location is associated with a reduction in car ownership. In their SEM model, an **increase in accessibility** between the old and the new location *did not* lead to changes in car ownership but did lead to a reduction in driving (Xinyu Cao et al., 2007b).

J. Cao and Cao (2014)’s quasi-panel of movers indicates that the density of business establishments and the perceived proximity to work at the new location seems to lead (causal effect) to a reduction in car ownership. However, the variables are barely significant. The goal of that study was to specifically investigate if a **new light-rail line** had an impact on car ownership after controlling for RSS. The results indicate that the specific light-rail corridor in Minneapolis had no independent effect on the number of cars compared to the control corridors. In other words, they conclude that the effect of the light rail on car ownership only happens *through residential selection*. This does not mean that the opening of a new rail line in a city has no impact on car ownership, but rather that the effect works by changes to the built environment around the stations (densification) and by allowing transit-oriented households to relocate themselves closer to a rail station where they are more likely to align their behaviour and car ownership level with their preference. Thus, if there is strong *latent demand* for transit-oriented neighbourhoods, then such a transit improvement, along with building more housing nearby, could allow many people to reduce their car ownership level. In the long-term, such an effect is only likely to reduce overall car ownership in a region if

a greater proportion of new housing is built in transit-oriented development than in suburban-style developments.

Still using the same method (quasi-panel of movers), Xinyu Cao et al. (2019) demonstrated the causal influence of the distance to the centre. They showed that residents moving toward the city centre in two Norwegian cities (Oslo and Stavanger) had a causal effect on reducing car ownership, while those moving outward increased car ownership. Oslo residents were more likely to shed cars following an inward move and less likely to add a car following an outward move than Stavanger's residents (a smaller city).

Klein and Smart (2019) specifically investigated how life events and changes to the built environment prompted households to either increase or decrease their level of car ownership using two separate models. First, individual built environment attributes changes tested (population density, accessibility by transit, walkability index and moving in or out of NYC) have individually less impact than most life events. However, collectively, those four indicators can have a substantial effect on car ownership decisions. This is notably the case when people are moving in or out of neighbourhoods with very **high values for transit accessibility, density, and walkability index score**. Specifically, in the case of the reducing car ownership model, the authors suggest the presence of threshold effects where people have substantially higher odds of shedding one car when they move in neighbourhoods above specific transit accessibility values (in combination with density and walkability, which inevitability comes with it). Moving to New York City has an additional and substantial positive effect on the probability of reducing car ownership. Conversely, moving to a neighbourhood with better or worst values for those variables but without being in the country's top percentile of highly accessible census tracts, does not have much impact. These results echo findings from a neighbourhood typology of all US census tracts where only the "Old urban" type residents, representing 4 % of the US population and located in a few major metropolitan areas, had a substantially different travel behaviour (VMT, share of driving and transit trips) (Voulgaris, Taylor, Blumenberg, Brown, & Ralph, 2017). Klein and Smart (2019)'s model also controls for various life events that often coincide with residential relocation and is thus robust to simultaneous changes in various sociodemographic aspects. In B. Clark, Chatterjee, et al. (2016)'s study, an increase **in the number of bus stops** near the home when relocating was marginally significant ($p < .10$) on the likelihood of moving from one to zero car while an increase in **population density** (a proxy for many things) was significant and positively associated with

moving from 2 to 1 car. Furthermore, those already living in London were generally more likely to reduce car ownership following life events, suggesting that car ownership is less of a necessity and more volatile in a large city with high-quality transit service (and, likely, more constraints on parking).

3.4.3.3 Changing preferences for car ownership

This last question investigates if preferences for car ownership *have changed* over time. Many studies published between 2008 and 2015 began reporting on the “peak-car” phenomenon. Observed trends in many industrialized countries started showing signs of saturation in passenger travel by most modes, and a decline in car use as measured by vehicle-kilometres travelled (Metz, 2010; Millard-Ball & Schipper, 2011; Puentes & Tomer, 2008). Car ownership did not seem to have followed this trend. Millard-Ball and Schipper (2011) report that it has kept increasing but at a slower pace than before. A trend that is also observed in the province of Québec (see section Chapter 2). One exception is the United States which saw a dip in car ownership rates between 2008 and 2013 (David & Boundy, 2021). These disturbing trends prompted further investigation into the possible reasons for this “peak-car”, with a special issue of *Transport Reviews* in 2013 (P. Goodwin & Van Dender, 2013). One explanation that quickly gained prominence is that younger generations, most notably the Millennials (Generation Y) born roughly between 1980 to 2000, had lower driver’s licensing rates (Delbosc & Currie, 2013; Sivak & Schoettle, 2012), were driving less and were owning fewer cars than previous generations (Baby boomers and Generation X) (B. Davis, Dutzik, & Baxandall, 2012; Kuhnimhof, Buehler, Wirtz, & Kalinowska, 2012). However, parallel to this youth decline, seniors own more cars and drive them more than ever before (Kuhnimhof, Zumkeller, & Chlond, 2013a, 2013b). In other words, the Baby Boomers born between 1945 and 1965, who are becoming the seniors of our societies, are more motorized than the generation before them.

These studies (and many more) show clear evidence of **cohort effects** on travel and car ownership. Cohort effects mean that the *relationship* between observed sociodemographic characteristics and car ownership has been changing over time and is linked explicitly to generational trends.

First, pseudo-panel and panel approaches show an increase in car ownership over time from unobserved factors. For example, in their pseudo-panel analysis of car ownership in Montréal using three iterations of the large-scale OD Survey (1998, 2003, 2008), Anowar et al. (2016)

controlling for a variety of sociodemographic and built environment characteristics show through the inclusion of a time-elapsed term since 1998 that car ownership propensity has increased with time. Specifically, the tendency for three versus two cars has increased. Their method does not provide information on which factors might explain this trend. It is unclear whether the built environment variables they included were considered constant over time or computed at each time point. Papu Carrone and Rich (2021) also show a positive correlation between a time-dependent variable and car ownership in Denmark between 2007 and 2017 despite controlling for changes in the built environment (accessibility by transit and density) over that period. Furthermore, by including time-varying age cohort variables, they confirmed young and senior cohort effects. In only ten years, those aged between 18 and 37 years old had a *decreasing propensity* of owning one car compared to none, while all age groups showed an *increased propensity* to own two or more cars, with a more pronounced trend for those aged 38 to 67 years old.

Klein and Smart (2017)'s study using the US Panel Study of Income Dynamics with data from 1999 to 2013 confirms that the Millennial generation (Born between 1980 and 1998) did indeed have lower car ownership levels (measured as lower access to a car; cars per adult in their household) than would be expected from the older generations at the same age. However, they conclude, based on the result of a more complete model which controls for income, wealth, race and built environment features (population density, accessibility by transit), that most of the difference is explained by lower economic status (i.e., lower employment, lower income, lower wealth). Specifically, the “dependent” Millennials (still living with their family at the time of data collection) have fewer cars, but those that became economically independent from their family owned more cars than would normally be expected, considering those other factors. In short, Klein and Smart (2017) argue that economic conditions in the US around the 2008 financial crisis might be a key factor behind a change in mobility and car ownership patterns of younger generations. On a brighter note, they also report that the effect of **accessibility by transit is stronger** on car ownership for Millennials than any other generation.

The discussion of factors explaining the “peak-car” phenomenon also investigated possible **changes in attitudes and lifestyle preferences** (P. Goodwin, 2012), most notably for younger generations (Chatterjee et al., 2018). Some suggested an evolution of the “public sentiment about the role of cars in cities” through the emergence of a subculture of car-free living (Lee-Gosselin, 2017). Is there evidence for such changes in attitudes specifically toward car ownership, and can

this explain changes in car ownership among the younger generation? True longitudinal datasets where attitudes are measured at multiple points in time for the same person are very rare.

One example is the work by Olde Kalter, La Paix Puello, and Geurs (2020). They used a latent transition model to investigate changes in mode use frequency as a function of changes in attitudes toward car use and car ownership between two repeated waves of the Netherlands Mobility Panel (2014 and 2016). During that short period, they found that attitudes were very stable, with about 80 % remaining in the same attitude latent class. When changes did happen toward either a more car-oriented class or a less car-oriented class, it did not affect the frequency of car use. Unfortunately, they did not model car ownership or changes in car ownership.

In the Netherlands, Oakil, Manting, and Nijland (2016) concluded that increased urbanization of young adults (aged 18-29 in 2012/2013), including among young families with children, as well as a sharp increase in singlehood likely, explains the countrywide downward trend in car ownership among this generation. In their model, young families were more likely to own cars than singles or couples, but delays in having children and an increase in childlessness will likely sustain the downward trend in car ownership.

3.4.3.4 Summary of influences on car ownership changes

The most influential factors leading to changes in household car ownership are changes to household composition (coupling/decoupling, an adult leaving the household, birth of a child). This is followed by changes to income, employment, graduation, and retirement. Residential relocations have an ambiguous impact. These vary by country and depend on the inclusion or not of built environment variables. Most of those events are habit-disrupting and specific events (the birth of a child, graduation from university, a relocation, a new job, etc.) represent windows of opportunities for transportation planning policies to encourage a voluntary change in car ownership or prevent adding vehicles. Something suggested by Aguilera and Cacciari (2020) and tested successfully for travel behaviour by Verplanken and Roy (2016). Changes to built environment characteristics (usually measured following a residential relocation) seem to have a marginal or moderate upward/downward effect on car ownership in the expected direction (a move to more suburban settings lead to an increase in car ownership, while a move to more central, denser, more mixed-used and more transit-accessible areas lead to a slight decrease in car ownership). Klein and Smart (2019) suggest that built environment changes matter substantially

for car ownership *only* when moving to and from areas with very high transit accessibility (e.g., New York City and other large cities' urban core).

3.5 Mobility tools ownership modelling

As cities and even countries are becoming more multimodal, there has been an increased interest to broaden the scope of car ownership modelling by including the choice to possess tools giving access to other modes of transportation. So what exactly are mobility tools?

3.5.1 Concept of mobility tools

Before the rise of mobility-as-a-service and mobility tool and ownership modelling, Bunch and Chen (2007, p. 542) were already conceptualizing the concept of mobility services in which the primary tool is car ownership:

“In general, the situation faced by any household is the requirement to allocate a portion of its income stream to acquire the most desirable flow of “mobility services” in conjunction with its other valued activities. For the vast majority of households, the major portion of such services is obtained through periodic purchase of specific consumer durables – automobiles – that are held and used for some period until they are either replaced or scrapped.”

While the modelling of car ownership has been extensively studied, only a tiny fraction of studies jointly modelled the ownership of several mobility tools (cars, two-wheel motor vehicles, bicycles, public transport passes, driver's licenses, carsharing membership, etc.). It seems that the term *mobility tool* is mainly used by Axhausen and colleagues in Switzerland, who are among those who have studied the issue (Becker et al., 2017; Beige & Axhausen, 2006; Beige & Axhausen, 2012; Ciari, Balmer, & Axhausen, 2007; Loder & Axhausen, 2018; Scott & Axhausen, 2006; Weis, Axhausen, Schlich, & Zbinden, 2010). Also from Switzerland, Kowald, Kieser, Mathys, and Justen (2017) prefer the term “mobility resource”.

In Canada, a few studies conducted more recently in Toronto by Habib and colleagues also explicitly used the term *mobility tool* (Fatmi & Habib, 2016; Fatmi, Habib, & Salloum, 2014; Habib & Sasic, 2014; Habib, Weiss, & Hasnine, 2018). Other studies that have jointly modelled car ownership and bicycle ownership (e.g., Pinjari et al., 2011) (Pinjari et al., 2011) or with bicycle and two-wheel motorized vehicles (Yamamoto, 2009) do not use the term.

The definition of *mobility tools* also appears to be evolving in the work of Axhausen and colleagues. In their early work, they define the concept simply as ownership of different types of vehicles (SUVs, cars, minivans) and transit passes (Scott & Axhausen, 2006), sometimes adding a driver's license as an additional tool (Beige & Axhausen, 2006). An essential aspect of their mobility tool concept is that it represents a *commitment* to using a particular mode of transport (Beige & Axhausen, 2006). In a more recent study, Becker et al. (2017, p. 27) define the term as an item that, following a substantial acquisition or subscription payment, provides access to a particular mode of transportation at zero or very low marginal transaction cost. They include in this concept four types of mobility tools offered in Switzerland: the private car, the regional annual subscription to all public transport services, the national annual subscription to all public transport services and the subscription to the national station-based carsharing service. The authors do not include bicycles and motorized two-wheelers, stating that they do not have a high enough acquisition cost to meet the above definition and are unsuitable for all four seasons. Such a definition of mobility tools thus remains contextual to Switzerland, where a national season ticket offering unlimited access to public transport can cost between 3700 Swiss francs (2nd class) and 6000 Swiss francs (1st class) per year.

In Canada, Fatmi et al. (2014) take up the first formulation of the concept by Beige and Axhausen (2006). Habib et al. (2018) also added bicycle ownership, which is generally excluded from studies conducted in Switzerland.

In the Montréal context, several mobility tools that fit into the different definitions above can be identified. At the personal level, we note the possession of a driver's license at the age of 17 (SAAQ, 2019), the possession of a motor vehicle, the possession of a moped (scooter or moped) and the possession of a bicycle⁶. At the collective level, we count subscriptions to the various transportation companies in the region, such as monthly passes, annual passes (OPUS year-round) or seasonal passes (4-month passes). In terms of shared mobility services, it is possible to have an annual or monthly subscription to the BIXI bikesharing service (BIXI Montréal, 2019), to become a member of *Communauto* and have access to their traditional station-based carsharing service, their fleet of free-floating vehicles, or both services (Communauto, 2022). Despite the variety of

⁶ As demand for e-bikes and cargo bikes grow in the future, “bicycle” could be further split into different subtypes.

mobility tools available, the survey data available in Montréal do not necessarily include as much detail on the types of subscriptions to each mode.

3.5.2 Modelling methodologies

Modelling a set of mobility tools held by households rather than just car ownership allows for a better consideration of the interactions between the different tools in the decision-making processes of households. Moreover, many of these tools may be affected by the same latent variables, such as attitudes and lifestyle preferences. Becker et al. (2017) criticize the idea of modelling, for example, the subscription to a carsharing service by taking car ownership and public transport subscriptions as explanatory variables, neglecting the fact that the decision to subscribe to carsharing is likely part of a single decision-making process (presented as simultaneous) by households on a mobility portfolio. It would be more accurate to consider the decisions to acquire all the tools simultaneously, considering them all as endogenous variables.

Using large-scale travel survey data from Osaka, Japan, and Kuala Lumpur, Malaysia, Yamamoto (2009) compares two approaches to simultaneously model car ownership, bicycle ownership, and two-wheeled motorized vehicle ownership. The first approach is a trivariate binary Probit model. The model includes deterministic and random terms and allows for maximum likelihood estimation. The interaction between the three vehicle types is modelled two-by-two (auto/bike, auto/motorcycle, bike/motorcycle) by allowing a correlation between the random terms in the model. The second approach is a multinomial logit model (MNL) based on the principle of maximizing the utility of choices, where each combination ("bundle") of vehicle types is modelled. The utility of each combination is not the sum of the utilities of each vehicle type in the combination. Instead, the model allows for the inclusion of a specific and unique utility for each combination, allowing for greater flexibility than the probit model. The modelling results illustrate that the MNL performs better than the Probit model for both datasets (Osaka and Kuala Lumpur) by, among other things, allowing for a better representation of the "bundle" structure of ownership of the three vehicle types. Both methods, however, do not allow for the *number* of each type of vehicle owned by households. Furthermore, the author compares the results with and without the inclusion of the income variable for Kuala Lumpur and concludes that the model performs considerably better with its inclusion, confirming that this variable has a significant positive effect on car ownership but a negative influence on motorcycle and bicycle ownership. The absence of

this variable for Osaka thus violates the assumption of the presence of important variables, calling into question the conclusions on the different coefficients obtained for the Japanese city from the two models (MNL and Probit).

In one of the first formulations of a mobility tool ownership model, Scott and Axhausen (2006) use data from a stated preference web survey to study the interactions between public transport season tickets and car ownership (all types, small cars and large cars). After indicating their main places of activity, respondents were asked to choose for each adult in the household the type of car (including no car) and the type of public transport pass (none, monthly, annual). The costs of their choices were then estimated and presented to them, allowing them to modify their initial decisions. Then, simultaneous ownership of automobiles and transit passes was modelled using a bivariate ordered Probit model. Unlike Yamamoto (2009), the model allows for the number of public transit passes and the number of cars owned by households to be considered. The interaction between both tools is modelled by allowing error terms in each equation to be correlated through a bivariate normal distribution function. The model can be estimated by maximum likelihood, thus allowing a generalization of the results. Like many other endogenous modelling approaches, unobserved factors (such as preference for luxury cars) are accounted for via a random error term for each household. The results of their model confirm several elements. First, there is a strong negative correlation between the number of transit passes and the number of cars, suggesting a substitution effect. The higher the number of transit passes, the lower the number of vehicles. Income is positively correlated with car ownership and negatively correlated with transit passes. Thus, car preference increases with income, specifically for larger vehicles. Otherwise, the other variables have similar effects to those observed in the traditional literature on car ownership, i.e., with an increase in distance to the city centre and to work, the propensity for car ownership increases.

In sum, despite the limitations of modelling based on 160 respondents to a stated preference web survey, the work of Scott and Axhausen (2006) illustrates the importance of considering the simultaneous modelling of transit subscriptions and car ownership because of the substitution effect observed between the two. Ownership of one tool cannot simply be regarded as exogenous in the modelling of another.

In more recent work, Becker et al. (2017) use data from the 2005 and 2010 Swiss National Travel Surveys to jointly model ownership of a mobility portfolio at the *individual level*. This portfolio

includes car access (by the survey respondent to the household car), ownership of national or regional annual public transport passes, and subscription to the national carsharing service. Since the objective is to specifically model the interactions between carsharing and other mobility tools, only licensed drivers are considered. To achieve this, they use a multivariate probit model with sample selection. This sample selection principle is necessary to model the public transport subscription in two levels. The first is the possession of a subscription, and the second is the type of subscription (regional or national). The interaction between the four types is modelled by considering all 12 possible combinations of ownership and estimating the probability of owning each of these combinations. Another strength of their approach is to have included attitudinal variables in the model. The specific attitudes included consist of two latent factors obtained by factor analysis on responses to 10 questions. These questions dealt with attitudes toward pricing measures (congestion, parking, gasoline, tunnel/bridge) and investments to be made with the funds collected (road network, public transit network, bicycle network, environmental infrastructure). The first factor ("PROFEES") is characterized by positive attitudes toward increasing car pricing and negative attitudes toward using these funds for road infrastructure. And the second factor, "PROINFRA" is characterized by a positive attitude toward investment in public transit, cycling and environmental infrastructure. Their modelling results confirm the effects reported in most previous studies regarding the relationship between the automobile and the built environment and public transit. It is noted that general accessibility to employment opportunities and micro-accessibility to public transit (a measure that accounts for level-of-service) favour public transit subscriptions and disfavour the car. Without surprise, peripheral and rural areas are associated with greater car ownership. Regarding carsharing, several results are interesting. For example, general and employment accessibility is insignificant, but accessibility to high-frequency public transit substantially increases the probability of subscribing to carsharing. Second, the distance to a carsharing station did not significantly affect the propensity to subscribe to the service. The authors suggest that this could be explained by a homogeneous distribution of stations and good accessibility to the stations with public transport. Attitudes also play an important role, with high scores on both factors (pro-sustainable infrastructure and pro-auto pricing), both having a positive effect on the propensity to subscribe to public transit and carsharing (pro-infra not significant for carsharing) and a negative effect on access to the automobile.

Finally, the model confirms important interactions between the different tools. Access to a private car is negatively and strongly correlated with public transport and carsharing subscriptions, indicating a possible substitution. However, the model does not explain well the fact that 40% of car owners are also members of the carsharing service. Second, carsharing is strongly and positively correlated with public transport subscriptions, indicating a strong complementarity between the two services.

In sum, the modelling performed by Becker et al. (2017) relies on a large, reliable (the mobility survey is linked to the census in Switzerland) and population-representative dataset. It demonstrates the importance of incorporating attitudes into the modelling of the tools and controlling for other unobserved latent preferences that can better explain the correlation between the different tools. However, their approach does not consider residential self-selection effects (Van Acker et al., 2014; van Wee, 2009), which are known to be very important in influencing car ownership by environmental variables. Indeed, as with the car alone, preferences for carsharing and public transit may lead people to locate where these options are available.

In Canada, a few studies have been conducted on mobility tool ownership (Fatmi & Habib, 2016; Fatmi et al., 2014; Habib & Sasic, 2014; Habib et al., 2018). However, none of those studies included carsharing. For example, Fatmi et al. (2014) used data from the Transportation Tomorrow Survey (2006), the Origin-Destination Survey in Toronto, to model mobility tool ownership among 17- to 19-year-olds. This age group is chosen because it represents a critical period in forming youth mobility habits due to the decisions about several mobility tools that occur at this age (e.g., driver's licenses and car ownership). Five combinations of three mobility tools (driver's license, access to a household car, and monthly public transit pass) are studied using a latent-class multinomial logit model (LC-MNL). This approach models the presence of heterogeneity in the population arising from unobserved factors such as individual preferences or attitudes. The modelling is done at the personal level, not at the household level. Comparing the model fit of the LC-MNL with a sample MNL, Fatmi et al. (2014) confirm the results obtained by Anowar, Yasmin, et al. (2014) for car ownership: that the LCM performs better. These results suggest that using a latent-class discrete choice model should be considered for modelling mobility tool ownership that includes carsharing in the third contribution of the present thesis. Their segmentation into two classes is done only on sociodemographic variables. The first class seems to be mainly composed of the younger (closer to 17 than to 19) living with their parents, and the

second is composed of the older (closer to 19) living alone or in roommates with other students. Among the interesting results, we note that the size of the individual's household is associated with a high probability of having several mobility tools (combination #1). Conversely, smaller household sizes and a "roommate" type composition are associated with an increased likelihood of having only one transit pass (combination #2). These households are generally closer to the centre, where the population density is higher. It is also observed that individuals from wealthier neighbourhoods had a higher probability of owning a driver's license in a household with a car (combination #3) and a lower probability of holding a public transit pass (combination #2).

Note that the primary mode of transportation is used as an exogenous variable in the model, which is unusual and somewhat rare in car ownership models. Indeed, the relationship between the ownership of mobility tools and their use is rather endogenous. For example, the authors indicate that individuals whose primary mode of transport is walking had a greater probability of not owning mobility tools (combination #5). The use of these variables nevertheless allows the authors to observe that the influence of travel characteristics on the ownership of mobility tools is more substantial among the first class (younger, living far from the centre with their parent) than in the second (older, living in a shared apartment closer to the centre). Fatmi and Habib (2016) used the same modelling framework (LC-MNL) to analyze mobility tool ownership among older adults in the Greater Toronto Area.

Despite the modelling challenges of incorporating more mobility tools (bikesharing, carsharing, personal bicycles), approaches such as the one developed by Becker et al. (2017), Fatmi and Habib (2016); Fatmi et al. (2014) need to be extended with the objective of more adequately understanding the multiple interactions between mobility tools decisions and availability of shared mobility services in increasingly multimodal urban environments.

3.6 Impacts of shared mobility on car ownership

A few studies have sought to understand the impacts of shared mobility services on car ownership. As the findings from mobility tools modelling have already been presented, this section aims to present results obtained from other approaches. This section focuses on carsharing and bikesharing services. For carsharing, evidence is reported by type of service (traditional round-trip station-based carsharing, free-floating ("one-way") carsharing and peer-to-peer) and by methodology

(user survey, car ownership modelling). Some studies assessed the *potential* impact of carsharing on vehicle ownership and travel behaviour using stated-choice experiments (e.g., Firnkorn & Müller, 2015; Le Vine, Lee-Gosselin, Sivakumar, & Polak, 2014). These studies are not reviewed here as the focus is on observed choices.

Furthermore, ridehailing services (taxi services provided through a mobile app) are often considered shared mobility. Aguilera and Cacciari (2020) reported mixed evidence of their effect on car ownership reductions. Some studies found no effect, while others found that the most frequent users were more likely to reduce car ownership. Their impact is not reviewed here.

3.6.1 Impacts of bikesharing

The availability of bikesharing services seems to have yet to be incorporated as an explanatory variable of car ownership models in Western countries. One possible reason is that it is assumed unlikely that this type of service alone will influence a household's likelihood of owning vehicles. Among recent reviews of bikesharing and its impacts (e.g., Fishman, 2016; Fishman, Washington, & Haworth, 2013, 2014; Ricci, 2015; Shaheen, Martin, Cohen, & Finson, 2012), only Fishman et al. (2013) mention a relationship with car ownership. Mainly, they mention that in three major cities in China (Beijing, Shanghai, and Hangzhou), bikesharing users have higher levels of car ownership than non-users, but this would be specific to the Chinese context. In North America, Shaheen et al. (2012) observed through surveys of members of early bikesharing services (Boston, Minneapolis, Toronto, and Montréal) that a small percentage of users have sold their vehicles or are considering selling their car since becoming members of a bikesharing service. For those users who had sold their vehicle, a subsequent question asked them to assess the extent to which their bikesharing membership had contributed to this decision. The full results aggregated across the four cities are shown in Figure 3.6.

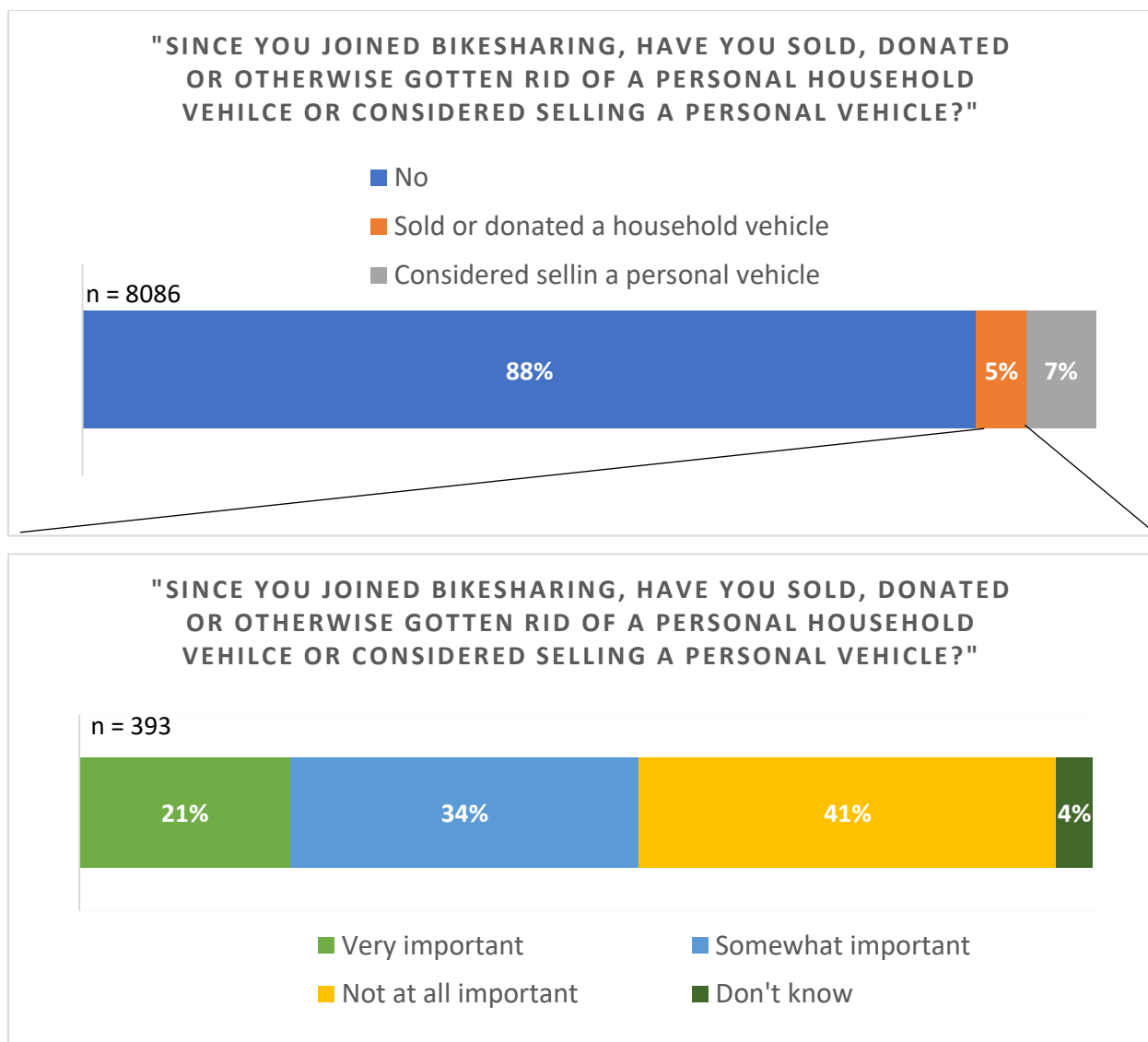


Figure 3.6 Impact of bikesharing on car ownership among surveyed members in Boston, Minneapolis, Toronto and Montréal. Results from Shaheen et al. (2012, p. 86).

Combining the results of the two questions, bikesharing subscriptions influenced car ownership reduction for about 2% of respondents. Again according to their survey data, this proportion would be slightly higher for Montréal at 3.6%.

In short, the influence of bikesharing on car ownership appears limited. The conclusions of this type of survey are subject to the limitations that are generally associated with it, namely that (1) only members are surveyed, and they are not representative of the entire population, (2) it is challenging to know whether the sample surveyed is representative of all members and service

users (even if the sample size is large), (3) perceptions and changes in mobility patterns are self-reported and not independently observed, and (4) the results are not necessarily generalizable. The same limitations apply to the surveys of carsharing service members discussed in the following subsection.

Given these limitations, it cannot be assumed that bikesharing services have a real effect on household vehicle ownership decisions. This suggests that more research is needed. A first step could be to include a variable capturing the number of bikesharing stations around the home location when bikesharing services are available. A step further would be to include bikesharing subscriptions in joint mobility ownership models to assess potential correlations with car ownership and carsharing decisions.

3.6.2 Impacts of carsharing services

Carsharing is a mobility service that began in Switzerland and was popularized in Europe and North America in the 1990s. Carsharing can be either commercial (“business-to-consumer”) or peer-to-peer. The former is the most common form (Shaheen, Cohen, et al., 2018). In **peer-to-peer carsharing**, car owners rent or lend cars to other individuals. This can be informal, locally organized through clubs or non-profits or, most commonly, through a platform provided by a third-party company (e.g., Turo). **Commercial carsharing** provides members with a fleet of vehicles that can be accessed with or without a reservation for short or medium-term rentals (Wielinski, 2018). The rate is charged either by the hour and/or distance travelled (e.g., station-based) or by the minute (e.g., free-floating) (E. Martin & Shaheen, 2016). The service has grown significantly in terms of membership and fleet size over the past decade, being present in 2016 in 46 countries and over 2000 cities worldwide (Shaheen, Cohen, et al., 2018).

With its fast growth in popularity in recent years, there have been many discussions about the potential for various forms of carsharing to reduce household car ownership, and vehicle-kilometres travelled (VKT). And if so, by how much? What are the key factors leading people to choose carsharing as a substitute for one or all the household cars? How does the nearby availability of carsharing vehicles affect the choice of car ownership versus carsharing services? Does the form (station-based, free-floating, peer-to-peer) of carsharing services have different impacts? These questions are of great interest to urban transport planning policies aiming to curb car ownership levels within cities. Although not reviewed here, reductions in car ownership are

also used by researchers to estimate reductions in VKT. The idea is that, yes, some users would drive a little bit more by joining carsharing than they would otherwise have without a car. However, a proportion of users would substantially reduce their VKT by selling one vehicle or not buying one because of the service. On the aggregate, the research found that the latter reduces VKT more than the former increases it (e.g., E. W. Martin & Shaheen, 2011)

This final section of the literature review summarizes how carsharing impacts car ownership and the methods used to estimate those effects. The impacts are presented by forms of carsharing (peer-to-peer, commercial “station-based” and commercial free-floating or one-way) and by the method used.

3.6.2.1 Station-based (or “traditional”) carsharing

Station-based carsharing is the oldest form of carsharing and, thus, the one that has been the most studied since its inception. Vehicles are parked at dedicated locations (“stations”), must be returned at the same place, and require reservations.

Evidence from carsharing members’ surveys

To measure the impact on household car ownership decisions, early studies relied on surveys of carsharing members, sometimes comparing them with control groups from similar non-member populations (e.g., Cervero, Golub, & Nee, 2007; E. W. Martin, Shaheen, & Lidicker, 2010; Sioui, Morency, & Trépanier, 2013).

The first method consists of comparing carsharing users (from surveys targeting users) to a representative sample of the general population of the area served by the service. This is what Sioui et al. (2013) did in Montréal. They used a survey from Communauto’s members and data from the 2008 large-scale Origin-Destination survey of the region to compare the mobility behaviours of carsharing member households with similar representative households within the region. The study illustrates that households with carsharing membership are statistically different from the general population in terms of sociodemographic attributes (age distribution, household size, occupation status), mobility behaviours (modal share and trip purpose) and the number of cars owned. In terms of car ownership, they own an average of 0.13 vehicles compared to 0.89 for the reference population. This finding suggests that, yes, carsharing seems to be associated with car ownership decisions for those who subscribe to the service. However, the method does not

demonstrate that carsharing causes a *reduction* in car ownership. An important cofounder is the self-selection effect. Their study shows an apparent self-selection effect due to sociodemographic characteristics but cannot measure the extent of potential unobserved effects arising from preferences and attitudes.

In the second method, car ownership reduction estimates are obtained by summing two effects: households who got rid of one vehicle after joining a carsharing service and households who forgo adding vehicles to their fleet thanks to the service. Both are assessed by direct questioning of members. In one of the first assessments of the issue, Cervero et al. (2007) used a survey of members of the City CarShare service in San Francisco. They report that surveyed service members would have reduced their number of vehicles slightly compared to non-members, but that carsharing would have mainly allowed them to avoid adding cars to their household fleet. Such conclusions remain weak due to the methodological limitations of this type of survey and the sample size (approximately 600).

To obtain more rigorous results, E. W. Martin et al. (2010) conducted a large-scale online survey in 2008 of 9,700 members (6,281 retained for analysis) of 11 services in North America (including *Communauto* in Montréal). The survey is built on a before-and-after retrospective design where respondents are asked to evaluate different parameters about their car ownership and use in the year before they adopted the service and at the time of responding to the survey. Their results indicate that the households surveyed went from an average of 0.47 vehicles per household before becoming a member to 0.24 after adopting the service. For the Canadian subsample, the rate went from 0.31 before to 0.13 after. Both statistics are significant, given the sample size. The bulk of the reduction comes from households that went from one to zero vehicles and, to a lesser extent, from households that went from two to one vehicle. Then, using their results to "scale up" the effects to the entire carsharing market, the authors conclude that each carsharing vehicle would remove between 4 and 6 private vehicles and would have prevented the addition of 5 to 7 additional vehicles (considering the share of respondents who reported not purchasing additional vehicles because of carsharing). This sums to a total of 9 to 13 vehicles potentially taken off the streets for *each* carsharing vehicle in use. The estimate of the share of inactive members (probably much larger than the active members who responded to the survey) is the main limitation of this scaling. Furthermore, such a survey, despite a considerable sample size, cannot be generalized to the entire population either because of the distinct sociodemographic profiles of carsharing members

compared to the general population. Even among carsharing members, it is difficult to assess the extent to which surveyed members have the same profiles as non-surveyed members.

Moreover, despite attempts to exclude some confounding factors (e.g., relocation/change of jobs with retrospective questioning), the methodology used does not allow for the investigation of the full range of other factors that may have affected households' decisions to dispose of their vehicles. A similar survey on a smaller scale was also conducted among *Communauto* members in Montréal and reported in Braham (2011)'s paper (in French). The weighted results of this survey indicate that 39.6% of subscribers would have disposed of their vehicle thanks to *Communauto* and 77% would have given up a future acquisition. They conclude that in Montréal in 2010, each station-based carsharing vehicle replaced ten private vehicles, leading to an aggregate reduction of 12 000 vehicles. This replacement rate is in line with E. W. Martin et al. (2010)'s rate for North America.

Many other researchers applied variations of the same methods of retrospective direct questioning of carsharing members of various North American and European cities to assess car ownership (e.g., Giesel & Nobis, 2016). Becker, Ciari, and Axhausen (2018) conveniently reported those results (published before 2018) in a summary table. Some of those results are reported in Table 3.6 along with other studies not mentioned by Becker et al. (2018). The reported replacement rate of both effects (replacement and foregone purchase) varies from a ratio of 3.5 to 1 to 23 to 1.

Table 3.6 Impact of station-based carsharing on vehicle ownership based on members survey.

Study	Location	Reduction in car ownership	Foregone purchase of a car	Replacement rate
Muheim and Reinhardt (1999)	Switzerland	15-20 %	20-25 %	1:3.5
Cervero and Tsai (2004)	San Francisco, CA	21%	28%	1:7
Lane (2005)	Philadelphia, PA	25%	29%	1:23
Braham (2011)	Montréal, QC	40%	77%	1:10
E. W. Martin et al. (2010)	US and Canada	22%	25%	1:9-13 ^a
Giesel and Nobis (2016)	Berlin and Munich, GER	15%	-	-
Steer Davies Gleave (2017)	London, UK	14%	34%	1:11
Namaz and Dowlatabadi (2018)	Vancouver, BC	32%	49%	1:5-12 ^a
Jain, Rose, and Johnson (2022)	Melbourne, AU	26%	-	-

Note: ^aThe first value in the range is solely based on claimed discarded vehicles and the second adds the number of foregone purchases.

To be clear, many more studies dating before or after Becker's study exist but are not reported here. Specific results from Jain et al. (2022) are worth mentioning. First, they used not one but two retrospective time points (in addition to the "now" point): one year before joining carsharing and at the time of joining the service. This revealed interesting patterns that were not previously reported. It appears that many carsharing users reduced car ownership *prior* to joining carsharing and, thus, likely joined the service in response to a reduction in their car ownership level. Then, carsharing seems to have allowed some users to not return to their original car ownership levels. Figure 3.7 reproduces a figure from Jain et al. (2022) (with permission from the authors) as it clearly illustrates the effect.

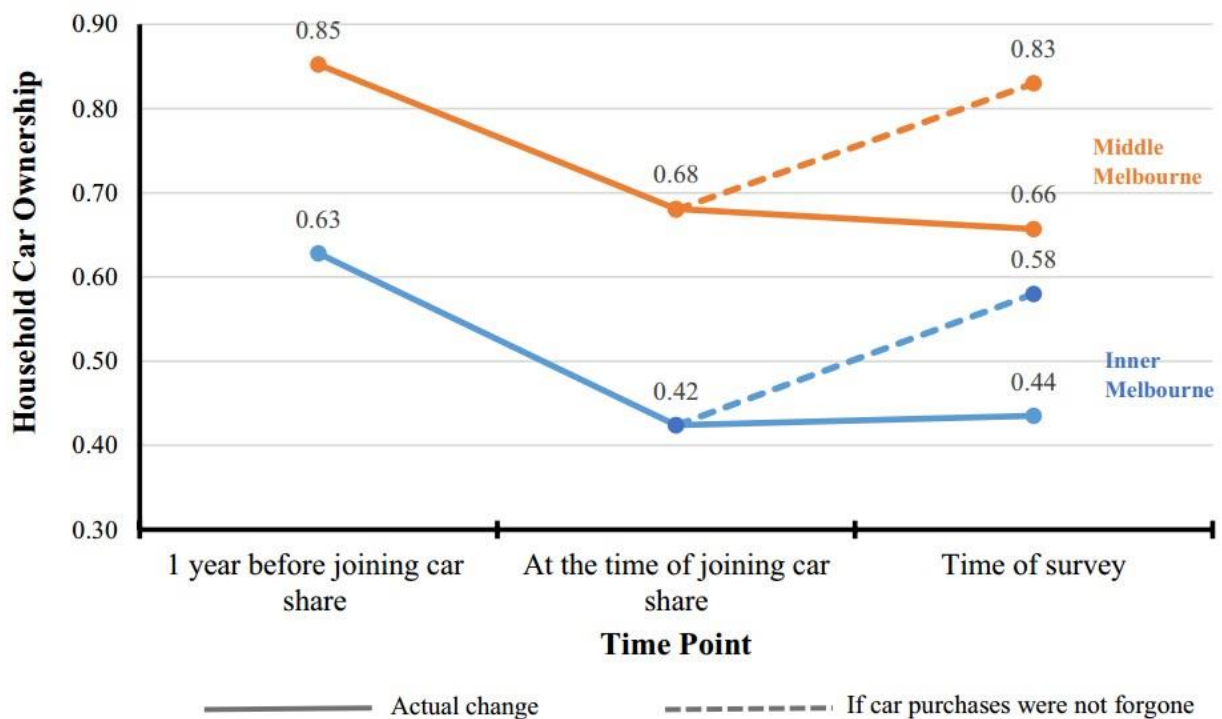


Fig. 3 Change in car ownership for car share members, inner and middle Melbourne (n = 651)

Figure 3.7 Changes in car ownership for station-based carsharing users in Melbourne, Australia. Figure from Jain et al. (2022, p. 513) reproduced with the authors' permission.

The authors report two main reasons for the reduction in the year before joining the service. The first is an increased awareness of the high fixed cost of car ownership (e.g., insurance), thus leading future carsharing users to sell their car in anticipation of joining the service. The second is the loss of a vehicle due to a crash. The other contribution of their study is showing similar car ownership

reduction effects (in anticipation and foregone purchases) for the inner city and middle suburbs locations in Melbourne. However, in inner-city locations, the effect is from one to zero car (or not buying that first car), while in the suburb, it mostly serves to sell or avoid buying a second car.

Evidence from car ownership modelling

One alternative method to assess the impact of carsharing within a region is to determine how *exposure* to the service impacts household car ownership levels. In this approach, accessibility to station-based carsharing vehicles is treated as an exogenous variable in car ownership models. For example, Klinevicius et al. (2014) sought to measure the impact of exposure to carsharing (Communauto) in Montréal (number of stations within a 500 m radius) on car ownership by controlling for different socioeconomic variables. The effects were assessed at aggregate and disaggregate levels using linear regression models and three iterations of the large-scale Montréal Origin-Destination survey (1998, 2003, 2008). At the aggregate level, the dependent variable was the average household car ownership rate within census tracts (CT). At a disaggregate level, household car ownership was treated as a continuous variable. Both models indicate a significant negative effect of the number of carsharing stations within 500 m for 2008, but not for 1998 and 2003. However, the influence is marginal compared to the other variables considered. The significant effect only for 2008 may indicate that the expansion of the service has reduced household car ownership. The strength of the approach comes from using three years of large-scale representative travel surveys. However, some important modelling limitations may confound those results. The zonal aggregate model did not control for spatial dependence, a critical issue for such models as described in section 3.3.1. Without such control, coefficient estimates obtained and tests of significance are likely biased. The modelling formulation for the disaggregate model was a linear regression, thus treating car ownership (number of cars in households) as a continuous outcome. This is problematic because the number of vehicles owned is left-censored and not a true unconstrained continuous variable going against best practice in car ownership modelling to treat it as an ordered or unordered categorical variable. Furthermore, accessibility to transit was not considered in both models because the variable *distance from the nearest metro station* was dropped due to a high correlation with the carsharing availability variable. This important omission thus further confounds the results.

Mishra, Clewlow, Mokhtarian, and Widaman (2015) used a more robust methodology with a subset of the 2010-2012 California HH Travel Survey to assess whether survey respondents who reported being members of carsharing services had a similar rate of car ownership than the non-member control group extracted from the same survey. The control group is selected using a nonparametric matched-sampling method to obtain a control sample that is equivalent in terms of sociodemographic and built environment characteristics to adequately compare mobility behaviour. In other words, this method aims to control the self-selection of households choosing to subscribe to carsharing services. Note that the pairing is not perfect but close, not allowing ideal control of the influence of all confounding variables. The two groups are then combined, and the number of vehicles in the household and the rate of access to vehicles in the household are modelled by an ordered Probit regression with mediation analysis. Their results confirm those of Sioui et al. (2013), i.e., households that are members of carsharing services have significantly and substantially lower car ownership rates than non-members. The propensity to own vehicles (the latent variable in a probit model) is 0.3 to 1.3 standard deviations lower for members than non-members. This difference is more important in urban than suburban areas. In sum, Mishra et al. (2015)'s approach is one of the more rigorous and robust found in the literature (apart from joint mobility tool ownership modelling). They argue that it confirms not only the association but also the causal effect of carsharing on car ownership within the limit of cross-sectional data. Two other limitations are acknowledged. First, the pairing method does not allow for differences in unobserved variables like attitudes, likely affecting the intention to join carsharing. Second, the reverse causality is not assessed either. That is: the car ownership level before joining the service is very likely affecting the probability of joining carsharing.

3.6.2.2 Free-floating carsharing (“one-way”)

Free-floating carsharing (also called “one-way” or “point-to-point”) is more recent than the station-based form. According to E. Martin and Shaheen (2016), it was first introduced to North America by *Car2go* in Austin, Texas. In Montréal, *Car2go* launched its service in 2013, prompting the station-based operator Communauto also to launch a free-floating service (Wielinski, 2018). Unlike station-based carsharing, vehicles in free-floating schemes are either parked on the street or in reserved parking in delimited zones (“service areas”) within cities. The vehicles can be taken out of the zone during the trip but must be returned anywhere within the zone at the end of the trip.

However, because the system is fundamentally different from the traditional station-based carsharing, notably by being oriented toward shorter car trips within the city, it likely has a different impact on car ownership and travel behaviour. This means its effects have to be evaluated separately from the traditional form.

Evidence from surveys of carsharing members

Following the rapid growth of free-floating carsharing in North America between 2010 and 2015, E. Martin and Shaheen (2016) surveyed *Car2go* users in five cities: Calgary, San Diego, Seattle, Vancouver and Washington, D.C. They used the same method of direct retrospective questioning as they used for their station-based carsharing survey. They asked respondents if they had sold a vehicle because of Car2go and if they had foregone buying one since they started using the service. Following a re-weighting of their survey sample to reduce the weight of very active users who are more likely to answer the survey, they conclude that 2 to 5 % of Car2go users sold their vehicle due to the service and another 7 to 10 % declared not having acquired a vehicle. Those proportions are then converted to substitution rates to account for the size of the *Car2go* fleet in each city. They conclude that for every *Car2go* vehicle, 1 to 3 private vehicles were sold, and another 4 to 9 were “suppressed” due to foregone acquisition for a total of 7 to 11 personal vehicles removed. This estimate is slightly less than the 9 to 13 ratio they obtained from their station-based study (E. W. Martin et al., 2010). Scaled to the five cities, this resulted in a net reduction of 28 000 vehicles. Similar methods were used by other researchers in other cities in North America and Europe. Studies reported by Becker et al. (2018) and more recent ones are presented in Table 3.7.

Table 3.7 Impact of free-floating carsharing on vehicle ownership based on members survey.

Study	Location	Reduction in car ownership	Foregone purchase of a car	Replacement rate
Firnkorn and Müller (2011)	Ulm, Germany	4%	10%	-
E. Martin and Shaheen (2016)	US and Canada	2-5%	7-10%	1:7-11
Giesel and Nobis (2016)	Berlin and Munich, GER	7%	-	-
Le Vine and Polak (2019)	London, UK	4%	30%	-
Becker et al. (2017)	Basel, Switzerland	-	8%	-
Steer Davis Gleave (2017)	London, UK	19%	27%	1:13
Becker et al. (2018)	Basel, Switzerland	6%	-	-
Namaz and Dowlatabadi (2018)	Vancouver, BC	10%	32%	1:6-26 ^a

Note: ^a The first value in the range is solely based on claimed discarded vehicles and the second adds the number of foregone purchases.

Becker et al. (2018)'s study is worth mentioning because, unlike their predecessors in Table 3.7, they stepped up the robustness of their analysis by conducting a *two-wave panel survey* one year apart with a free-floating user group and a general driver's population control group. Statistical weights were also applied to correct for age and gender selection bias. Travel behaviour was assessed using a one-week travel diary collected with a GPS-tracking smartphone app. They argued that the method addresses some of the biases associated with retrospective direct questioning of changes in car ownership and travel behaviour, such as recall bias, strategic response, attribution bias and unobserved heterogeneity. First, as with most surveys of carsharing users versus non-users, their results confirm strong self-selection effects. In the first wave, the free-floating group reported 0.27 vehicles per household versus 0.84 for the control group. Rates similar to those found by Sioui et al. (2013) in Montréal for station-based carsharing versus similar general population households. Differences in car ownership between the two waves were assessed using a difference-in-difference approach. They conclude that free-floating members reduced their vehicle ownership between the two waves by 0.06 vehicles per household (or 24 %) on average from their original 0.27 vehicles per household. In total, 6 % reduced their car ownership level. The difference with the control group is significant, despite that group having also reduced their vehicle ownership due to other factors. In short, their results from a more robust methodology obtained reduction effects in line with E. Martin and Shaheen (2016)'s results of 2 to 5 %. One

possible explanation, and a possible caveat, is the context of Becker et al. (2018)'s study. The city of Basel in Switzerland has a population of about 160 000 inhabitants. It has a high-quality public transit system, it is the least car-oriented city in Switzerland with a drive mode share of 18 % for all trips and has the lowest car ownership rates (~350 vehicles/1000 people) of medium and large Swiss cities. This makes the city an “ideal” place for carsharing to flourish and raises issues of transferability of results to larger and more car-oriented cities.

More recently, in a typical retrospective survey of London free-floating carsharing users, Le Vine and Polak (2019) found that (1) users have higher income and education than the general population, (2) that 30 % of respondents decided not to acquire a car, 4 % sold their car and 2 % plan to sell it in the near future and (3) that those with lower income relative to other users were more likely to have disposed of a vehicle as opposed to not buy one. The 30 % value is much higher than other studies, but the 4 % is in line with the results presented in Table 3.7. The authors did not provide substitution rates like other studies.

Results from car ownership modelling

None of the studies reported so far in this literature review included accessibility to free-floating carsharing services when modelling household car ownership. This might be due to the difficulty in computing good metrics to assess the availability of free-floating vehicles. Being “in the zone” would simply be a dummy variable, likely applicable to entire cities or some central neighbourhoods. More precise indicators based on the average availability of vehicles (in vehicle hours per day) or probabilities at any given instant to have a vehicle within a threshold distance would have to be calculated from historical free-floating GPS data.

3.6.2.3 Peer-to-peer carsharing

Peer-to-peer (P2P) carsharing has been much less studied than forms of carsharing. This means a much smaller number of studies looked at the impacts on vehicle ownership. Shaheen, Martin, and Bansal (2018) used the same method as they used for station-based and free-floating carsharing: an online survey with direct retrospective questioning. They targeted 1150 users of P2P carsharing apps in the US (Canada was not included this time). Results indicate that 2 % of respondents sold a vehicle due to joining a P2P carsharing service and 14 % indicated that they would have bought a car otherwise. This suggests a lower proportion than the two other types of service. Something

confirmed by Jain et al. (2022), who reported, like for station-based services, that many joined P2P carsharing in response to a reduction in car ownership in the year leading up to joining the service. That reduction was less than that of station-based members. The service also allowed them to not buy an additional car in the future, again, to a lower extent than station based.

3.6.2.4 Summary of carsharing impacts on household vehicle ownership

First, as illustrated by Sioui et al. (2013) for Montréal and reported in published literature reviews on carsharing for various forms (Schmöller & Bogenberger, 2020): those who joined the service differ from the general population on several sociodemographic characteristics. In Europe and North America, carsharing users live in smaller households, have higher than average income, and have higher education levels. As for age: free-floating users tend to be younger than station-based users. But the latter are not seniors either. Shaheen, Martin, et al. (2018) report similar findings for peer-to-peer carsharing users. Unfortunately, this makes it hard to extrapolate car ownership impacts obtained from the most common method to assess the effect of carsharing: retrospective direct questioning using online surveys of users. Such sociodemographic differences are also likely to hide even more significant differences in preferences and attitudes.

Second, even when controlling for some sociodemographic and comparing members to a representative sample (Sioui et al., 2013) or more robust methods using modelling and propensity score matching (Mishra et al., 2015), carsharing members have *substantially lower* car ownership levels. This is also true for car ownership levels when joining the service (thus before any reduction due to carsharing) when compared to control groups from the general population (Becker et al., 2018) or the region's average (Namazu & Dowlatabadi, 2018). While the comparison between the two forms of carsharing (station-based and free-floating) in the same survey is rare when this is done, results suggest that station-based members had substantially lower car ownership levels than free-floating users, the latter being close to the region's average (for Vancouver) (Namazu & Dowlatabadi, 2018). One explanation for lower car ownership rates of carsharing users at the time of joining the service was provided recently by Jain et al. (2022), who showed that users had much higher car ownership levels one year prior to joining the service than at the time of joining, having sold their car in anticipation of selecting carsharing instead.

Third, all studies based on members' surveys, either with retrospective questioning, two-wave panel, with or without sample correction, show that joining carsharing allowed a small fraction of

users to dispose of one or more of their vehicles and a larger fraction not to buy a vehicle they claimed they would otherwise have purchased. Results also show that station-based carsharing has a consistently greater impact on car ownership reduction than free-floating carsharing. However, the reduction estimates for both forms of carsharing vary substantially, from a few percentage points to up to 30 %. This is likely due to differences in sample size, response rates, selection biases, methodology differences, and context. Indeed, each city has a unique transportation system, built environment and mobility culture, which are never accounted for in those studies.

Fourth, due to the rarity of such combined services, very few studies reported analyzing the impacts of the two forms of commercial carsharing together. One exception is Namazu and Dowlatabadi (2018) in Vancouver, who analyzed station-based members (Modo) and free-floating members (Car2go) and members of both services. Their results on car ownership reduction reported in Table 3.8 suggests that having access to a free-floating service in addition to a station-based service does not further reduce car ownership than having just the station-based subscription. But the car ownership levels before suggests a similar population of both services and of *Modo* users only, which is different from the *Car2go-only* population.

Table 3.8 Comparison of car ownership reduction in Vancouver for free-floating users, station-based users, and users of both services. Based on the results from Namazu and Dowlatabadi (2018, p. 42)

[Vehicle / household]	Free-floating (FF) only	Station-based (SB) only	FF and SB
Before	1.08	0.68	0.69
After	0.98	0.36	0.35
% of reduction in CO	-9%	-47%	-49%

Note: All differences are statistically significant based on t-tests conducted by the authors.

Montréal's unique context in that regard should be assessed. The same operator (Communauto) offers its members access to station-based and free-floating vehicles with an integrated pricing plan. For example, with the integrated pricing, the rate for free-floating changes to the more advantageous rate of the station-based vehicles after a few hours of usage. This allows the use of free-floating vehicles for day(s)-long rentals and not only short-term trips within the city. The behaviour of members in such carsharing ecosystem has been analyzed (Wielinski, 2018), but not the specific impact on household vehicle ownership.

Finally, access to carsharing vehicles, notably station-based vehicles, should be more commonly integrated into car ownership modelling to provide estimated impact from other sources than surveys from members. Only two studies reviewed in this dissertation have done so (Klincevicus et al., 2014; Mishra et al., 2015). The first and second contributions of this thesis include accessibility to carsharing vehicles in the explanatory variables. The third contribution goes one step further by modelling car ownership and carsharing as a joint household decision, which was only previously done by Becker et al. (2017).

CHAPTER 4 METHODOLOGICAL FRAMEWORK

This thesis aims to elaborate a framework of how various factors influence car ownership decisions and, more broadly, *mobility tools* ownership decisions. To reach this objective, a methodological framework for the entire thesis is proposed. The foundation of this framework is the development of an integrated spatial database that fuses various datasets. This database is then used to compute the different outcome variables to be modelled and the numerous explanatory variables tested and incorporated into the developed models of car ownership and mobility tool ownership.

The following section presents a schematic of the general methodological framework. Section 4.3.1 details the three main datasets, primary surveys used in the three contributions and the complementary data sources. A presentation of the integrated geospatial database structure follows this. Because built environment variables are key factors in all the modelling methods, a detailed description of *how* those variables are computed using the most accurate and state-of-the-art methods is presented in section 4.5. Finally, a summary of the modelling methods used for the three papers is presented in the last section (4.6).

4.1 General methodological framework

The general approach used for this thesis is laid out in Figure 4.1.

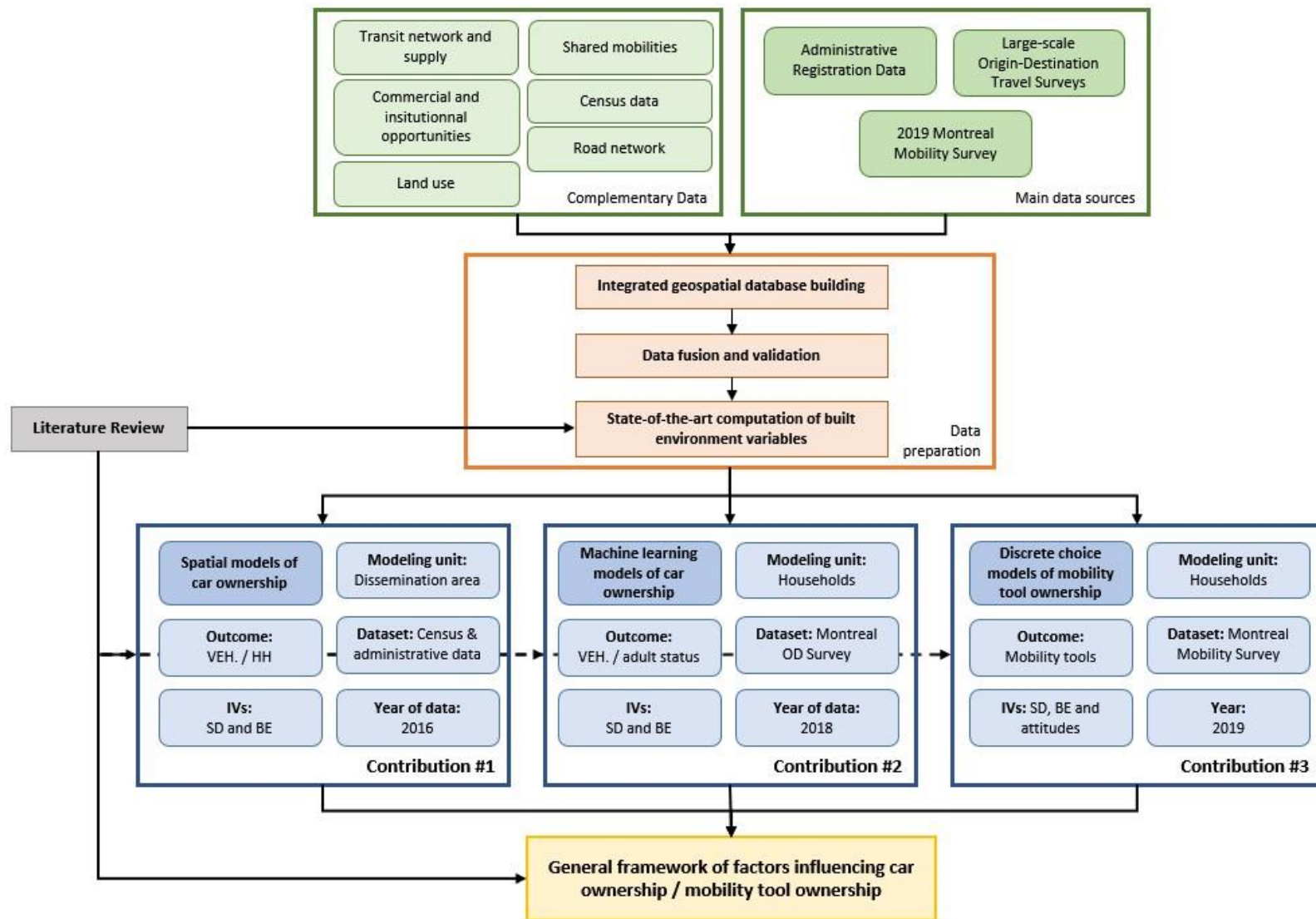


Figure 4.1 General methodological framework (SD: sociodemographic, BE: Built environment, HH: household, IV: Independent variables)

4.2 Studied region

All the analyses presented in this thesis are conducted using data from Montréal, Québec, Canada. The region of Montréal is chosen for two reasons. First, it has a complex mobility ecosystem with numerous public and shared mobility alternatives and a wide variety of built environments. The second reason is the availability of data. Access to multiple surveys and complementary datasets is possible because Polytechnique Montréal's Chaire Mobilité has partnered with several regional private and public actors.

The first contribution, Chapter 6, focuses on the Island of Montréal. The second contribution (Chapter 7) expands the region to include the suburbs of Laval and Longueuil (see Figure 4.2). Due to data limitations, the third contribution (Chapter 8 and Chapter 9) is also constrained to the Island of Montréal. The region and its subregion used for analysis are described in Table 4.1.

Table 4.1: Characteristics of the studied region and subregions

Region	Population (2016)	Households (2016)	Surface area [km ²]	Population density [pers./km ²]	Used for
Greater Montréal Area ^a	4.45 M	1.89 M	9148	487	-
Montréal, Laval and Longueuil	2.78 M	1.21 M	1032	2690	Contribution #2
Island of Montréal	1.94 M	0.87 M	500	3873	Contribution #1 and #3

Note: ^a Montréal's census Metropolitan area

In 2018, the transit system in the Greater Montréal Area had three components, a metro system of four lines and 68 stations, a bus system of 348 lines and a commuter train system of six lines converging toward the CBD. The region is illustrated in Figure 4.2.

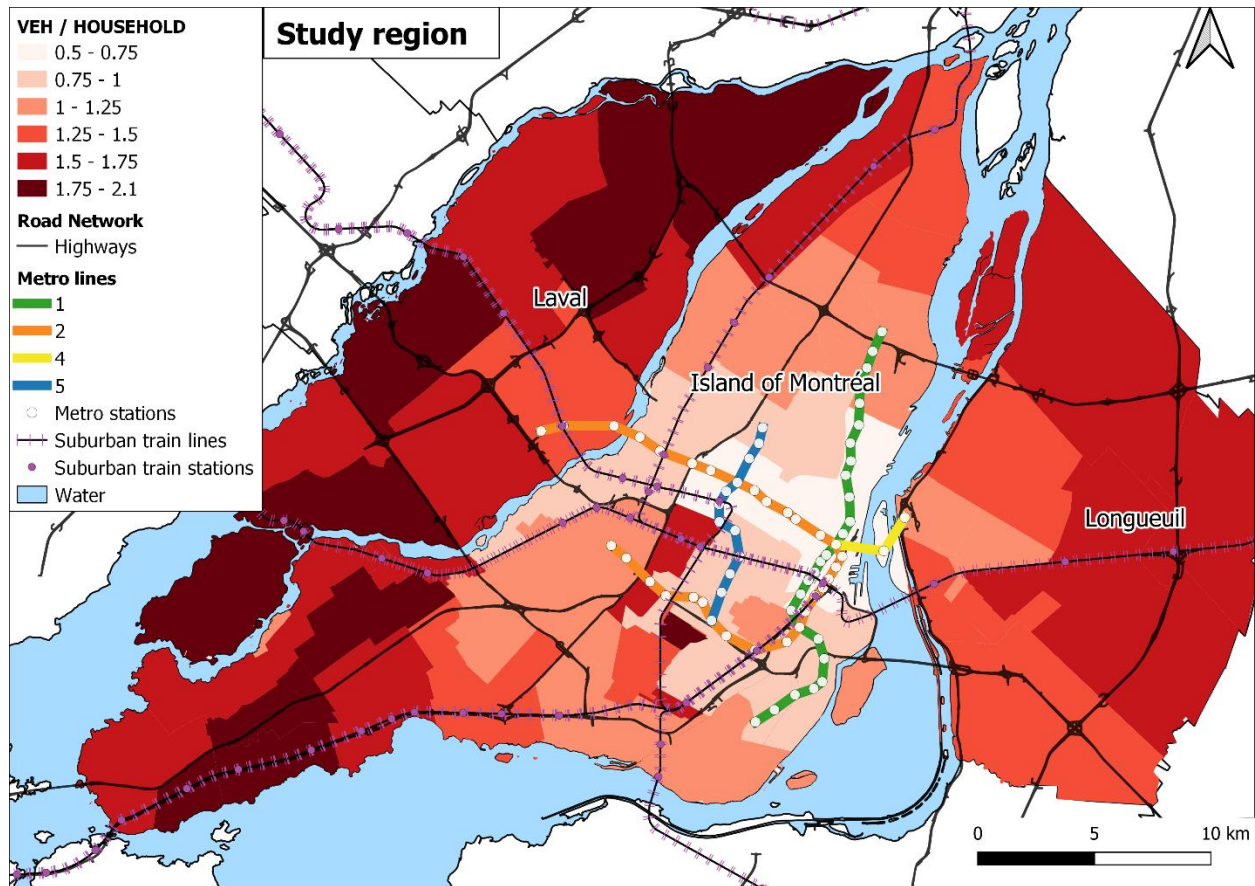


Figure 4.2 Map of the studied region with weighted average car ownership rates [in vehicles per household] by municipal sectors. Data source: OD Survey 2018.

4.3 Building an integrated geospatial database

4.3.1 Main data sources

Three primary datasets are used for the analyses. The first is a dataset of administrative registration data, the second is the Montréal large-scale Origin-Destination survey, and the third is the City of Montréal Mobility Survey.

4.3.1.1 Administrative registration data

The dataset was provided by the *Société de l'assurance automobile du Québec* (SAAQ), the authority responsible for driver licensing and vehicle registration in the province of Québec. While the dataset is provided under their open-data policy, it is not publicly available online. The dataset was requested in December 2018 and obtained in October 2019. The request was made to

aggregate the values at the Dissemination Area (DA) level (2016 Census delimitations). The DA is the smallest standardized geographical unit of the Canadian Census for which all census variables are available. It is smaller than the more commonly used Census tract (CT) and has an average population of 400 to 700 persons (Canada, 2019). It is similar in size to the American census block group.

The dataset contains the number of people with a driver's licence, the number of non-commercial vehicles registered (cars, light trucks and total) and the number of unique addresses with a registered vehicle within each DA of the Montréal Census Metropolitan Area (CMA). The data was provided for the last five census years: 1996, 2001, 2006, 2011 and 2016.

4.3.1.2 Montréal 2018 large-scale Origin-Destination travel survey

This is a telephone-based and web-based survey (since 2018) conducted every five years in the metropolitan area of Montréal to record the trips of about 4-5 % of resident households over one fall weekday. The 2018 edition collected data from 73 421 households housing a population of 168 883. The survey is conducted using a stratified sampling and weighting method based on the 2016 Canadian Census to be representative of the population of the surveyed region. The dataset contains household-level variables, including precise geocoded coordinates, individual-level variables for all members of each surveyed household and trip information about every trip by each household member ($\geq$ five years old) made on the day preceding the survey interview. In terms of car ownership information, only the number of private vehicles owned by each household is known. Since 2018, the survey also has information on other mobility tool ownership (transit pass, bikesharing, carsharing membership)

4.3.1.3 City of Montréal 2019 Mobility Survey

The City of Montréal Mobility Survey (CMM-survey) was designed on a web-based platform named Evolution, developed by the Chaire Mobilité at Polytechnique Montréal. It was distributed and promoted by the City of Montréal for one month (from May 8 to June 7, 2019) using the portal *Réalisons Montréal* (<https://www.realisonsmtl.ca/>) and shared using social media and other means. The survey area was limited to the City of Montréal and the 15 other municipalities on the Island of Montréal. Its original goal was to explore the determinants of travel behaviour, including the incentives and deterrents to using various modes, the difficulties encountered in adopting

sustainable travel behaviour and reducing car ownership. The survey asked questions about individuals, household composition, car ownership, usual places of work or school for a typical week for all adults of the households, other usual places visited by car and general attitudinal questions about mobility and the car.

Due to the nature of the data collection process, the sample is non-probabilistic and cannot be used to make inferences about the general population of the study area. Despite this, the sample can nonetheless be used to study participants' behaviours and the relationship between variables. A total of 2577 respondents completed the questionnaire representing households with a total population of 5804 people. The sample's distribution differs from the reference population as measured in the 2016 Canadian census in terms of household size, age of household members and spatial location of households (Morency, Verreault, Bourbonnais, Laviolette, & Chabin, 2019). Fewer single-person households and more two-person households responded, while a similar proportion of larger households responded (compared to the census data). Those aged 25 to 44 are overrepresented, those aged 16 to 24 are slightly underrepresented, and those aged 65 and above are highly underrepresented. There is also a spatial misrepresentation with higher response rates in the central neighbourhoods than in the eastern and western suburban areas of the Island of Montréal.

4.3.2 Additional data sources

Additional datasets are obtained from various sources to enrich the three primary datasets presented in the previous section. Datasets were obtained through three mechanisms: a partnership between the Chaire Mobilité and the organization providing the dataset (e.g., OD Surveys, Carsharing), access provided by Polytechnique Montréal's library (e.g., DMTI Spatial datasets) or Open access (freely available online). The list of all datasets imported in the integrated geospatial database is presented in Table 4.2.

Table 4.2 List of datasets and sources used in the thesis project

Dataset	Source	Access type	Years	Used for
Montréal OD Travel Survey	ARTM	Partnership Chaire Mobilité	2008, 2013, 2018	Modelling, Computing transit accessibility
Administrative Vehicle and Licensing Registration Data	SAAQ	Requested, Open Access	2001, 2006, 2011, 2016	Modelling
City of Montréal Mobility Survey	Ville de Montréal	Partnership Chaire Mobilité	2019	Modelling
Canadian Census Data	Statistic Canada	University Access	2001, 2006, 2011, 2016	Modelling and Computing BE and SD Variables
Canadian Census - Workplace data	Statistic Canada	Partnership Chaire Mobilité	2006, 2011, 2016	Computing BE variables
Landuse	CMM	Open Access	2012, 2014, 2016	Computing BE variables
Enhanced Point of Interest (EPOI)	DMTI Spatial	University Access	2006, 2011, 2016	Computing BE variables
Health Institutions Educational Institutions	Données Québec	Open Access	2006, 2011, 2016	Computing BE variables
Bikesharing Stations (BIXI)	Ville de Montréal	Partnership Chaire Mobilité	2009- 2018	Computing BE variables
Carsharing stations and vehicles	Communauto	Partnership Chaire Mobilité	2015, 2018	Computing BE variables
Free-floating carsharing zone	Ville de Montréal	Partnership Chaire Mobilité	2016	Computing BE variables
General Transit Feed Specification	Transit Agencies	Open Access	2013, 2016, 2018	Computing BE variables and Transit access
Road Network	Adresse Québec, OSM	Open Access	2019	Computing BE variable and accessibility

4.4 Database and data processing software

All software used in the present thesis are open-source (except for Excel). The datasets are imported within a relational database using PostgreSQL (v. 9.6) and its spatial extension PostGIS (v. 2.3). The SQL language makes it easy to manipulate tables with a large amount of data. It can be queried easily from spreadsheet software (e.g., Excel), spatial visualization software (e.g., QGIS) and statistical analysis coding languages (e.g., R, Python).

While most spatial joints and other spatial operations were performed directly with PostGIS, spatial visualization and the creation of maps was done using QGIS (v. 3.16 Hannover). QGIS and

PostGIS were also used to compute walking accessibility buffers using a methodology described in section 4.5.1.

Some basic data manipulation to create variables for modelling was conducted directly on the PGSQL tables using the SQL language, while most data manipulation and preparation was done in R using a variety of packages. The platform *Transition*, developed by Polytechnique's Montréal Mobility Chair, was used to compute transit accessibility maps (Bourbonnais, 2014-2019; Bourbonnais, Faucher, Morency, & Trépanier, 2014-2019) described in 4.5.3.

Modelling for the three contributions was also executed in R using open-source packages from the Comprehensive R Archive Network (CRAN) repository. For the first contribution (Chapter 6), spatial modelling and analysis were done using *spdep* and *spatialreg* (Bivand, 2019, 2020). For the second contribution (Chapter 7), modelling using Gradient Boosting Machines (GBM) decision trees was done using *xgboost* (Chen & He, 2021) and *gbm* (Ridgeway, 2020). For the third contribution (Chapter 8 and Chapter 9), discrete choice models were estimated using *mlogit* (Croissant, 2020) and *gmnl* (Sarrias & Daziano, 2017).

4.5 Preparing the built environment variables

The literature review revealed a large variety of built environment variables incorporated in car ownership models. Studies usually include one or more of the following: density (residential, employment), diversity (entropy or other land-use diversity indexes), design (average block size, intersections, streets, highways, or bikeways), transit availability (proximity/presence of a rail station and bus stops), accessibility to diverse destinations by various modes (car, walking, transit) and distance to CBD or local centres. Additionally, because there is no standardized way to compute built environment variables, each neighbourhood characteristic is often measured using different methods. The final selection of which built environment variable to use and how to compute them is based on the literature review of car ownership modelling (section 3.3), on the variable most commonly reported in the meta-analysis of the impact of the built environment on travel behaviour by Ewing and Cervero (2010) and on sensitivity analysis conducted for each contribution.

The first step in preparing built environment (BE) variables is to determine the size and shape of the areas within which the variables are aggregated. The question is explored in-depth in Chapter

7. The methodology to compute BE variables chosen for the present thesis and used for all three contributions follows the concept of “sliding neighbourhood” (Gehrke & Wang, 2020) and, more precisely, “network bands” (J. Y. Guo & Bhat, 2007). The approach consists of computing network distance buffers where each point on the boundary can be reached within the same time or distance value, thus accounting for the street network connectivity. It is argued to be conceptually and methodologically more appealing because it is the closest to representing how individuals might perceive their neighbourhoods (J. Y. Guo & Bhat, 2007).

4.5.1 Preparing the walking distance buffers

For the first contribution (Chapter 6), the walking-distance buffers are computed from the centroid of the dissemination areas (the modelling unit for this first analysis). For the disaggregate modelling, the precise coordinates of each surveyed household in the 2018 OD Travel Survey and the City of Montréal 2019 Mobility Survey are used respectively as departure points.

For the methodology to be reproducible, the walking distance buffers are computed using open-source software and tools freely available online. QGIS’s Network Analysis tool (QGIS Project, 2022) is used. The tool takes as input a layer (a shapefile) of origin points and a network layer. The network layer used for all calculations is OpenStreetMap (OSM)’s pedestrian network. This network was selected over other street network layers from other sources because it includes pedestrian shortcuts and links through back alleys, parks, and pedestrian plazas, thus, providing a more accurate representation of the “neighbourhood” accessible on foot. The output is a multiline layer of all network links accessible within the specified distance (e.g., 1 km). The layer is then imported into the PGSQL database and transformed into a layer of polygons using PostGIS’s ConcaveHull function (PostGIS Project, 2022). Note that this last step can also be performed directly in QGIS’s using the Convex Hull function, but the results are not as precise, and computation is not as efficient.

Each polygon represents an area (hereafter called “walking distance buffer”) that can be reached on foot within the specified distance (or time) around a dissemination area’s centroid or a surveyed household. The layer of polygons is then used to perform spatial joins and compute density, network design, diversity index, and sum up the number of commercial and transportation opportunities within the buffers.

An example of walking distance buffers of various sizes around fictional households for two types of neighbourhoods is presented in Figure 4.3. Except for the second contribution (Chapter 7), which aims to *test* which buffer sizes should be used, all variables are computed within a 1 km walking distance buffer unless otherwise stated (e.g., 400 m for access to bus stops).

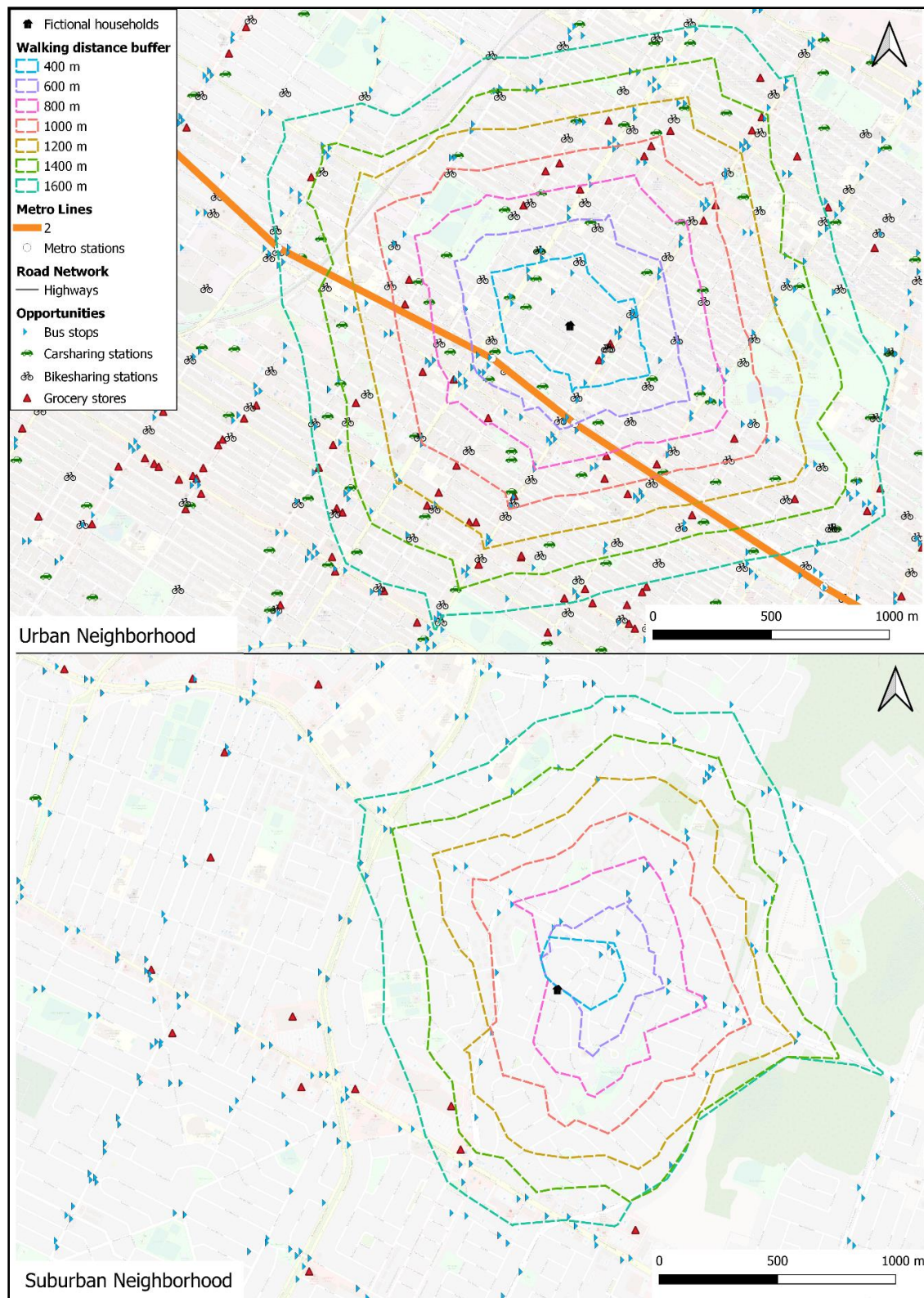


Figure 4.3 Examples of walking distance buffers for a central (top) and suburban (bottom) neighbourhoods

4.5.2 Computing the built environment variables

For the first contribution (Chapter 6), residential density is measured within the areal modelling unit, the dissemination area, as the total population or households divided by the total surface area of the unit. For the disaggregate models, densities are measured within the walking distance buffer around each surveyed household. Residential density (people per km squared and households per km squared) is calculated using spatial intersection between the walking distance buffers and the smallest census unit for which population is available, the dissemination block (a subdivision of the dissemination areas). Dissemination blocks are usually the size of a street block. For this reason, they can generally be assumed spatially homogenous in terms of population density. The population density within a walking distance buffer (WDB) around a household k is computed following Equation 1:

$$Pop\ density_k = \frac{\sum_i^J Pop_{DBi} W_{DBi}}{Area_{WDB_k}} \quad (4.1)$$

Where DB_i is one of J dissemination blocks intersecting with the WDB_k , and W_{DBi} is the proportion of the Dissemination block contained within the walking distance buffer:

$$W_{DBi} = \frac{Area(within\ WDB_k)_{DBi}}{Area_{DBi}} \quad (4.2)$$

In other words, the total population within a walking distance buffer is a weighted sum of the population within each dissemination block intersecting with the buffer.

Neighbourhood design

According to Ewing and Cervero (2010) and Stevens (2017) meta-analyses, two variables commonly used in travel behaviour research are *intersection density* and the *percentage of four-way intersections*. The former is a proxy for street block size and the latter for street connectivity, which is recognized to be associated with travel behaviour according to both meta-analyses. They are combined to obtain *four-way intersection density* within each buffer to reduce the number of variables and capture the potential effect of both aspects. Visual inspection on the map suggests that the indicator appears to be a good discriminant between North American traditional grid-style

small-block neighbourhoods (≥ 30 four-way intersections per square km) and suburban-style neighbourhoods with curving streets forming loops, three-way intersections and many cul-de-sacs (≤ 15 four-way intersections per square km).

The urban household in Figure 4.3 (top) has a density of 72 four-way intersections per square km (within the 1-km walking buffer), while the value for the suburban household (bottom) is 10.

Diversity

Diversity is assessed using Shannon's Entropy index introduced to travel behaviour research by Cervero and Kockelman (1997). For the aggregate spatial modelling in Chapter 6, the entropy is computed within each Dissemination area. For disaggregate modelling using travel surveys (Chapter 7, 7 and Chapter 9), a variation of the disaggregate version of the Entropy Index (EI) proposed by Potoglou and Kanaroglou (2008) but using the walking distance buffer instead of a 500 m radius is used. It is calculated as follows:

$$EI_{WDB_k} = - \sum_{i=1}^t \frac{p_i \ln(p_i)}{\ln(t)} \quad (4.3)$$

Where p_i is the proportion of the area occupied by the land use category i within walking distance buffer k , and t is the number of land-use types considered. The calculation includes five land-use categories: residential, commercial, offices, leisure and parks, and institutional. Categories not deemed relevant to characterizing a neighbourhood from a daily needs travel behaviour perspective (e.g., industrial, agricultural, vacant lots) are excluded. The variable takes the value of 0 if only one land-use category is present and 1 if all five land-use types are equally represented within the buffer.

Regional accessibility

Montréal's downtown (Central Business District) is the primary employment centre in the metropolitan area. Regional accessibility is thus measured as the Euclidean distance to the centre of the CBD.

Local accessibility to opportunities

Several opportunities from different datasets were considered and computed to assess walking accessibility: grocery stores (including large chain stores and local fruit-and-vegetable stores, which are very common in Montréal's central neighbourhoods), pharmacies, general retail businesses, day-care facilities, and primary schools. Access to all these opportunities is computed the same way: by summing the number of each within walking distance buffers around the dissemination Area's centroid (paper #2) and around the surveyed households (papers #3,4 and 5). However, due to high correlations between accessibility to various opportunities, only one variable could be used within each modelling framework. Following various sensitivity analyses, only the variable *number of grocery stores* within a 1-kilometre walking distance is used in the final models of all three contributions.

Accessibility to shared mobility resources

Walking accessibility to bikesharing and carsharing services were assessed in two ways: 1) by summing the number of bikesharing stations and carsharing stations within walking distance buffers, and 2) by summing the number of bikesharing anchor points and the number of vehicles at each station within the buffers.

Accessibility to public transit

The first method used to assess how good public transit is in a neighbourhood is to measure accessibility to the entry points of the transit network. Accessibility to metro and commuter train stations is computed in two ways: the presence (dummy) of a metro station's entrance within the walking distance buffer (1 km) and walking distance (in km) to the nearest station. Accessibility to the bus network is computed in two ways: first, by summing the number of bus stops within the walking distance buffer (e.g., 400 m) and second, while considering the level-of-service (LOS) at those bus stops. The variable is computed using the GTFS of all transit agencies within the region for a weekday following Equation 4:

$$Bus\ LOS_{WDB} = \sum_{S_i}^{S_j} \sum_{L_p}^{L_P} \sum_{D_k}^{D_K} T_{24h} \quad (4.4)$$

Where T is the number of trips over 24 hours in direction D_k for bus line L_p passing at stop S_i . In short, it sums up the total number of bus trips passing at all the bus lines for all directions and

stopping at all the bus stops within the walking buffers. For example, if a household has two bus stops within its 400 m walking distance buffer where at S_1 , Line 1 runs every 10 minutes (6 trips/hour) from 6 AM to midnight in both directions and at S_2 , line 2 runs every 20 min. (3 trips/hour) from 7 AM to 7 PM, the bus LOS for this household will be $6 \text{ trips/hour} * 18 \text{ hours/per day} * 2 \text{ directions} + 3 \text{ trips/hour} * 12 \text{ hours/per day} * 2 \text{ directions} = 288$. A correction is made so that if the same bus line in one direction stops at two consecutive stops within the buffer, it is counted only once.

In short, this method gives a more accurate estimate of the level-of-service of the bus network than simply summing the number of bus stops. All measures of accessibility to transit described in the present section are tested and used in contributions 1 and 2. For contribution 3, accessibility by transit is used and described in the next section.

4.5.3 Accessibility by transit

A novel method is proposed to measure accessibility to destinations by transit. The measure used considers walking time to and from the public transport access points, so access to transit is considered through this. The platform *Transition*, developed by Polytechnique's Montréal Mobility Chair, was used to compute transit accessibility maps (Bourbonnais, 2014-2019; Bourbonnais et al., 2014-2019). The final variable represents the percentage of all the Montréal metropolitan area work destinations accessible within 45 minutes by transit during the morning peak period.

The platform *Transition* takes as input the design of the transit network and the transit schedule in the form of General Transit Feed Specification (GTFS). GTFS of all the transit agencies operating in the area in 2018 were imported into the software, which encompasses bus, metro, and commuter train services. Each surveyed household's coordinates were then entered as the origin from which the transit access maps would be calculated. The following parameters were selected: a 15-minute walk maximum access time at the origin or destination (walking speed of 5 km/h or roughly 1.4 m/s), a 10-minute maximum transfer wait time, and a total travel time of 45 minutes, which is slightly more than the mean home-to-work travel time by transit in Montréal (41 minutes) according to the 2016 Canadian Census (Statistique Canada, 2017b).

As transit frequency can be highly variable throughout the day, it is essential to select a realistic departure time to assess transit accessibility to common destinations. For this, the 2018 Montréal Large-scale OD Survey is used. Destination locations and time of departure were extracted from the survey for work trips by adults. The dominant hour of departure is between 7 and 8 AM, during which 28 % of all trips to a work destination depart. Transit accessibility maps were then created using *Transition* with departure times every 15 minutes between 7 and 8 AM on a weekday. Each household's final map (or polygon) is the average surface area accessible by transit in less than 45 minutes within this hour of departure. The last step of the procedure is to sum up the number of work trip destinations extracted from the 2018 OD survey with departures within that dominant hour (7 to 8 AM) within each household's transit access polygon. Finally, to normalize the variable, that sum is divided by the total number of work destinations (for the entire metropolitan region) extracted from the OD survey with departure times between 7 and 8 AM. The final variable is thus the percentage of all the Montréal metropolitan area work destinations accessible within 45 minutes by transit during the morning peak period. The same procedure was repeated for shopping and leisure trips. The departure times determined from the OD survey were 10 to 11 AM (shopping) and 6 to 7 PM (leisure). The final measures for the three trip purposes were compared. While the percentage of shopping and leisure destinations was less than that for work destinations (due to a wider dispersion of destinations and lower transit frequency during the dominant departure hours of these trips), the three measures were highly correlated ($> .9$). All three measures are tested in the latent-class MNL of the third contribution (Chapter 8).

4.6 Overview of modelling methodologies

This section summarizes the modelling methodologies used in the papers #2, #3 and #4 presented in this thesis (Chapters 6, 7 and 8). More details, including mathematical formulations, can be found in the respective methodology sections of the three chapters.

4.6.1 A Spatial model of car ownership

This first paper was presented (speaker session) at the Transportation Research Board (TRB) Annual Meeting in January 2021 and later published in the *Transportation Research Record* (TRR) in October 2021.

For this first contribution, car ownership rates are modelled at a finely aggregated geographical scale to explore the role of various built environment and sociodemographic characteristics while controlling for spatial dependence. When modelling a phenomenon at an aggregate level where the modelling units are contiguous geographical areas, spatial modelling methods are needed to control for positive spatial autocorrelation, a type of spatial dependence that arises when adjacent areas exhibit similar values of the variable being analyzed. This leads to correlated error terms and violation of the independence of observation assumption, both of which can lead to inconsistent and biased coefficient estimates.

The objective of the paper is to investigate how the observed spatial correlation in car ownership rates observed at the level of Dissemination Areas can be explained by *within-neighbourhood* sociodemographic and built environment characteristics, the same observed characteristics in nearby areas (i.e., *contextual effects*), unobserved characteristics both within each area and in nearby areas and potential *endogenous effects* where the behaviour of households in neighbouring areas affects the behaviour of households within a given area.

To achieve this, a modelling framework is proposed to identify a spatial model specification adequately suited for investigating these questions and to obtain robust estimates of the relationship between car ownership rates and the built environment, including accessibility.

Those different explanations for spatial dependence can be modelled by including three main types of spatial interaction terms in a regression (Elhorst, 2010). To control for exogenous spatial spillover effects (the effect of observed characteristics in neighbouring areas), a spatial lag of X_s (SLX) model can be used. To control for spatial dependence arising from *unobserved effects*, a spatial error model (SEM) can be used. To control for *endogenous effects* (the behaviour, i.e., car ownership rates in the nearby areas), a simultaneous autoregressive model (SAR) is used. Contemporary state-of-the-art spatial models, however, use two spatial interaction terms. LeSage (2014); LeSage and Pace (2009) recommend either the spatial Durbin Model (SDM) with a spatially lagged dependent variable and spatially lagged explanatory variables or the spatial Durbin error model (SDEM) with spatially lagged explanatory variables and a spatially autocorrelated error term.

The challenge is to determine which model is the best suited to model the phenomenon being analyzed. Following an in-depth theoretical analysis underpinning both models, the SDEM is

preferred to the SDM on theoretical grounds, ease of interpretation of results and considerations for how some explanatory variables are measured. A methodological framework to empirically validate the model selection based on the work of Elhorst (2010), LeSage and Pace (2009) and Anselin (1988) is proposed. Additionally, three ways of defining which neighbouring areas should be used to account for exogenous (observed and unobserved) and endogenous effects are tested: Queen's contiguous neighbours, K-Nearest neighbours (with $K = 10$ to 40 , by jumps of 5) and neighbouring areas within a maximum threshold distance (800 to 1600 m, by jumps of 200 m).

The modelling uses a dataset containing the total number of registered non-commercial vehicles within each dissemination area (DA) of the Island of Montréal in 2016. That number is divided by the total number of households in each DA according to the 2016 Canadian census to obtain the outcome variable: the average number of vehicles per household (for the DA). In terms of explanatory variables, the five following neighbourhood sociodemographic characteristics are used: household median after-tax income, % of homeowners, % of households with children, % of the population aged 20-34 years old, % of the population aged 65 or above and the six following built environment variables: household density, entropy index (five categories), bus level-of-service (400 m walking distance buffer), presence of a metro station (800 m walk), number of grocery stores (800 m walk) and number of carsharing stations (800 m walk). The SLX and SDEM models tested also consider the values of all sociodemographic and built environment variables within neighbouring dissemination areas except for the accessibility measure computed within walking distance buffers.

4.6.2 A Gradient boosting machine (GBM) decision trees of car ownership

The second contribution was first presented at the Transportation Research Board (TRB) Annual Meeting in January 2022 and later published in the *Journal of Transport Geography* in October 2022.

The objectives of this second contribution are two-fold: 1) investigate how the relationship between car ownership and built environment attributes can vary when calculated within different sizes of walking distance buffers (400 m to 1600 m, by jumps of 200 m) and 2) investigate the presence of possible threshold (or “non-linear”) effects of built environment attributes on household car ownership.

The analysis makes use of recent progress in machine learning methods by building a series of models using Gradient Boosting Machines (GBM) decision trees. The method was selected over more traditional discrete choice models for three reasons: 1) it is a non-parametric method more robust to the presence of multicollinearity (Hastie, Tibshirani, & Friedman, 2009, ch. 10), a common problem when incorporating several features of the built environment in a single model; 2) its ability to investigate non-linear relationships by producing partial dependence plots (W. Zhang et al., 2020); 3) its ability to rank the most relevant explanatory variables, a critical aspect for making policy recommendations about which variable to target for a maximum effect on travel behaviour.

GBM works by growing an ensemble of small decision trees where at each iteration, a new tree is fitted to the residuals of the current ensemble and added to the ensemble while leaving the previous trees unchanged (Hastie et al., 2009, ch. 10). It uses the principles of stochastic gradient descent algorithm where parameters are changed iteratively in the direction of the gradient of the loss function following Friedman's (2001, 2002) generalized boosting algorithms. Furthermore, the method is not susceptible to multicollinearity because the algorithm will not choose a variable that does not correlate well with the outcome variable but shares a lot of variances with a more robust predictive variable when splitting variables during the tree-growing process. The method is also highly customizable, and the modelling can be fine-tuned to maximize prediction by varying several hyperparameters.

Interpretation of results from machine-learning models can sometimes be problematic as these algorithms are often black boxes that return predictions without information on the direction of influence. To address this, two useful analytic tools to get insights from the modelling process are available through packages (*gbm* and *xgboost* in R) implementing GBM decision trees. Both tools are critical elements to reaching the objective of this paper.

The first tool is the *relative significance of explanatory variables*. When using GBM decision trees, it is not possible to test the significance of each explanatory variable. The indicator gives a percentage of how much each variable contributed to explaining the modelled outcome variable. The results are often standardized to sum to 100 % for all variables in the model. However, the relative influence does not indicate the direction of each variable's influence on the outcome. The

tool is used to assess how the association of various built environment variables with household car ownership varies when measured within different buffer sizes.

The second tool is the *partial dependence plot*. It is a plot of the average change in the outcome variable (or in the log-odds of each category in the case of a categorical outcome) as a function of the value of *one* explanatory variable, holding every other variable constant at their mean. They are used to analyze threshold effects in the relationship between various BE attributes and household car ownership when measured within buffers of varying sizes.

The modelling is conducted using the 2018 Montréal Origin-Destination travel survey for the subregion containing the Island of Montréal and the suburbs of Laval and Longueuil. The modelling unit is the household, and to obtain the outcome variable, the number of cars is normalized to household size by dividing the number of vehicles by the number of adults (18 or above), which is then transformed into three distinct vehicle ownership statuses: no car, one or more cars shared by two or more adults (i.e., less than one car/adult), and full motorization (i.e., more than or equal to 1 car/adult). The models are estimated separately for one-adult households (1adultHH) and multiple-adult households (2+adultsHH).

4.6.3 A Latent-class discrete choice model of mobility tools ownership

The third paper was submitted for publication in *Transportation Research Part A: Policy and Practice* in September 2022.

This third contribution has two objectives: first, to investigate the role of sociodemographic, the built environment and car and travel-related attitudes on the complex substitution patterns between car ownership and carsharing membership in an urban context with high availability of carsharing vehicles; second, to investigate how attitudes might moderate the effect of the built environment (BE) and household sociodemographic (SD) characteristics on the joint choice of car ownership/carsharing.

Due to clear endogeneity in the choice of car ownership and carsharing, the approach taken is part of a more holistic framework of *mobility tool* ownership modelling where both ways for households to access a car are estimated jointly. Furthermore, because previous research reported the presence of important unobserved heterogeneity (i.e., variations in the choices that cannot be explained by observed sociodemographic and built environment characteristics) in the decisions

of how many cars to own (e.g., S. H. Kim & Mokhtarian, 2018) and to a greater extent on the decision to subscribe to a carsharing service (e.g., Mishra et al., 2015; Sioui et al., 2013), the modelling framework selected aims to account for taste heterogeneity in the joint choice. The latent-class multinomial logistic model (LC-MNL) is chosen as an easy-to-estimate modelling method that provides an intuitive way to account for and investigate the role of taste heterogeneity in the choice being modelled (Hess et al., 2011).

The LC-MNL is a semi-parametric approach that relaxes the assumption of the irrelevance of independent alternatives (IIA) of the simple MNL. The population is assumed to be segmented into a discrete number of classes, each having different tastes concerning the choice process. The IIA property still holds within each class. The model comprises two parts estimated simultaneously: a probabilistic segmentation model and a choice model. The segmentation model takes a logit form. The choice model is selected here as the multinomial logistic model because it has been demonstrated to be superior to ordered models in modelling car ownership (see section 3.3.2.1). The proposed framework uses four latent attitudinal variables in the segmentation model. The latent variables were obtained in a first step from a principal component analysis (PCA) of 12 measured indicators. Only household sociodemographic and built environment characteristics are entered in the choice model. In other words, the segments are based only on the attitudinal factors, thus allowing to test the hypothesis that attitudes might moderate the effect of SD and BE on the joint choice of car ownership/carsharing (e.g., the influence of income or transit accessibility depends in part on an individual's attitudes). The proposed framework is illustrated in Figure 4.4.

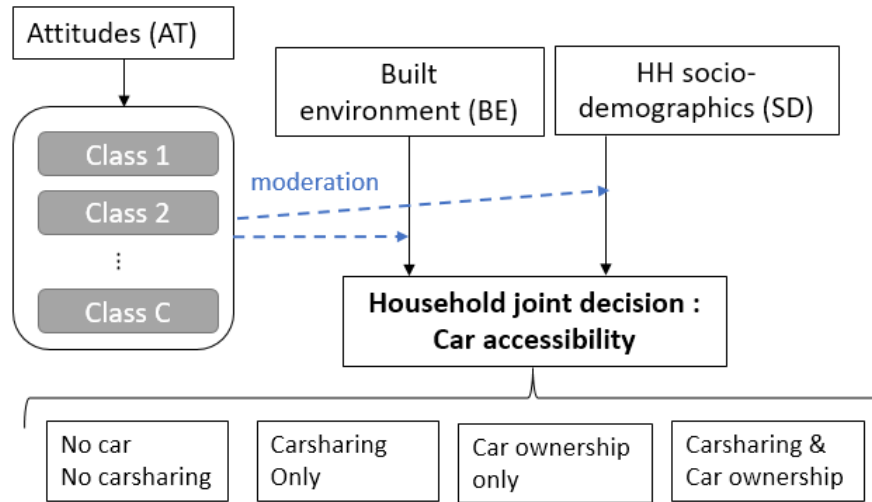


Figure 4.4 Proposed latent-class choice modelling framework

The modelling is done using a one-time Mobility survey collected for the City of Montréal in May 2019 in which a set of 12 statements about the instrumental, affective, and symbolic aspects of the car and the preferred transport mode were measured. The joint car ownership/carsharing membership decision is modelled at the *household level* using four mutually exclusive categories: 1) no car and no carsharing, 2) carsharing only, 3) car ownership only, and 4) car ownership and carsharing. Individual attitudes from the respondent are used as a proxy for household-level attitudes. The four attitudinal factors obtained from the PCA are “car appreciation”, “car values”, “social identity”, and “independence”. The five household sociodemographic variables are the number of adults, the presence of children, the average age of household adults, the number of workers and the median income in the dissemination area (as a proxy for the unmeasured household income). The three built environment characteristics are population density within a 1-km walking distance buffer, the number of station-based carsharing vehicles (1-km walk) and the percentage of metropolitan area work destinations accessible by transit with a departure time between 7 and 8 AM.

CHAPTER 5 ARTICLE 1 : PERSISTANCE DE L'AUTOMOBILITÉ ? ANALYSE EN TROIS PERSPECTIVES⁷

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RÉSUMÉ

Le phénomène de « peak-car », la croissance de l'usage des modes actifs et collectifs et un regain d'intérêt pour des aménagements urbains plus denses, mixtes et à échelle humaine, soulèvent la question du déclin des mobilités automobiles. Un cadre d'analyse en trois perspectives est utilisé pour évaluer d'une part, si ce déclin est réel et d'autre part, si celui-ci s'accompagne d'un changement de paradigme dans la planification des transports et de l'aménagement urbain qui indiquerait la fin de l'*automobilité*. La question est appliquée spécifiquement pour la province de Québec et ses deux régions métropolitaines, Montréal et Québec. Comme première perspective, l'analyse des indicateurs de motorisation et d'utilisation de l'automobile indique un accroissement soutenu des mobilités automobiles au cours des deux dernières décennies. Comme seconde perspective, l'analyse des documents officiels de planification et de politiques-cadres de la mobilité révèle des constats justes des enjeux de mobilité, mais une reconnaissance inégale de la dépendance à l'automobile. De plus, aucun des documents municipaux et métropolitains ne présente d'objectifs précis de réduction de l'usage de l'automobile et de la motorisation. Finalement, dans une troisième perspective, les projets d'infrastructures prioritaires ne sont pas tous cohérents avec les objectifs et visions des documents de planification. En effet, les bénéfices attendus d'ambitieux projets de transport collectif sont compromis par des projets de développement autoroutiers autant à Montréal qu'à Québec. Les justifications de ces projets routiers sont issues d'un paradigme de planification classique largement démontré comme dépassé et inadéquat. La priorité qui leur est donnée semble relever d'une résistance politique au

⁷ A translation to English of the paper is provided in the Annex A.

changement de paradigme. Prises ensemble, ces trois perspectives tendent à démontrer qu'en dépit de certains signes positifs, le déclin des mobilités automobiles qui s'appuie sur un changement réel de paradigme de mobilité ne semble pas être amorcé au Québec.

Mots clés : Dépendance automobile, automobilité, planification urbaine, politiques publiques, infrastructures de transport.

5.1 Introduction

Les conséquences environnementales, sociétales et économiques de l'*automobilité* – le paradigme de mobilité centré sur l'automobile personnelle – sont largement documentées (e.g. Gärling & Steg, 2007; Héran, 2011) et ce paradigme est appelé à devoir changer rapidement face à l'urgence climatique. À partir de 2009, plusieurs études commencent à rapporter un essoufflement de la croissance des mobilités automobiles (mesurées en véhicules-kilomètres parcourus) (P. Goodwin, 2012; P. Goodwin & Van Dender, 2013; Millard-Ball & Schipper, 2011; Newman & Kenworthy, 2011; Puentes & Tomer, 2008). Ce phénomène nommé « peak-car » suscite beaucoup d'intérêt et de nombreux facteurs sont avancés pour tenter d'en expliquer les causes : conjoncture de facteurs économiques, changement des pratiques de mobilité chez les jeunes, densification, amélioration de l'offre de mobilité durable, influence des technologies de l'information, changements démographiques, etc. (P. Goodwin, 2012). Dans leur plus récent livre sur la dépendance à l'automobile, Newman and Kenworthy (2015a) accordent une grande importance à la réurbanisation des villes par une densification et une réorientation des politiques de transports vers les modes durables pour expliquer ce phénomène. En contrepartie, des études plus récentes présentent un portrait un peu moins optimiste. Par exemple, Focas and Christidis (2017) concluent qu'il serait prématuré de parler d'un changement de paradigme de la mobilité automobile pour l'ensemble de l'Europe. Aux États-Unis, Mislinski (2019) observe une reprise de la croissance des véhicules-kilomètres parcourus totaux depuis 2013 (même en contrôlant pour la croissance de la population), ce rebond n'ayant pas encore permis de rejoindre les niveaux de 2005. Leard, Linn, and Munnings (2019) concluent même que les véhicules-kilomètres parcourus continueront à croître au même rythme qu'avant le plafonnement.

Parallèlement à ces tendances d'évolution des mobilités automobiles, on observe une grande diversification des options de mobilité dans les villes européennes et nord-américaines. Par

exemple, on note une renaissance importante de la pratique du vélo utilitaire encouragée par un développement rapide des infrastructures cyclables (Buehler & Pucher, 2012; Pucher & Buehler, 2017) et des systèmes de vélopartage (Fishman, 2016), incluant au Québec et à Montréal (Morency, Trépanier, Frappier, & Bourdeau, 2017; Vélo Québec, 2016a, 2016b). De nombreuses villes nord-américaines rapportent une augmentation de l'offre et de l'achalandage du transport collectif depuis 2000 (Boisjoly et al., 2018), une tendance aussi observée au Québec (Gouvernement du Québec, 2018a). L'accès à l'automobile tend aussi à changer avec un décuplement de l'offre de service d'autopartage et des membres de ces services dans le monde (Shaheen, Cohen, et al., 2018). Une tendance particulièrement marquée à Montréal (Wielinski, Trépanier, & Morency, 2019).

L'évolution des tendances de mobilité étant intimement guidée par le développement du territoire et le développement des infrastructures de transport, le principal objectif de ce travail est de chercher à savoir **si l'approche de planification des transports et d'aménagement du territoire, centrée depuis des décennies sur l'automobile, est en transformation**. De cette question centrale découlent plusieurs sous questions de recherche. En s'intéressant au cas des régions métropolitaines de Québec et de Montréal, il s'agit tout d'abord d'évaluer si l'*automobilité*, mesurée ici par les usages et la possession de l'automobile, est en déclin. Par la suite, est-ce que les documents de planification dont se dotent les pouvoirs publics sont cohérents et sont suffisants pour soutenir une transition vers des pratiques de mobilité plus durables et moins autodépendantes ? Finalement, est-ce que les grands projets d'infrastructures et les stratégies gouvernementales priorisés sont cohérents avec la vision, les objectifs et les cibles de ces documents de planification ? Notre hypothèse est qu'une réponse positive à l'ensemble de ces questions pourrait signifier un changement complet de paradigme marquant la fin de l'*automobilité*. Une réponse positive à seulement certaines de ces questions marquerait plutôt un changement partiel de paradigme qui pourrait confirmer ce que Banister (2008, p. 74) identifie comme un chemin schizophrénique (*schizophrenic paths*). C'est-à-dire une situation où l'on reconnaît l'existence des enjeux, où l'on planifie de les résoudre, mais où finalement on continue à faire ce qu'on a toujours fait sans adopter de stratégies ou actions réellement en mesure de changer la situation.

Pour répondre à ces questions, nous proposons un cadre d'analyse en **trois perspectives**. La **première perspective** consiste en un diagnostic de la situation et vise à quantifier l'évolution de

la mobilité automobile en termes de niveaux d'utilisation et de motorisation à l'aide de données statistiques et d'enquêtes. La **deuxième perspective** d'analyse est une évaluation de la réponse des pouvoirs publics aux enjeux de mobilité dans leurs documents officiels de planification. La **troisième perspective** est une évaluation de la cohérence entre les documents de planification, les projets d'infrastructures majeurs et les stratégies gouvernementales priorisées pour améliorer la mobilité sur le territoire. La province de Québec, et plus spécifiquement les régions métropolitaines de Montréal et de Québec, sont prises comme cas d'étude.

Le reste de l'article se décline comme suit. Une revue des écrits existants sur les limites des approches de planification passée, l'analyse de la cohérence des politiques publiques et l'évaluation des impacts attendus de projets d'infrastructure est d'abord proposée. Suit la présentation détaillée du cadre d'analyse en trois perspectives. L'analyse de chaque perspective est ensuite présentée, suivie des conclusions que permet de tirer l'analyse à l'égard des questions de recherche énoncées.

5.2 Revue de la littérature

D'après Metz (2013), le phénomène de « peak-car » marquerait une transition entre la troisième et la quatrième ère de déplacement. Dans cette quatrième ère, les distances moyennes parcourues par jour et par personne (notamment en voiture) ont cessé de croître⁸, ayant atteint la saturation (Metz, 2010), et la croissance future des distances totales parcourues par les sociétés sera principalement attribuable aux changements démographiques. Toutefois, ce plafonnement des mobilités automobiles signifie-t-il un déclin de la *dépendance à l'automobile* ? Et plus largement, est-ce le signe ou même le résultat de l'amorce d'un *changement de paradigme en mobilité* ?

En s'appuyant sur le concept de dépendance à l'automobile énoncé par Gabriel Dupuy (1999) selon qui celle-ci va plus loin que le seul système de mobilité, englobant un système d'organisation de notre société allant des chaînes d'approvisionnement à l'organisation des activités des individus en fonction de leur accès à l'automobile (effet de « club »), il peut être avancé qu'un déclin soutenu, profond et permanent des mobilités automobiles ne soit possible que par une transformation profonde des sociétés. Cela signifie qu'un virage important dans les fondements de

⁸ Metz (2013) souligne que cette stabilisation exclut les déplacements par avion qui eux sont encore en forte croissance.

la planification des transports, de l'aménagement du territoire et de la gestion de la demande doit se produire. Cette transformation du paradigme de planification doit aussi s'accompagner d'engagements politiques forts qui se concrétisent dans les projets et politiques publiques prioritaires pour favoriser la mobilité durable qui soient suffisamment porteurs pour surpasser la dépendance à l'automobile (Banister, 2008).

En effet, l'approche classique de planification longterm favorisée par les autorités planificatrices s'appuie sur une hypothèse de demande automobile toujours croissante. Pour répondre à cette demande qui se manifeste sous forme de congestion, la solution est donc d'augmenter la capacité routière. Cette approche de « predict and provide » traite le trafic automobile comme un liquide (Newman & Kenworthy, 2015b), un flux dont on cherche à optimiser le déplacement sur le réseau en augmentant sa vitesse. Une telle approche de planification néglige les différents effets de demande induite pourtant largement reconnus et démontrés aujourd'hui par plusieurs études empiriques (e.g. Cervero, 2003; Duranton & Turner, 2011; P. Goodwin, 1996). Elle néglige aussi les effets à double sens et à long terme entre le développement des infrastructures de transport et l'utilisation des sols (Masson, 1998; Wegener, 2014). En somme, en planifiant essentiellement pour la voiture, une telle approche en favorise grandement sa possession et son utilisation au détriment des modes durables par une diminution des densités, une ségrégation des usages, un éparpillement des lieux d'activités et une augmentation des distances.

Les externalités croissantes, notamment environnementales, l'incapacité à résoudre les enjeux de congestion et à améliorer la qualité de vie de l'approche classique sont connues depuis de nombreuses années déjà (Newman & Kenworthy, 2015b). Les exercices de planification plus récents prennent donc appui sur un désir de changer le paradigme de développement en misant notamment sur des stratégies intégrées de transport et d'urbanisme (Masson, 1998) et sur des projets de développement qui reposent sur des investissements en transport collectif structurants et une densification mixte du milieu bâti. Le « Transit-Oriented Development » (TOD) est l'une des moutures exemplifiant cette nouvelle approche et est d'ailleurs au cœur du Plan métropolitain d'aménagement et de développement (PMAD) de Montréal (Douay & Roy-Baillargeon, 2015).

5.2.1 Cohérence des approches de planification et des projets d'infrastructures

Malgré des objectifs et ambitions de changement énoncés dans les documents de planification autant en Amérique du Nord qu'en Europe, de nombreux travaux ont permis d'illustrer que la

réalisation d'une stratégie d'ensemble cohérente entre les différentes échelles de planification et les projets prioritaires semble se heurter à de nombreux obstacles. Dans une analyse de la planification des déplacements en France, Hérin (2017) critique l'approche sectorielle de planification, c'est-à-dire la priorisation d'un seul mode à un endroit donné. Il confirme que cette approche est incapable de produire une cohérence d'ensemble. En exemple, les stratégies du « tout au transport public » qui ont succédé au « tout à l'auto » sont notamment remises en cause puisqu'elles génèrent une forme de dualité des approches où le transport collectif est priorisé uniquement en zone dense et où l'on considère que l'automobile doit encore être maintenue en périphérie puisque ce serait le seul mode de transport possible. On sous-estime ainsi largement les nuisances des transports motorisés. Hérin (2017) rapporte aussi un exemple pertinent à l'égard de la présente analyse réalisée ici au Québec, soit celui du Schéma de cohérence territoriale (SCoT) de Lille où l'on affirme vouloir réduire la congestion routière en investissant dans les transports collectifs et en encourageant les modes actifs tout en continuant de développer le réseau routier.

Buhler, Bendinelli, Lethier, and He (2018) ont utilisé la *textométrie* pour analyser les discours des politiques urbaines au sein des documents de planification. Les auteurs appliquent cette méthode automatisée à deux éditions, séparées d'environ 10 ans (2000 et 2010), des Plans de déplacements urbains (PDU) de 18 agglomérations françaises, pour un total de 36 documents afin de pouvoir identifier des contrastes dans les discours qui seraient difficilement observables par la lecture humaine. L'analyse révèle ainsi deux types de discours par rapport à l'automobile. Le premier cherche davantage à substituer et limiter l'automobile alors que le second se concentre sur l'ajout et la promotion d'alternatives à la voiture, mais sans remettre en question sa place dans la ville. La comparaison des deux éditions révèle aussi une transition vers une volonté d'action plus importante, mais exprimée en termes plus abstraits, ce qui pourrait s'expliquer par un désir des agglomérations de ne pas révéler toutes leurs cartes en prévision de négociation futures sur certains projets d'infrastructures. Une telle stratégie avait déjà été révélée par l'étude des documents de planification de trois agglomérations françaises par Reigner and Hernandez (2007) qui avaient cherché à analyser les interactions des agglomérations avec l'État, propriétaires des réseaux supérieurs, dans l'articulation des objectifs, des actions et des projets de leur PDU. Pour ce faire, Reigner et Hernandez ont réalisé un inventaire exhaustif de l'ensemble des projets mentionnés dans les documents locaux de planification afin de révéler les modèles de déplacement vers lesquels souhaitent tendre les représentants de ces agglomérations. Le portrait d'ensemble révèle

ainsi un désir de connectivité des réseaux routiers supérieurs en périphérie pour contourner et accéder à la ville avec, en parallèle, le souhait d'aménager un cœur urbain durable et attractif où l'automobile est maîtrisée. Cette dualité des approches (mentionnée aussi par Kaufmann (2003) et Héran (2017)) n'est toutefois pas ouvertement explicitée dans les documents de planification, illustrant la stratégie politique des représentants locaux de cacher leurs cartes afin de maximiser leurs chances de voir leurs projets réalisés.

Les politiques de transports au Québec ont déjà fait l'objet de plusieurs travaux et analyses critiques. Par exemple, Paulhiac and Kaufmann (2006) se sont intéressés aux politiques de transport et d'aménagement dans la région de Montréal à partir des logiques d'actions des politiques de transports urbains en Europe afin de déterminer si la ville peut être un « modèle » dans le contexte nord-américain comme le sont Berne et Zurich en Suisse. Paulhiac et Kaufmann se basent d'abord sur les caractéristiques de la ville (densité, centralité forte, part d'utilisation des transports collectifs) pour déterminer que Montréal se rapproche plus des villes Européennes que des autres villes canadiennes et américaines. En ce qui a trait aux relations transport-urbanisme dans les politiques publiques des dernières décennies, les auteurs soulignent que les autorités misent beaucoup sur le développement de nouvelles infrastructures et de leurs vertus structurantes. Malgré cette croyance et ce souhait de bonifier l'offre de transport collectif, les auteurs notent, à l'époque, l'absence de planification stratégique intégrée du transport et de l'aménagement. Paulhiac and Kaufmann (2006) concluent que malgré la présence de ce qui est identifié comme un référentiel favorable aux transports collectifs dans la métropole, la bonification significative de l'offre n'arrive pas à se matérialiser, se heurtant régulièrement à l'enjeu du financement du transport collectif qui découle largement d'autres paliers de gouvernement. Scanu (2014) a procédé à une analyse des discours des acteurs urbains ayant participé aux processus de consultations publics entourant l'élaboration du Plan de Mobilité durable de la Ville de Québec (2011). En s'appuyant sur la perspective théorique des problèmes sociaux et sur les principes de narration et de coalition discursive, l'auteur illustre qu'il existe trois narratifs de mobilité durable, chacun tenu par un regroupement d'acteurs distincts. On retrouve ainsi une vision de la mobilité durable (construite autour d'un futur tramway) comme vecteur de croissance économique, de développement immobilier et d'attractivité locale et internationale ainsi qu'une vision citoyenne plus axée sur les besoins d'équité, d'accessibilité et de mixité des citoyens actuels de la ville. La première vision, portée notamment par le comité responsable de l'élaboration du plan et les élites

économiques, amène l’auteur à suggérer que l’utilisation du mot « durable » serait une façon pour les élites économiques de cacher les réelles motivations de croissance économique derrière un discours environnemental.

Dans une analyse similaire à la présente analyse, Legacy, Curtis, and Scheurer (2017) explorent les enjeux de gouvernance et les oppositions politiques entre divers paliers de gouvernement dans la planification des transports en Australie. Dans une perspective théorique, les auteurs s’appuient sur les principes de dépendance au sentier (de l’anglais, « path dependency ») en planification des transports pour expliquer les décisions d’augmentation de capacité routière dans trois cas d’analyse à Sydney, Melbourne et Perth. Les documents de planification des transports et de l’aménagement du territoire, les communiqués de presse gouvernementaux, les médias sociaux et quelques entrevues auprès d’acteurs clés sont utilisés pour alimenter la réflexion. D’une part, les auteurs observent la création d’un consensus de priorisation du transport collectif (« consensus-turn ») afin d’augmenter l’accessibilité dans les documents de planification du transport et de l’aménagement au niveau métropolitain au début des années 2000. Parallèlement, un antagonisme de type « top-down » semble naître depuis quelques années alors que des décisions politiques au niveau du gouvernement fédéral et des gouvernements d’états favorisent le développement d’importantes infrastructures routières. Des processus opaques et des mécanismes d’évaluation biaisés semblent guider ces projets allant à l’encontre des objectifs locaux de planification, mais aussi à l’encontre des principes de consultation publique et de formation de décisions consensuelles qui doivent en émerger. Les auteurs voient ici une tentative, par les élites politiques, de réintroduire les solutions d’automobilité du passé. Une application similaire du principe de dépendance au sentier comme méthode d’analyse des barrières discursives à la mobilité durable en Nouvelle-Zélande conclut qu’une fois les politiques pro-routes établies, les arguments des organisations gouvernementales sont acceptés par le public comme étant la norme, inhibant ainsi l’émergence d’opposition aux récents et futurs projets routiers (Imran & Pearce, 2015).

En somme, l’analyse de la cohérence entre les discours politiques, les documents de planification et les projets et politiques de transport priorités est un thème récurrent dans la littérature scientifique permettant notamment d’identifier des parallèles entre la situation au Québec et ailleurs dans le monde. Toutefois, la combinaison d’une analyse des tendances de mobilité, des documents de planification de trois paliers de gouvernement différents et des projets

d'infrastructures planifiés comme outil de réflexion sur un possible changement de paradigme en mobilité au Québec ne semble pas avoir été réalisée.

5.2.2 Impacts attendus des projets d'infrastructures

Sans chercher à faire une évaluation approfondie de chaque projet de développement de transport collectif retenu pour la présente étude, il convient de déterminer si, dans leur concept général, ces projets permettent de contribuer à l'atteinte des cibles de mobilité durable, notamment la diminution de l'utilisation de l'automobile et l'augmentation de l'usage des modes collectifs et actifs. En s'appuyant par exemple sur les travaux de Litman (2019), il est estimé que la bonification des services de transport collectifs entraîne de nombreux bénéfices directs et indirects sur la société, l'environnement et l'économie provenant notamment d'une réduction des déplacements automobiles et d'une transformation du développement urbain et de l'usage des sols.

Des évaluations réalisées sur des projets spécifiques de nouvelles lignes de trains légers sur rail à Portland (OR, É.U.), qui peuvent s'apparenter au développement du Réseau express métropolitain (REM) dans la région de Montréal, indiquent par exemple que les corridors ayant bénéficié de l'intervention s'étaient densifiés, que les ménages y effectuaient beaucoup plus de déplacements à pied et en transport collectif et présentaient une augmentation moindre en véhicules-kilomètres parcourus en automobile comparé à des corridors autoroutiers similaires sans interventions (Ewing & Hamidi, 2014). Les auteurs confirment l'importance d'une approche intégrée de développement de quartiers TOD compacts et mixtes pour aller chercher les effets multiplicatifs des investissements en transport collectif et ainsi soutenir un *ralentissement* de la croissance de l'usage de l'automobile. Cet effet est notamment possible en raison de l'influence combinée des variables de l'environnement bâti sur les comportements de mobilité (Ewing & Cervero, 2010).

Finalement, comme des projets d'augmentation de la capacité routière sont aussi proposés en parallèle de ces projets de transport collectif, il importe aussi de savoir quels sont les impacts généralement attendus de ce type de projet. Tel que précédemment illustré, il est peu probable que ces projets contribuent à réduire la congestion, si ce n'est qu'à très court terme. Il est aussi improbable que ceux-ci permettent d'atteindre les objectifs de réduction du nombre de déplacements en automobile et de la part modale de l'automobile en raison du principe de la *Loi fondamentale de la congestion routière* (Duranton & Turner, 2011). Considérant aussi les effets sur le développement urbain d'infrastructures de transport autoroutières (Cervero, 2003), leur

réalisation risque plutôt d'augmenter la motorisation en plus de compromettre les bénéfices attendus des projets de transport collectif.

5.3 Cadre d'analyse

Pour explorer la question du déclin ou de la survie des mobilités automobiles, nous proposons d'évaluer la réponse de l'État à la problématique que posent le recours massif à l'automobile et la mise en œuvre de la mobilité durable. Pour y arriver, un cadre d'analyse en trois perspectives est élaboré afin de reproduire le processus que suivent les autorités planificatrices pour répondre à cet enjeu majeur du XXI^e siècle. Le schéma d'analyse proposé est illustré par la Figure 5.1.

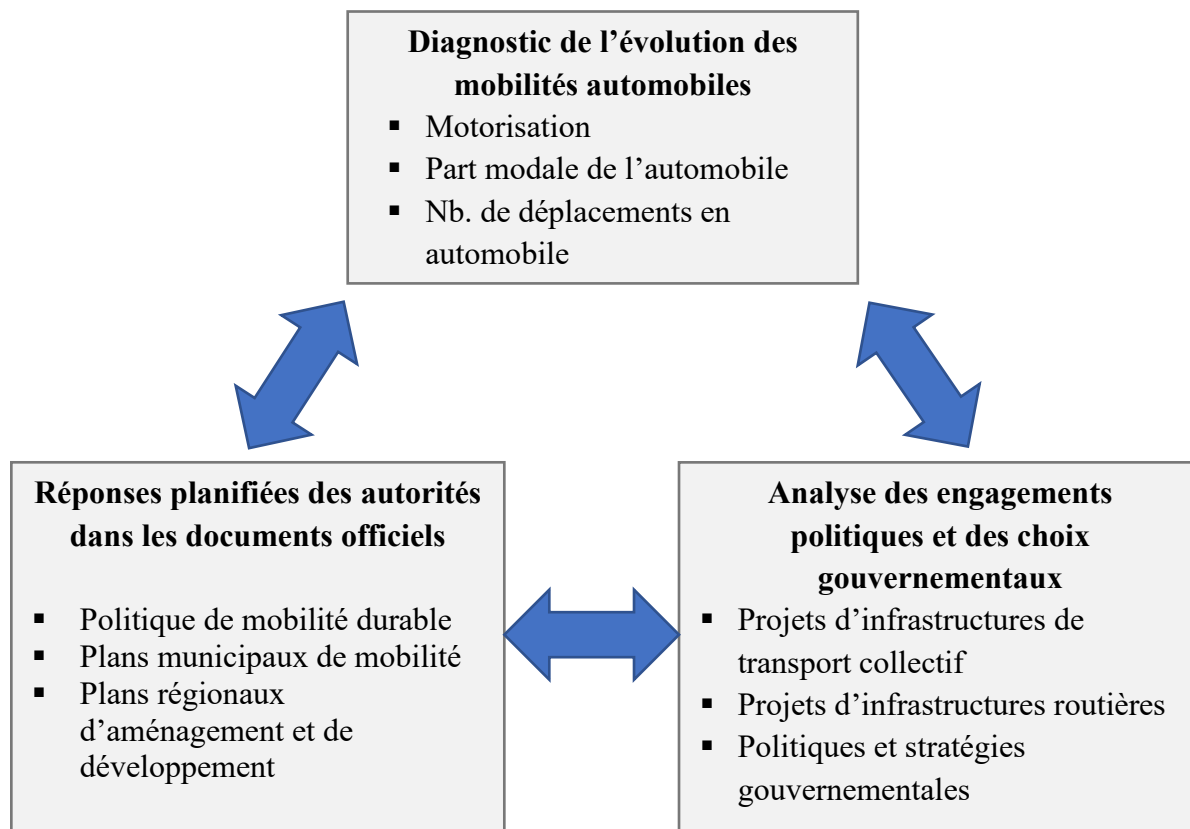


Figure 5.1 Cadre d'analyse en trois perspectives de l'automobilité

5.3.1 Perspective 1 : Diagnostic de la mobilité et de la motorisation

Pour poser un diagnostic sur l'état de la mobilité par automobile, trois indicateurs clés sont sélectionnés en fonction des données disponibles pour le territoire d'étude. Un indicateur est choisi pour caractériser l'évolution de la motorisation et deux autres indicateurs sont utilisés pour caractériser l'utilisation de l'automobile.

Pour la motorisation, **l'indicateur** choisi est le nombre d'automobiles (voitures et camions légers⁹) de promenade¹⁰ immatriculées au Québec par millier d'adultes (16 ans et plus, soit l'âge légal pour conduire). Celui-ci est estimé en combinant les données d'immatriculation provenant de la Société d'assurance automobile du Québec (SAAQ) pour la période de 2000 à 2017 (SAAQ, 2022)¹¹ et les données d'estimations annuelles de population de Statistique Canada (2022). Pour compléter l'analyse, une tentative de comparaison de l'évolution de la motorisation entre le Québec, le Canada et les États-Unis est réalisée. Cette comparaison est effectuée sur la base des véhicules par 1000 habitants et non par adulte puisque c'est le format dans lequel les données américaines sont disponibles. Les données pour le Québec et le Canada sont celles compilées annuellement par Statistique Canada (2018a) depuis les données provinciales. Cette compilation des véhicules immatriculés comprend toutes les voitures et les camions légers de moins de 4500 kg, ce qui inclut les véhicules de promenade et les véhicules à usage commercial, industriel ou institutionnel. Pour les États-Unis, les données en véhicule par habitant proviennent des travaux de Sivak (2017) qui a obtenu le nombre de « light-duty vehicles » (voitures, pick-up, VUS et camionnettes) de la Federal Highway Administration.

Pour quantifier l'évolution récente de l'utilisation de l'automobile, il n'est pas possible d'utiliser le nombre de véhicules-kilomètres parcourus annuellement puisque l'enquête qui permettait d'obtenir cet indicateur pour le Québec et le Canada a été discontinuée en 2009 (Ressources Naturelles Canada, 2011). Pour pallier cette limitation, le **premier indicateur** choisi est celui de

⁹ La SAAQ (Société d'assurance automobile du Québec) regroupe dans la catégorie « camions légers » les véhicules utilitaires sports (VUS), les pick-up et les petites camionnettes.

¹⁰ La SAAQ identifie les « véhicules de promenade » comme ceux détenus par les individus et dédiés à l'usage personnel et non commercial.

¹¹ Les données ne sont pas disponibles par région administrative avant 2000.

la part modale des déplacements effectués en auto solo. Trois sources de données sont utilisées : les données sur le mode de transport le plus régulièrement utilisé pour le navettage domicile-travail provenant des recensements canadiens de 2001 et 2016 (Statistique Canada, 2017c), les faits saillants des enquêtes Origine-Destination (OD) de la région de Montréal de 2003, 2008 et 2013¹² (AMT, 2013) et les faits saillants des enquêtes OD de la région de Québec de 2006, 2011 et 2017 (Ministère des Transports du Québec, 2008, 2015a, 2019a). Ces enquêtes OD sont des enquêtes téléphoniques basées sur le ménage et réalisées tous les cinq ou six ans avec un échantillon d'environ 4,5% pour Montréal et 9% pour Québec. Ce type d'enquête permet d'avoir un portrait précis de la mobilité pour une journée moyenne de semaine d'automne sur le territoire d'enquête. Une enquête de ce type à l'échelle provinciale n'est pas encore disponible.

Finalement, le **deuxième indicateur** d'utilisation de l'automobile est le nombre total de déplacements effectués en automobile. Les trois mêmes sources que l'indicateur de parts modales sont utilisées.

5.3.2 Perspective 2 : Réponses planifiées des autorités dans les documents officiels

Trois types de documents officiels guidant le développement du système de mobilité et de l'aménagement du territoire dans la province et les deux régions d'études sont sélectionnés pour la présente analyse.

Le **premier type de document** est la Politique de mobilité durable du Gouvernement du Québec 2018-2030 (Gouvernement du Québec, 2018c). Il s'agit du premier document de ce genre à l'échelle provinciale. La politique couvre les déplacements des personnes et des marchandises par tous les modes de transport et pour l'ensemble du territoire de la province.

Le **deuxième type de document** est le Plan métropolitain d'aménagement et de développement (PMAD). Les plans pour les régions de Montréal (CMM, 2012) et de Québec (CMQ, 2013) sont analysés. Pour Montréal, le plan couvre notamment la planification du transport terrestre, le développement du territoire, les critères d'aménagement urbain et la protection des milieux

¹² Les données de l'enquête O-D de 2018 ne sont pas disponibles à la date de rédaction de cet article (mai 2020).

agricoles et naturels sur l'ensemble du territoire de la Communauté métropolitaine de Montréal (CMM) constituée de 82 municipalités. Pour Québec, le plan couvre la planification et le développement du territoire et des mobilités de façon intégrée sur le territoire de la Communauté métropolitaine de Québec (CMQ) constituée de 28 municipalités.

Le **troisième type de document** est le Plan de transport (Montréal) ou le plan de mobilité (Québec). Le plan de transport de la ville de Montréal date de 2008 (Ville de Montréal, 2008) et la Ville travaille actuellement sur un nouveau plan intégré de mobilité et d'urbanisme. Le plan de Mobilité durable de la Ville de Québec est en vigueur depuis 2011 (Ville de Québec, 2011). Les territoires d'application de ces plans sont les limites administratives de ces villes.

Pour chacun de ces documents, quatre éléments sont recensés et analysés. Le premier est le cadrage du problème, c'est-à-dire le diagnostic posé sur l'état de la situation concernant spécifiquement l'utilisation et la possession de l'automobile privée. Il s'agit de répondre à la question : est-ce que l'enjeu de la dépendance à l'automobile est identifié et souligné ? En ce sens, est-ce que l'augmentation de la motorisation, l'augmentation de l'utilisation de l'automobile, l'évolution de la forme urbaine et les conséquences de la surutilisation de l'automobile sont identifiées ?

Le deuxième élément est la définition de la vision de chacun des documents (ou des grandes orientations en l'absence de vision clairement énoncée). Le troisième est la liste des objectifs liés à la motorisation et aux déplacements des personnes, plus spécifiquement la réduction de l'utilisation de l'automobile et l'augmentation des usages des modes actifs et collectifs. Finalement, le quatrième élément est le recensement des cibles chiffrées en lien avec les objectifs identifiés.

5.3.3 Perspective 3 : Analyse des engagements politiques et des choix gouvernementaux

La troisième et dernière étape de ce processus d'analyse consiste à analyser les principaux projets d'infrastructures de transport priorisés par les autorités gouvernementales depuis l'adoption de ces plans et politiques. L'objectif est d'évaluer la cohérence entre les projets priorisés, la vision, les objectifs et les cibles établis dans les documents officiels de planification rapportés dans la deuxième perspective d'analyse. Pour répondre à cet objectif, les principaux projets d'infrastructures routières pour les régions de Montréal et Québec sont identifiés depuis la liste

des projets routiers du Ministère des Transports du Québec (2019c). Pour les projets de transport collectif, comme ceux-ci ne sont pas réalisés ni financés par une seule agence gouvernementale, il n'y a pas de liste officielle des projets réalisés, en cours et à l'étude pour l'ensemble de la province, tenue par le gouvernement. Pour identifier les principaux projets considérés, le document *Les 12 travaux du transport collectif au Québec* produit par les organismes Trajectoire Québec and Équiterre (2018) est utilisé. Les projets sont retenus s'ils respectent les critères d'inclusion suivant :

5.3.3.1 Critères d'inclusion des projets

- Projet majeur d'infrastructure visant à augmenter la capacité routière ou l'offre de transport collectif. Les projets de réfection des infrastructures existantes n'ajoutant pas de capacité sont exclus.
- « Majeure » faisant référence aux coûts du projet et aux impacts attendus du projet sur la mobilité urbaine et sur le développement du territoire.
- Le projet doit avoir obtenu l'aval du gouvernement et être en cours de construction ou en cours de planification avancée (des sommes importantes ayant déjà été dépensées).

Pour limiter les projets analysés, un maximum de deux projets majeurs d'infrastructures routières et deux projets majeurs de transport collectif par région sont sélectionnés.

5.3.3.2 Méthode d'analyse des projets

Les questions suivantes permettent de guider l'analyse de ces projets :

- Ces projets sont-ils mentionnés dans les documents de planification analysés ?
- En s'appuyant sur la littérature scientifique concernant les impacts reconnus de ce type de projets est-il jugé probable ou improbable que ceux-ci contribuent à l'atteinte de la vision établie dans les cinq documents de planification ?
- En s'appuyant sur la littérature scientifique concernant les impacts reconnus de ce type de projets, ceux-ci permettront-ils de contribuer à l'atteinte des objectifs et des cibles identifiés dans les documents de planification (impact positif) ou en retarderont-ils l'atteinte (impact négatif) ?

- S'il est jugé que les projets retarderont l'atteinte des visions, objectifs et cibles (impact négatif), quels sont les arguments énoncés pour justifier la réalisation de ces projets ?
- Ces arguments sont-ils typiques de la résilience d'une approche traditionnelle de planification des transports et des enjeux politiques liés à la dépendance à l'automobile ?

5.3.4 Projets sélectionnés

5.3.4.1 Projet 1 : Région de Montréal - Prolongement de l'autoroute A-19

Le prolongement de l'autoroute 19 est étudié par le ministère des Transports depuis son inauguration dans les années 1970. Le projet de parachèvement de l'autoroute est relancé en 2010 par le gouvernement afin de transformer un tronçon de 8 kilomètres de l'actuelle route 335 (1 voie par direction) en « autoroute urbaine » comprenant dans chaque direction 2 voies de circulation et une voie réservée au transport collectif, au covoiturage et aux véhicules électriques entre l'autoroute 440 dans la ville de Laval et l'autoroute 640 à Bois-des-Fillion, sur la Rive-Nord (Ministère des Transports du Québec, 2019d). Le projet comprend aussi une piste multifonctionnelle pour piétons et cyclistes.

En 2018, le gouvernement confirme la configuration finale retenue et donne officiellement le feu vert au projet en octroyant le décret environnemental pour entamer les travaux préparatoires (Ministère des Transports du Québec, 2019d). Les estimations préliminaires indiquent des coûts entre 500 et 600 millions de dollars canadiens et sa complétion est prévue pour 2025 (La Presse canadienne, 2018). Le projet est retenu pour l'analyse car il respecte les critères établis et est le plus important projet confirmé d'augmentation de la capacité routière dans la région de Montréal.

5.3.4.2 Projet 2 : Région de Montréal - Prolongement de la Ligne bleue du Métro de Montréal

Le prolongement de 5 stations et 5,8 km de la ligne bleue du Métro de Montréal vers l'Est est discuté depuis les années 1980 (Corriveau & Caillou, 2018). Le projet a récemment franchi des étapes importantes avec la confirmation du financement par les gouvernements provinciaux et fédéraux à l'été 2019 et le lancement de son bureau de projet au printemps 2019 afin de réaliser les plans et devis (Gouvernement du Canada, 2019a; Ministère des Transports du Québec, 2019e). Les travaux préparatoires doivent débuter en 2020, les travaux d'infrastructure en 2021 et la mise

en service est prévue pour 2026 (STM, 2019). Les coûts du projet sont estimés à 4,5 milliards de dollars canadiens (Radio-Canada, 2019b). Le projet respecte les critères de sélection et représente l'un des deux plus importants projets de transport collectif en cours dans la grande région de Montréal.

5.3.4.3 Projet 3 : Région de Montréal - Réseau express métropolitain (REM)

Le plus important projet de transport collectif en construction au Québec est le Réseau express métropolitain (REM) piloté et financé en grande partie par la Caisse de dépôt et placement du Québec (CDPQ). Le REM est un projet de métro léger automatisé de 26 stations et 67 km desservant les banlieues nord, ouest (incluant l'Aéroport de Montréal) et sud de Montréal. La construction du projet a débuté en 2018 et sa mise en service complète est prévue pour 2023. Le projet est financé par CDPQ, le gouvernement fédéral et le gouvernement provincial et son coût est estimé à 6,3 milliards de dollars canadiens (CDPQ Infra, 2019). Le projet respecte les critères de sélection et représente le plus important projet d'ajout d'offre de transport collectif dans la région de Montréal.

5.3.4.4 Projet 4 : Région de Québec - Troisième lien routier entre la Rive-Nord et la Rive-Sud

Le projet de troisième lien dans la région de Québec vise à relier, par un tunnel, l'autoroute 40 du côté nord du fleuve Saint-Laurent à l'est de Québec et l'autoroute 20 sur le côté sud du fleuve à l'est de la ville de Lévis. Si les premières études de faisabilité pour ce projet ont été réalisées dès les années 1970, celui-ci est récemment revenu à l'ordre du jour gouvernemental et est présenté sur le site du ministère des Transports comme une priorité gouvernementale (Ministère des Transports du Québec, 2019b). Un bureau de projet a été créé en 2017 et le projet a récemment (avril 2019) passé une étape importante, devenant un « projet en planification » pour lequel une somme de 325 millions de dollars canadiens a été réservée dans le Plan québécois des infrastructures 2019-2029 pour des études et pour la réalisation de plans et devis (Gouvernement du Québec, 2019a). Il est prévu que les travaux débutent avant 2022 et aucune date de complétion n'est présentement avancée. Une étude de faisabilité technique pour le tracé final choisi d'un tunnel passant sous la pointe est de l'île d'Orléans estimait les coûts du projet à plus de 4 milliards de dollars canadiens (Massicotte, 2016). Le projet répond aux critères de sélection et correspond

au plus important projet d'augmentation de la capacité routière en cours de planification dans la province.

5.3.4.5 Projet 5 : Région de Québec - Réseau structurant de transport en commun (RSTC)

Le réseau de transport structurant de la Ville de Québec est un projet de réseau de transport collectif qui comprend un trajet de Tramway de 23 km, un trajet de Trambus de 17 km et un réseau bonifié de Métrobus de 16 km en infrastructure dédiée (Ville de Québec, 2019b). Le projet a été dévoilé en mars 2018 par la Ville de Québec (Ville de Québec). Après quinze mois de négociations une entente a été conclue en août 2019 entre la Ville et les gouvernements provincial et fédéral pour assurer le financement complet du projet (Gouvernement du Canada, 2019b). Les premiers travaux du projet ont débuté et la livraison finale est prévue pour 2026. Les coûts totaux pour l'ensemble du projet sont estimés à 3 milliards de dollars canadiens (Ville de Québec, 2019a). Le projet répond aux critères de sélection et est le plus important projet de transport collectif dans la région de Québec.

5.3.5 Analyse complémentaire

En complément aux projets majeurs, les sommes totales d'investissements prévues dans les projets de réfection et de développement du transport collectif et du transport routiers pour les dix années à venir (2019-2029) par le gouvernement du Québec sont comparées à titre d'indicateur des intentions gouvernementales. Finalement, la stratégie québécoise d'électrification des transports s'appliquant à tous les types de transport (public et privés, collectifs et individuels) (Ministère des Transports du Québec, 2022) est aussi brièvement commentée en regard des questions de recherche posées.

5.4 Perspective 1 : Évolution de la motorisation et de l'utilisation de l'automobile

5.4.1 Indicateurs de motorisation

L'évolution de la motorisation (véhicules par 1000 adultes) de 2000 et 2017 pour l'ensemble de la province, la région administrative de la Capitale-Nationale, la région administrative de Montréal (île de Montréal) et les régions administratives de Laval, de la Montérégie, de Lanaudière et des

Laurentides qui comprennent les municipalités qui forment les banlieues de Montréal, est illustrée sur la Figure 5.2.

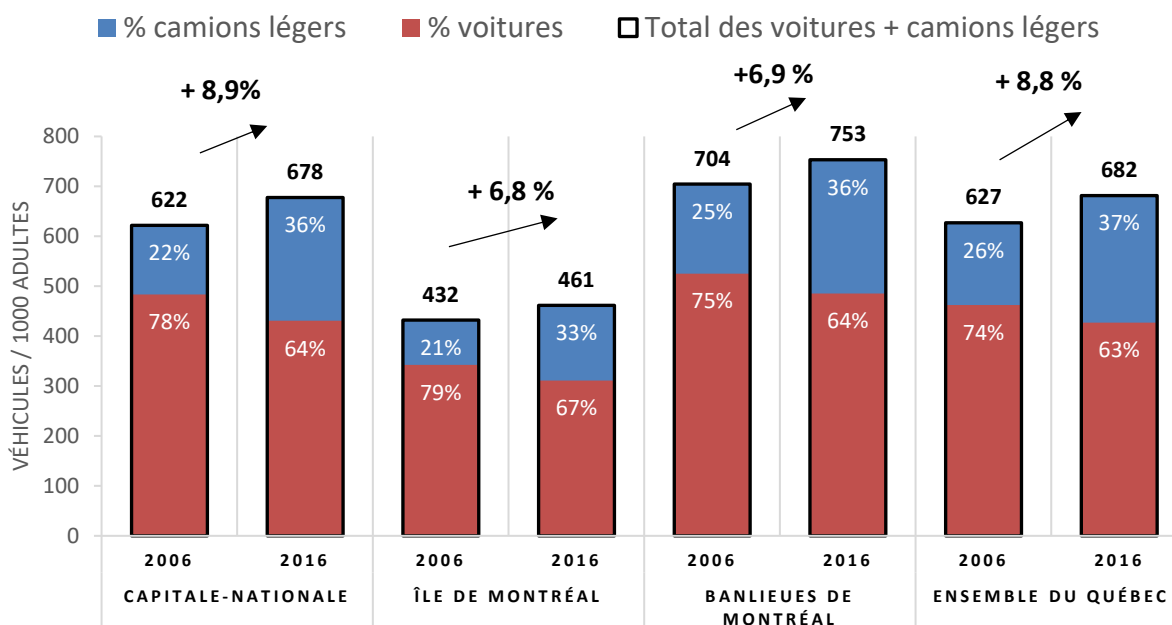


Figure 5.2 Taux de motorisation 2000 et 2016

Source : Le nombre de véhicules de promenade provient des données de la SAAQ (2018) et les estimations de population de Statistique Canada (2022). Calcul par les auteurs.

Dans l'ensemble du Québec, entre 2000 et 2017, le nombre de voitures et camions légers à usage personnel a augmenté de 38%, ajoutant en moyenne 77 000 véhicules annuellement sur les routes. Pour la même période, la population adulte a augmenté de 16,5%. La Figure 5.2 permet aussi d'observer une croissance plus faible de la motorisation sur l'Île de Montréal.

De plus, la Figure 5.2 illustre aussi la transformation du parc de véhicules, alors que la proportion de camions légers dans les véhicules de promenade est passée de 24 à 39% à l'échelle de la province entre 2000 et 2017. Cette tendance lourde découle de la popularité croissante des véhicules utilitaires sport (VUS) et des *pick-up* dans les ventes de véhicules dans la province (Pineau & Whitmore, 2018), y compris dans les milieux plus urbanisés comme à Québec et à Montréal. La popularité de ce type de véhicules n'est pas unique au Québec, ceux-ci occupent des parts de marché en croissance autant en Amérique du Nord qu'en Europe (Kommenda, 2019).

Pour compléter l'analyse, une comparaison est effectuée entre l'évolution de la motorisation (en véhicules par 1000 habitants, usages commercial et privé) au Québec, au Canada et aux États-Unis (Figure 5.3).

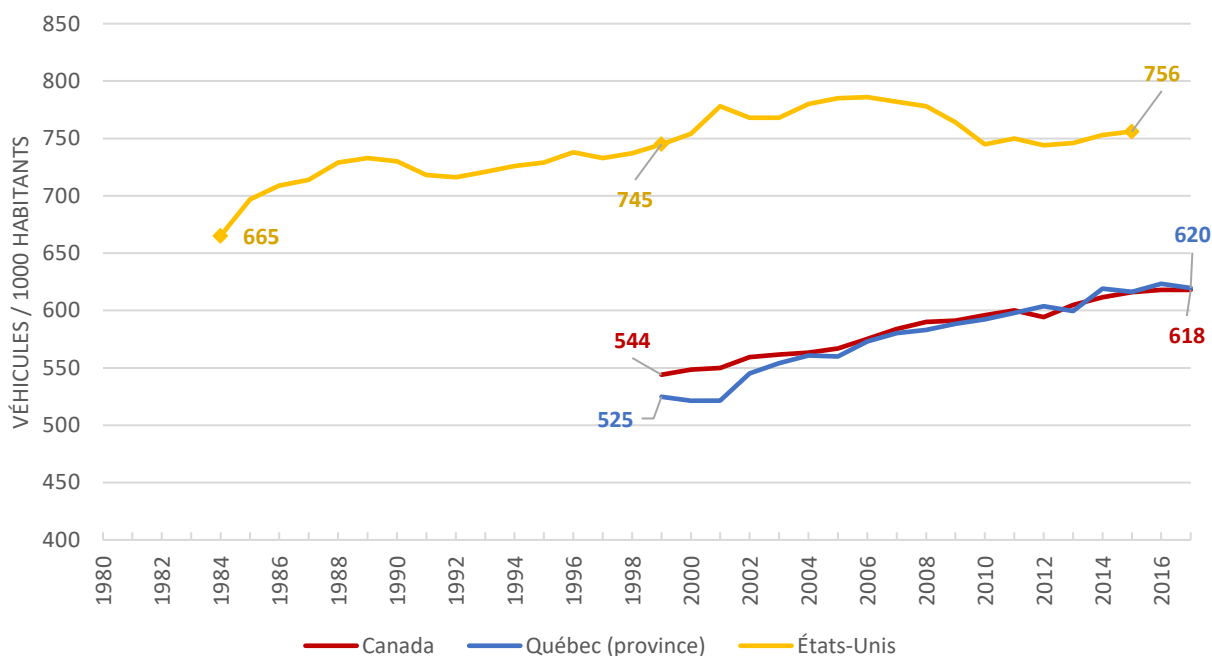


Figure 5.3 Évolution des taux de motorisation (véhicules/1000 habitants). Québec, Canada et États-Unis.

Sources des données : Statistique Canada (2018b) et Sivak (2017).

Le premier constat est que le taux de motorisation est bien supérieur aux États-Unis qu'au Canada et au Québec, et celui-ci semble avoir atteint un sommet en 2007, pour redescendre et rester relativement stable par la suite. Le deuxième constat est que ce phénomène de plafonnement de la motorisation n'est pas observé ni au Québec ni au Canada.

En somme, les données analysées permettent de conclure à une croissance soutenue de la motorisation depuis le début 2000 et laissent présager que le plafonnement de la motorisation ne semble pas encore atteint. Considérant que la possession automobile est un prédicteur important de l'utilisation de l'automobile (de Jong et al., 2004), favorisant le choix de l'automobile pour les déplacements et augmentant les distances parcourues avec ce mode au détriment des alternatives (Caulfield, 2011; Dieleman et al., 2002), cette tendance à la hausse de la motorisation risque

d'exacerber les nombreuses externalités qui découlent du recours massif à l'automobile pour les déplacements.

5.4.2 Indicateurs d'utilisation de l'automobile

Le premier indicateur d'analyse des usages est la part modale de l'automobile et des modes durables. Les statistiques sont d'abord présentées pour les déplacements domicile-travail depuis les données d'échantillon (25%) des recensements de 2001 et 2016. Les résultats pour l'ensemble de la province, la région métropolitaine de recensement (RMR) de Montréal et la RMR de Québec sont illustrés à la Figure 5.4.

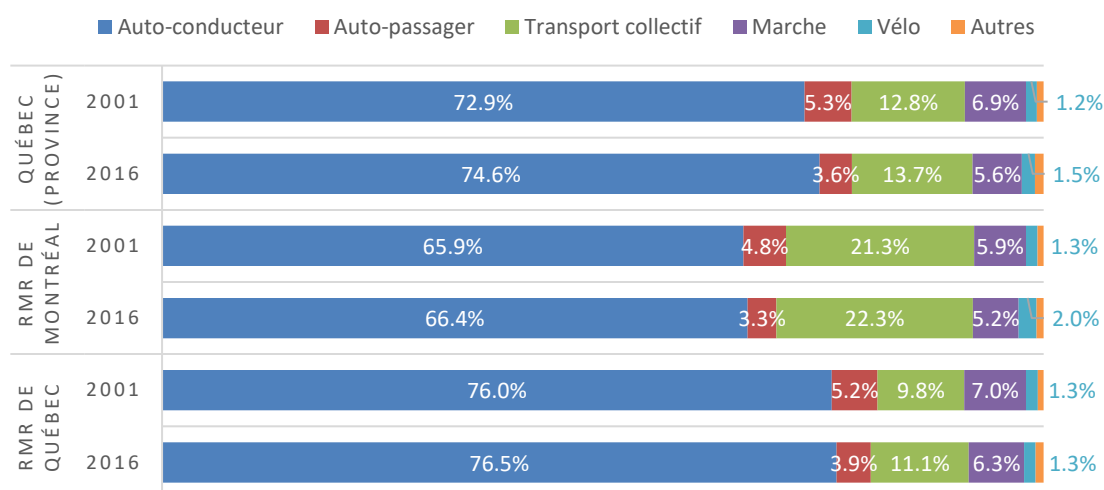


Figure 5.4 Répartition modale des déplacements domicile-travail. Données d'échantillon (25 %) des recensements de 2001 et 2016

Source : Statistique Canada (2017c), traitement par les auteurs.

La figure permet d'observer quelques tendances positives en 15 ans comme un léger accroissement de la part des déplacements domicile-travail réalisés en transport collectif dans les trois régions d'analyse (+0,9% pour la province, +1% pour Montréal et +1,3% pour Québec) et un accroissement de la part des déplacements faits à vélo pour l'ensemble de la province (+0,24%) et pour Montréal (+0,7%), mais pas dans la région de Québec.

Malheureusement, si ces gains se font grâce à un transfert modal depuis la voiture en solo, les résultats ne sont pas observables dans ces données puisque la part modale de l'auto a elle aussi augmenté pour la province et les deux régions d'analyse (+1,7% pour la province, +0,5% pour

Montréal et Québec). On observe plutôt un recul de la part des déplacements effectuée en auto comme passager (-1,7% pour la province, -1,6% pour Montréal et -1,3% pour Québec). Un recul de la marche est aussi observé (-1,3% pour la province, -0,7% pour Montréal et -0,7% pour Québec), qui pourrait s'expliquer par une augmentation des lieux d'emplois plus forte en banlieue que sur l'Île de Montréal (AMT, 2013) et une diminution des déplacements de navettage dont l'origine et la destination sont situées dans le noyau urbain (Savage, 2019).

Il demeure difficile d'estimer avec précision les facteurs pouvant expliquer ces changements. Néanmoins, il semble qu'une réduction de la part modale de l'auto solo soit possible en contexte nord-américain. En effet, dans la RMR de Vancouver, la part modale de l'auto solo pour les déplacements domicile-travail est passée de 79,2% en 2001 à 69,3% en 2016, un recul de 9,9% en 15 ans. Une tendance similaire est observée à Toronto, quoique moins forte, puisque la part des déplacements en auto solo a reculé de 3,9% durant cette période, passant de 71,4% en 2001 à 68,0% en 2016 (Statistique Canada, 2017c).

Ainsi, le quasi *statu quo* de la part des déplacements effectués en voiture n'est toutefois pas une bonne nouvelle puisque l'accroissement de la population et de l'activité *économique* signifie une croissance du nombre absolu de déplacements effectués en voiture solo. C'est ce que démontre le **deuxième indicateur** de suivi de l'évolution de l'utilisation de l'automobile. La Figure 5.5 illustre les changements entre 2001 et 2016 de la population ainsi que du nombre de déplacements domicile-travail selon chaque mode.

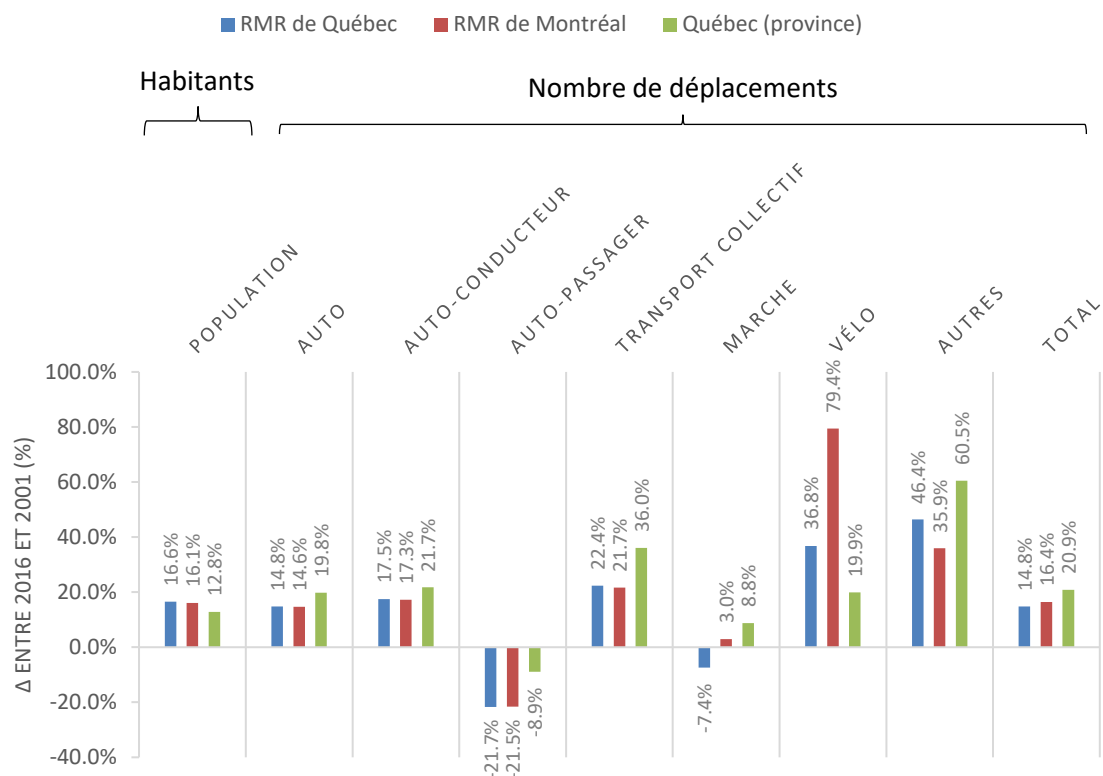


Figure 5.5 Évolution de la population et du nombre de déplacements par mode entre 2001 et 2016

Source des données : Population (Statistique Canada, 2016) et déplacements (Statistique Canada, 2017c).

Les données de la Figure 5.5 sont toutefois incomplètes puisqu'elles ne tiennent pas compte de la diversification des motifs de déplacements et de la diminution de l'importance relative des déplacements domicile-travail. Pour pallier cette limitation des données du recensement, les données des enquêtes Origine-Destination de Montréal et de Québec sont utilisées.

La part et le nombre de déplacements réalisés avec chaque mode de transport en période de pointe matinale dans la grande région de Montréal (territoires comparables en 2003, 2008 et 2013) sont illustrés au Table 5.1.

Table 5.1 Parts modales, nombre de déplacements et variation du nombre de déplacements.
Grande région de Montréal en 2003, 2008 et 2013.

Région de Montréal - MODES - Période de pointe du matin (6h à 9h)							
	Tous	Auto	TC	Bimode	Autres modes collectifs^a	Autres	Actifs
Parts modales							
2003C	100%	62.5%	16.1%	2.1%	8.8%	0.1%	10.2%
2008C	100%	59.9%	17.9%	2.9%	8.7%	0.2%	10.5%
2013C	100%	62.1%	17.4%	3.2%	6.8%	0.3%	10.3%
Nombre de déplacements							
2003C	2 018 000	1 262 000	325 000	43 000	178 000	3 000	206 000
2008C	2 083 000	1 247 000	372 000	60 000	181 000	5 000	219 000
2013C	2 310 000	1 434 000	401 000	73 000	156 000	6 000	239 000
Variation du nombre de déplacements							
2008/2003	3.2%	-1.2%	14.5%	39.5%	1.7%	66.7%	6.3%
2013/2008	10.9%	15.0%	7.8%	21.7%	-13.8%	20.0%	9.1%
2013/2003	14.5%	13.6%	23.4%	69.8%	-12.4%	100.0%	16.0%

Notes : Le « C » indique que la comparaison est effectuée selon même territoire d'enquête, soit celui de 2003.

^a Comprend le transport adapté, l'autobus scolaire et autres autobus.

Source : Enquête OD 2013 (AMT, 2013).

On note ainsi une part d'utilisation de l'automobile (conducteur et passagers confondus) plutôt stable entre 2003 et 2013 ainsi qu'une augmentation du nombre total de déplacements réalisés en auto de 13,6%. De plus, les faits saillants de l'enquête O-D 2013 révèlent une distribution inégale de la croissance de l'utilisation de l'automobile. Ainsi les couronnes sud et nord affichent une croissance de 25,8% entre 2013 et 2003 du nombre de déplacements en automobile en période de pointe du matin contre une augmentation de seulement 3,8% sur l'Île de Montréal (AMT, 2013). Les données de l'enquête O-D corroborent aussi la diminution des déplacements en auto comme passager observée dans les données du recensement puisque le taux moyen d'occupation des véhicules est passé de 1,23 en 1998 à 1,20 en 2013 (sur 24 h) (AMT, 2013).

Pour la région de Québec, le nombre de déplacements réalisés selon chaque mode de transport sur 24 heures est présenté au Table 5.2.

Table 5.2 Parts modales, nombre de déplacements et variation du nombre de déplacements.

Région de Québec - MODES - 24h								
	Tous	Auto-conducteur	Auto-passager	TC	Bimode	Autres modes collectifs^a	Autres	Actifs
Parts modales								
2006C	100%	59.9%	14.5%	6.7%	0.3%	4.8%	1.1%	12.7%
2011C	100%	62.6%	14.2%	7.6%	0.4%	4.5%	1.0%	9.7%
2017C	100%	63.3%	14.4%	6.6%	0.5%	3.8%	1.0%	10.4%
Nombre de déplacements								
2006C	2 031 900	1 217 900	294 500	135 600	5 700	98 200	22 200	257 800
2011C	1 905 100	1 191 900	271 100	144 600	8 400	86 100	19 400	184 300
2017C	2 125 900	1 346 500	305 500	139 900	10 500	81 400	20 600	221 500
Variation du nombre de déplacements								
2011/2006	-6.2%	-2.1%	-7.9%	6.6%	47.4%	-12.3%	-12.6%	-28.5%
2017/2011	11.6%	13.0%	12.7%	-3.3%	25.0%	-5.5%	6.2%	20.2%
2017/2006	4.6%	10.6%	3.7%	3.2%	84.2%	-17.1%	-7.2%	-14.1%

Notes: C : Le « C » indique que la comparaison est effectuée selon même territoire d'enquête, soit celui de 2003; ^a Comprend le transport adapté, l'autobus scolaire et autres autobus.

Source : Enquête O-D 2017 (Ministère des Transports du Québec, 2019a)

Ainsi à Québec, ces données démontrent que l'auto a gagné du terrain entre 2006 et 2017 alors que le nombre de déplacements comme conducteur a augmenté de 10,6%, soit une augmentation deux fois plus rapide que pour l'ensemble des déplacements (+4,6%) (Ministère des Transports du Québec, 2019a). Tout comme à Montréal, l'accroissement des déplacements effectués en automobile (sur 24 h) entre 2006 et 2017 est beaucoup plus important pour les résidents des couronnes nord (+29%) et sud (+ 44%) que pour ceux de l'agglomération de Québec (+6,5%) et de la ville de Lévis (+6,6%). Le taux d'occupation des automobiles a aussi légèrement diminué, passant de 1,24 en 2006 à 1,23 en 2017 sur une période de 24 h.

En somme, pour les deux régions à l'étude, malgré une croissance des déplacements en transports collectif et actif (notamment le vélo), on note aussi une augmentation importante des déplacements en auto solo. Cette croissance est principalement observable en périphérie, particulièrement dans les couronnes nord et sud des deux métropoles. Cette situation n'est pas surprenante lorsqu'elle est comparée à la croissance de la population. Ainsi, les travaux de Gordon, Hindrichs, and Willms

(2016) ont permis d'estimer qu'entre 2006 et 2016, 77% de la croissance de la population de la RMR de Montréal a eu lieu dans les banlieues autodépendantes et 6% dans les excroissances suburbaines (*exurban*)¹³. Pour Québec, 62% de la croissance de population de la RMR a eu lieu dans les banlieues autodépendantes et 35% dans les excroissances suburbaines. Il est aussi pertinent de faire le parallèle avec celui de l'accroissement de l'étalement urbain observé par Nazarnia, Schwick, and Jaeger (2016) qualifié d'exponentiel à Montréal et de très rapide à Québec. En somme, l'ensemble des statistiques rapporte une augmentation de la motorisation, une augmentation des déplacements en automobile et des répartitions modales relativement stables au cours des quinze dernières années lorsque l'échelle des régions métropolitaines est considérée.

5.5 Perspective 2 : Réponse planifiée des autorités dans les documents officiels

5.5.1 Enjeux et problématiques

Bien qu'ils ne soient pas exhaustifs, les statistiques et constats présentés à la section précédente illustrent un accroissement des mobilités automobiles. Le premier élément des documents de planification analysés est l'identification des enjeux liés à la dépendance à l'automobile. Plus spécifiquement il s'agit d'évaluer si l'accroissement de l'usage de l'automobile et de sa possession est identifié comme une source de problèmes. Il convient aussi d'évaluer si le lien entre le développement du territoire et du réseau routier et les enjeux d'accroissement des mobilités automobiles sont identifiés dans les documents. Le recensement pour chaque document est détaillé puis suivi d'un tableau récapitulatif.

5.5.1.1 Politique de mobilité durable (PMD)

Le concept de dépendance à l'automobile n'est pas explicitement mentionné dans le document et les formulations demeurent prudentes dans l'identification du tout à l'auto comme un enjeu majeur. Par exemple, il est indiqué que « La dynamique de croissance du nombre de déplacements

¹³ Voir Gordon et al. (2016) pour la définition des différents types de quartiers et la méthodologie de classification utilisée.

s’observe en premier lieu sur le réseau routier... » (p. 39). Le gouvernement souligne toutefois les enjeux liés au système actuel de mobilité, notamment les impacts négatifs sur la santé des citoyens (p. 20), les enjeux de sécurité routière (p. 20) et de congestion (p. 39), les enjeux d’inégalité (p. 21), les impacts environnementaux et sur les changements climatiques (p. 21). La politique mentionne certaines des causes de la situation problématique actuelle, par exemple la déficience des services de transport collectif et l’absence d’alternatives ainsi que l’impact de l’aménagement du territoire sur les pratiques de mobilité, en indiquant que celui-ci « favorise plutôt le recours à l’automobile et restreint les modes alternatifs. » (p. 21). Elle note aussi que « La croissance de l’économie, la diminution de la taille des ménages et l’augmentation concomitante des taux de motorisation et de la taille des véhicules sont des facteurs qui contribuent à ce phénomène [d’augmentation des GES du parc automobile]. » (p. 21).

5.5.1.2 PMAD – Montréal

La dépendance à l’automobile est soulignée à quelques reprises dans le plan. Ainsi, dans un encadré sur les approches durables d’aménagement du territoire, il est souligné que celles-ci ont généralement comme objectif la réduction de la dépendance à l’automobile (p. 52). Il est aussi indiqué que la réalisation de quartiers de type *Transit-Oriented Development* (TOD), soit l’orientation phare du PMAD, permettra « l’amélioration de la santé publique en réduisant la dépendance à l’automobile et en favorisant les déplacements actifs. » (p. 81). Dans ses constats sur l’évolution récente de la mobilité sur son territoire, la CCM souligne l’augmentation des déplacements en automobile et l’augmentation de la motorisation (p. 128) et fait le lien entre l’étalement urbain et l’augmentation des distances parcourues en automobile (p. 131).

5.5.1.3 PMAD – Québec

Le PMAD reconnaît très bien que le type de développement urbain favorisant l’éclatement des lieux d’activités et l’étalement urbain au cours des dernières décennies a contribué à un accroissement de la dépendance à l’automobile (p. 9 et 13) de laquelle découle de nombreux impacts négatifs sur la qualité de vie, les finances des ménages, les finances publiques, la perte d’espace naturel et des enjeux d’accessibilité (p. 13). Le plan note aussi l’augmentation constante des déplacements, principalement en automobile (p. 25) et que « Bien que la région métropolitaine de Québec possède le plus haut ratio de kilomètres d’autoroute par habitant au Canada, son réseau

autoroutier est de plus en plus saturé. » (p. 25). Dans l'explication des principes phares du plan, soit un aménagement urbain intégré à la mobilité durable, le plan illustre en parallèle que le type d'aménagement effectué jusqu'à présent favorisait l'utilisation de l'automobile (p. 125).

5.5.1.4 Plan de transport de la Ville de Montréal

Il s'agit du document qui exprime le plus explicitement l'enjeu de la dépendance à l'automobile. L'enjeu est ainsi présenté au sein même de la vision du plan (p. 13) : « ... Montréal veut réduire de manière significative **la dépendance à l'automobile** par des investissements massifs dans les modes de transport collectif et actif tels... ». La dépendance à l'automobile est d'ailleurs soulignée comme s'étant « malheureusement renforcée depuis quelques années » (p. 70). Sa réduction est un objectif fort du plan, l'expression revenant quatorze fois dans le document.

L'augmentation de la motorisation est aussi reconnue et identifiée comme source de problèmes puisqu'on cherche à « ...réduire les impacts négatifs attribuables à une croissance trop importante de la motorisation sur son territoire. » (p. 54). Bien qu'elle soit identifiée comme étant « mieux contrôlée que dans le reste de la région métropolitaine, mais tout de même en croissance... » (p. 141). La ville admet aussi d'emblée la contribution des transports aux changements climatiques et environnementaux attribuable à « l'omniprésence de l'automobile » (p. 39).

Finalement, la ville reconnaît bien les enjeux liés à l'exode vers les banlieues, notant que « L'essor démographique [des banlieues périphériques] accentue davantage la pression sur le maintien et le développement des infrastructures de transport. » (p. 53). En ce sens, la Ville rappelle qu'il importe « d'intégrer la planification des transports dans une perspective métropolitaine à celle de l'aménagement du territoire. » (p. 60). Le plan indique aussi qu'« A priori, il n'y a pas lieu d'augmenter la capacité autoroutière dans la région. » (p. 86) et souligne le lien entre le développement des autoroutes et leur influence sur l'aménagement du territoire (p. 86).

5.5.1.5 Plan de mobilité durable – Ville de Québec

Du côté de la Ville de Québec, celle-ci reconnaît dans son Plan de Mobilité durable (2011) que l'augmentation de la motorisation et du nombre de déplacements réalisés en auto est une tendance lourde contraire au développement durable (p. 18). Le plan indique aussi que « La poursuite du choix de la maison isolée en banlieue et la dépendance à l'automobile qui en découle conduisent à l'augmentation des émissions de gaz à effet de serre. » (p. 18) et que par conséquent, « La

croissance des villes devra se faire davantage par la densification... » (p. 17). La Villenote aussi dans l'analyse des tendances d'ici 2030 que « L'expansion des réseaux routiers sera considérée comme un gaspillage de ressources, à la fois en matière de territoire utilisé, de dépenses improductives pour les déplacements et de production de gaz à effet de serre. » (p. 17).

Le Table 5.3 recense, pour les cinq documents analysés, les mentions des notions de dépendance à l'automobile, d'augmentation de la motorisation et de l'usage de l'automobile et le lien entre le développement urbain et l'accroissement de l'automobilité.

Table 5.3 Résumé de l'analyse des enjeux liés à l'automobile dans les documents de planification.

Document	Dépendance à l'automobile	Hausse de la motorisation	Hausse de l'usage de l'auto	Conséquences négatives	Lien avec la forme urbaine
Politique de mobilité durable	Aucune mention directe	Oui (p. 21)	Indirectement via la hausse de la congestion.	Environnementaux, sociaux et économiques (p. 20-22)	Oui (p. 21)
PMAD – Montréal	Oui, deux mentions	Oui (p. 128)	Oui (p. 128)	GES (p. 131), Congestion (p. 138)	Oui, c'est le cœur du plan.
PMAD – Québec	Oui, trois mentions	Aucune mention.	Oui (p. 25 et 132)	Environnementaux, sociaux et économiques (p. 13)	Oui (p. 9)
Plan de transport – Montréal	Oui, 14 mentions	Oui (p. 54 et 141)	Oui (p. 49)	Environnementaux, sociaux et économiques (p. 41)	Oui (p. 41 et 44)
Plan de mobilité – Québec	Oui, trois mentions	Oui (p. 18)	Oui (p. 18)	Environnementaux, sociaux et économiques (p.18)	Oui (p. 17-18)

Ainsi, à l'exception de la Politique de mobilité durable, tous les documents reconnaissent explicitement l'enjeu de la dépendance à l'automobile. Tous reconnaissent, à l'exception du PMAD de Québec que l'augmentation de la motorisation est un enjeu et tous soulignent l'augmentation de l'usage de l'automobile. Ces documents reconnaissent aussi qu'un changement majeur dans la façon dont la mobilité et l'aménagement du territoire sont planifiés est nécessaire à l'atteinte des objectifs de développement durable. La Ville de Montréal parle même « ... d'un virage radical maintenant. » (Ville de Montréal, 2008, p. 39).

5.5.1.6 Vision, cibles et objectifs

Les visions énoncées dans les cinq documents de planification sont rapportées Table 5.4. Celles témoignant le plus fortement d'une réduction de la dépendance à l'automobile et de l'usage de l'automobile sont celles du Plan de transport de Montréal et du PMAD de Montréal (**texte en gras**). Dans les visions du PMAD de Montréal, du Plan de transport de Montréal et du Plan de mobilité de Québec est soulignée l'importance de développer le transport actif et collectif alors que la vision de la PMD parle plus largement de la mobilité durable et d'un écosystème de transport performant (texte souligné). Finalement, toutes les visions à l'exception de celle du Plan de transport de Montréal font état d'un lien entre l'aménagement du territoire et la mobilité (*texte en italique*).

Table 5.4 Visions des documents de planification.

Document	Vision
Politique de mobilité durable (PMD)	« En 2030, <u>le Québec est un leader nord-américain de la mobilité durable et intégrée</u> du 21 ^e siècle. <u>Sur un territoire aménagé dans une perspective de mobilité durable</u> , il dispose d'un <u>écosystème des transports performant, sécuritaire, connecté et sobre en carbone</u> , qui contribue à la prospérité du Québec et répond aux besoins des citoyens et des entreprises. » (Gouvernement du Québec, 2018c, p. 6)
PMAD – Montréal	« Cap sur le monde : bâtir une communauté compétitive, attractive, solidaire et responsable » et l'énoncé spécifiquement concernant le développement du transport : « En 2025, la communauté est l'un des principaux centres intermodaux de transport d'Amérique du Nord grâce à l'interconnexion des modes routier, aérien, maritime et ferroviaire. <i>Ces réseaux soutiennent avantageusement le développement de la région</i> et sont reconnus comme étant sécuritaires, fiables et fluides. Par-dessus tout, la <u>communauté a pris le virage du transport collectif</u> en développant adéquatement un réseau accessible, rapide, attrayant et flexible qui répond aux besoins des usagers et qui diminue significativement l'usage de l'automobile . Elle figure en tête de liste des régions métropolitaines les plus performantes en matière de contrôle de la production des gaz à effet de serre. » (CMM, 2012, p. 31)
PMAD – Québec	Le PMAD de l'agglomération de Québec ne présente pas d'énoncé de vision explicite Il s'appuie plutôt sur trois priorités desquelles découlent 13 stratégies : « Structurer en bâtissant une région métropolitaine <i>plus cohérente sur le plan de l'organisation du territoire et de la mobilité durable</i> . » « Attirer en offrant des milieux de vie et des lieux d'emploi de qualité en quantité suffisante pour accueillir la croissance et en complétant la mise en valeur de nos éléments identitaires. » « Durer en limitant les pressions de l'urbanisation sur les milieux naturels et agricoles, en utilisant judicieusement nos ressources et en veillant à la sécurité, à la santé publique et au bien-être des citoyens. » (CMQ, 2013, p. 9)
Plan de transport – Montréal	« Assurer les besoins de mobilité de tous les Montréalais, en faisant de notre agglomération un endroit agréable à vivre ainsi qu'un pôle économique prospère et respectueux de son environnement. Pour ce faire, Montréal veut réduire de manière significative la dépendance à l'automobile par <u>des investissements massifs dans les modes de transport collectif et actif tels le tramway, le métro, l'autobus performant, le train, le vélo et la marche ainsi que sur des usages mieux adaptés de l'automobile tels le covoiturage, l'autopartage et le taxi</u> . » (Ville de Montréal, 2008, p. 13)
Plan de mobilité – Québec	« La finalité du Plan de mobilité durable est de contribuer à faire de Québec une région attrayante, prospère et durable qui s'illustre notamment par une <i>forte intégration de l'aménagement du territoire et des transports</i> et dont la population <u>privilégie les modes de déplacement actifs et collectifs</u> . » (Ville de Québec, 2011, p. 27)

Par la suite, les objectifs et les cibles sélectionnés depuis les cinq documents analysés (Table 5.5) sont ceux qui sont liés directement aux éléments suivants : réduction de la motorisation, réduction de l'utilisation de l'automobile, augmentation de l'utilisation des modes de transport durable (collectif, actifs, alternatifs) et diminution des conséquences (congestion, émissions de polluants et de GES, impacts sur la santé) associées au niveau actuel d'utilisation de l'automobile.

Table 5.5 Objectifs et cibles des documents de planification.

Objectifs (ou orientations) (Or = Orientation, Obj = Objectif)	Cibles (ou critères) (C = cible, Cr = critère)
1. Politique de mobilité durable 2018-2030 (Gouvernement du Québec, 2018b, document synthèse, p.1-2)	
Or-1 : une mobilité au service des citoyens	C-1 : 70% de la population québécoise a accès à au moins quatre services de mobilité durable.
	C-2 : Réduction de 20% du temps de déplacement moyen entre le domicile et le travail.
Or-2 : une mobilité à plus faible empreinte carbone	C-4 : Diminution de 20% de la part des déplacements effectués en auto solo à l'échelle nationale.
	C-5 : Réduction de 40 % de la consommation de pétrole dans le secteur des transports sous le niveau de 2013
	C-6 : Réduction de 37,5% des émissions de GES dans le secteur des transports sous le niveau de 1990.
Or-3 : Une mobilité à l'appui d'une économie forte	C-9 : Réduction des coûts associés à la congestion pour les entreprises dans les régions métropolitaines de Montréal et de Québec. Non chiffrée.
	C-10 : Réduction de 20 % des dépenses brutes des ménages allouées au transport (en dollars canadiens constants de 2017).

Notes : ^a La PMD n'a pas d'objectif, uniquement des orientations et des cibles chiffrées.

^b Les PMAD n'utilisent pas le mot *cible*, mais plutôt des *critères* à respecter ou à atteindre.

Table 5.5 Objectifs et cibles des documents de planification (suite).

Objectifs (ou orientations) (Or = Orientation, Obj = Objectif)	Cibles (ou critères) (C = cible, Cr = critère)
2. PMAD – Montréal (CMM, 2012, document sommaire, p.15)	
Obj-1.1 : <i>Orienter 40 % de la croissance des ménages aux points d'accès du réseau de transport en commun métropolitain structurant</i>	Cr1.1 : 40% de la croissance des ménages en aire TOD.
Obj-2.1 : <i>Identifier un réseau de transport en commun qui permet de structurer l'urbanisation</i>	Aucune cible chiffrée.
Obj-2.2 : <i>Hausser à 30% la part modale des déplacements effectués en transport en commun à la période de pointe du matin d'ici 2021</i>	Cr-2.2 : Part modale TC ↑ à 30% d'ici 2021.
Obj-2.3 : <i>Optimiser et compléter le réseau routier pour soutenir les déplacements des personnes et des marchandises</i>	Cr-2.3.3 : <i>Réduction des délais et des retards occasionnés par la congestion.</i> Aucune cible chiffrée.
Obj-2.4 : <i>Favoriser la mobilité active à l'échelle métropolitaine</i>	Aucune cible chiffrée.
3. PMAD – Québec (CMQ, 2013, p. 32)	
Obj-2.2.1 : <i>Orienter le développement de manière à favoriser l'utilisation des modes de transports en commun et actif</i>	Cr-2.2.1 : Doubler les parts modales TC d'ici 2031 sur le territoire de la CMQ. Cible de 20% à l'heure de pointe du matin et 14% sur une base quotidienne.
Obj-2.2.2 : <i>Accroître la complémentarité et l'arrimage des services de transports en commun, adapté et actifs présents sur le territoire</i>	Cr-2.2.2 : Hausser la part modale du TA à 15% d'ici 2031. Doubler la part modale du vélo, soit de 1 à 2%, d'ici 2031.

Table 5.5 Objectifs et cibles des documents de planification (suite).

Objectifs (ou orientations) (Or = Orientation, Obj = Objectif)	Cibles (ou critères) (C = cible, Cr = critère)
4. Plan de transport – Montréal (Ville de Montréal, 2008, pp. 70, 98-99, 109, 127)	
Or-A1 : Mettre en place une meilleure offre de transport en commun	C-A.1.1 : Hausser de 8% l'achalandage du transport en commun d'ici 2012 et de 26% l'achalandage du transport en commun d'ici 2021.
Or-A2 : Favoriser les modes actifs Obj-2.1 : Augmenter de façon considérable les déplacements à pied en période de pointe d'ici 2021 Obj-2.2 : <i>Devenir, au cours des années qui viennent, la ville cyclable par excellence...</i>	Aucune cible chiffrée.
Or-B1 : Le réseau routier	C-B1.1 : Diminuer de 15% les déplacements en automobile à destination de Montréal en période de pointe par rapport aux déplacements anticipés en 2021 ^a . C-B1.2: Diminuer de 20% les déplacements automobiles anticipés d'ici 2021 (période de 24h).
5. Plan de mobilité – Québec (Ville de Québec, 2011, pp. 37-39)	
Obj-1 : Doubler d'ici 2030 la part modale du transport en commun à Québec et à Lévis	C-1 : Pour l'agglo. de Québec, hausser à 26% en PPAM et à 20% sur 24h la part modale du TC. Pour Lévis, hausser à 11% en PPAM et à 5% sur 24 h la part modale du TC.
Obj-2 : Augmenter les déplacements actifs d'ici 2030	C-2 : Pour l'agglo. de Québec, hausser à 17% à la part modale du transport actif (marche et vélo).

Notes : Il s'agit d'une cible indirecte puisque le plan indique que « L'atteinte des objectifs du Plan de transport, au chapitre des déplacements par mode, entraînerait une diminution de 15% des déplacements en automobile... »

Quelques observations peuvent être tirées de ces objectifs et cibles. Tout d'abord, seule la Politique de mobilité durable comporte une cible claire de réduction des déplacements en auto solo (C-4). Pour le Plan de transport de Montréal, ces « cibles » (C-B1.1, C-B1.2) sont plutôt ce qui est attendu de l'atteinte des autres objectifs du plan (voir les notes de bas de page 7 et 8). Cette absence de cibles claires ne semble donc pas être alignée avec la vision du Plan de transport qui vise à réduire la dépendance à l'automobile (Table A.5). Le même constat peut être tiré du PMAD de Montréal

dont la vision souhaite une diminution significative de l'usage de l'automobile alors qu'aucun objectif du plan n'y fait référence. En ce qui concerne la taille du parc automobile et la motorisation des ménages, aucun document ne comprend un objectif ou une cible spécifique à cet égard. On note toutefois que le gouvernement, dans sa Politique, souhaite une diminution des dépenses des ménages en transport (C-10). Considérant qu'à l'échelle provinciale, 90% des dépenses en transport des ménages sont des dépenses en transport privé et 10% seulement en transport public (Statistique Canada, 2018b), une réduction de l'ordre de 20% passe inévitablement par une réduction des dépenses liées à la possession automobile.

Des incohérences peuvent aussi être observées entre les cibles d'un même document, comme c'est le cas pour la Politique de mobilité durable. L'atteinte de la cible de réduction des temps moyens de déplacement (C-2) pourrait se retrouver en contradiction directe avec celle de réduire les déplacements en auto solo. En effet, à l'échelle provinciale, le navettage en auto solo affiche une durée moyenne de 23,4 minutes, derrière le transport actif (14 minutes), mais loin devant les 43,3 minutes pour les déplacements en transport collectif (Statistique Canada, 2017b). Même pour la région métropolitaine de Montréal où la congestion est souvent présentée comme endémique, le temps moyen pour le déplacement domicile-travail est considérablement plus court en auto solo (26,6 minutes) qu'en transport collectif (44,4 minutes) (Statistique Canada, 2017a)¹⁴. Si, à long terme, la stratégie de densification et de planification intégrée du territoire pourrait permettre l'atteinte des deux cibles, l'atteinte de celles-ci pour l'horizon 2030 est mise en doute.

En somme, à l'exception de la Politique de mobilité durable qui présente un objectif chiffré de réduction de l'usage de l'automobile, les autres documents ne font qu'identifier des objectifs d'augmentation (parfois non chiffrés) de l'utilisation des modes durables. Si les enjeux liés à l'automobilité sont généralement bien identifiés (Table 5.3), il semble que les objectifs et cibles fixés ne reflètent pas l'ambition de réduire les conséquences associées à ces enjeux.

La prochaine section cherchera donc à évaluer si les projets prévus pour la prochaine décennie permettront d'une part, de contribuer à l'atteinte des objectifs de ces documents, et d'autre part, au déclin des mobilités automobiles (usage et possession).

¹⁴ Les temps de déplacements du recensement sont des temps déclarés et non calculés.

5.6 Perspective 3 : Projets d'infrastructures et stratégies priorisés

L'adoption d'un plan de transport, d'un plan de mobilité durable ou d'une politique de mobilité a pour objectif de guider la mise en œuvre des stratégies, politiques et projets, qui permettent d'atteindre les cibles fixées et de réaliser les visions établies. En réalité, la dynamique complexe d'un système gouvernemental à trois paliers (municipal, provincial et fédéral) ayant chacun leur champ de compétences propres qu'ils doivent gérer avec un budget limité, rend ardue la coordination requise à la bonne réalisation des plans et politiques adoptés. S'ajoute à ces enjeux de mise en œuvre la réalité inhérente à un système démocratique d'une évolution des priorités politiques au gré des cycles électoraux (lesquels sont d'ailleurs décalés entre les trois paliers) qui, elles, s'adaptent aux différents changements sociaux, idéologiques et technologiques.

Dans un tel contexte, il n'est pas surprenant que les projets et actions à réaliser ne suivent pas à la lettre la priorisation prévue dans les plans et politiques ou encore ne soient tout simplement pas réalisés. La question qui est abordée dans cette troisième perspective d'analyse est celle de la cohérence entre le type de projets priorisés et les visions, objectifs et cibles des documents de planification. En s'appuyant sur les éléments de littérature scientifique recensés quant aux impacts généraux attendus de projets d'infrastructures routières et de transport collectif, la contribution estimée de chaque projet (positive, négative ou incertaine) à l'atteinte des objectifs et cibles des documents de planification est présentée Table 5.6.

Table 5.6 Analyse de la contribution attendue des projets d'infrastructures aux objectifs des documents de planification.

Contribution : (P) positive, (N) négative, (I) incertain.		Projets				
	Objectifs / Cibles	P1 : A-19	P2: Li. Bleue	P3 : REM	P4 : 3e lien	P5 : RSTC
Politique de mobilité durable	C-1 : 70% ont accès à 4 services de mobilité durable	P ^a	P	P	P ^a	P
	C-2 : -20% du temps de déplacement domicile-travail	N	I	I	I ^b	I
	C-4 : -20% à la part modale de l'auto-solo	N	P	P	N	P
	C-5 : -40% de la consommation de pétrole en transport	N	P	P	N	P
	C-6 : -37,5% des émissions de GES en transport	N	P	P	N	P
	C-9 : ↓ des coûts associés à la congestion pour les entreprises	N	I	I	I ^b	I
	C-10 : ↓ de 20% des dépenses des ménages en transport.	N	P	P	N	P
PMAD - Montréal	Obj-1.1 : 40% de la croissance des ménages dans les zones TOD	N	P	P		
	Obj-2.1 : Identifier un réseau de transport en commun structurant	N	P	P		
	Obj-2.2 : Hausser à 30% la part modale du TC en pointe AM (2025)	N	P	P		
	Obj-2.3 : Optimiser et compléter le réseau routier	P	N	N		
	C-2.3.3 : ↓ des délais et des retards dûs à la congestion	N	I	I		
	Obj-2.4 : Favoriser la mobilité active à l'échelle métropolitaine	N	P	P		
PMAD - QC	C-2.2.1 : Doubler les parts modales TC (2031) dans la CMQ.				N	P
	C-2.2.2 : ↑ part modale du TA à 15 % et x2 part modale du vélo (2031).				N	P
Plan de transport - MTL	C-A.1.1 : ↑ de 26% l'achalandage du TC (2021)	N	P	P		
	Obj-2.1 : ↑ les déplacements à pied en période de pointe (2021).	N	P	P		
	Obj-2.2 : Devenir la ville cyclable par excellence	N	I	I		
	C-B1.1 : ↓ de 15% les déplacements auto vers MTL en PPAM p/r à ceux anticipés (2021).	N	N	P		
	C-B1.2 : ↓ de 20% les déplacements auto anticipés sur 24 h (2021).	N	P	P		
Plan de mobilité - QC	C-1A : Pour l'agglo. de QC, ↑ à 26% en PPAM et à 20 % sur 24h la part modale du TC.				N	P
	C-1B : Pour Lévis, ↑ à 11% en PPAM et à 5% sur 24 h la part modale du TC.				N	I
	C-2 : Pour l'agglo. de Québec, ↑ à 17% à la part modale du TA.				N	P

^a Dans la mesure où ces projets prévoient l'inclusion d'une voie réservée pour covoiturage et autobus, il peut être estimé que l'ajout de service de TC là où il n'y en avait pas auparavant peut permettre à davantage de citoyens d'avoir accès à un service additionnel de mobilité durable.

^b Selon l'état d'avancement du développement urbain sur la rive sud de Québec au moment de l'ouverture du tunnel, il est possible que le nouveau lien permette de réduire de façon temporaire les temps de parcours et les coûts associés à la congestion. Ces gains toutefois tendent à ne pas perdurer dans le temps (Cervero, 2003).

5.6.1 Les projets d'infrastructures de transport collectif

La première considération est de savoir si ces projets étaient inscrits dans les documents de planification. Pour Québec, le concept général de construire un réseau structurant de transport collectif était directement inscrit dans le plan de mobilité durable de la Ville de Québec (2011, p. 53) bien que sa forme finale ait évidemment évolué depuis 2011. Le PMAD pour sa part se réfère au Plan de mobilité lorsqu'il mentionne le développement d'un réseau structurant (CMQ, 2013, p. 139). Pour Montréal, le prolongement de la ligne bleue du métro vers l'est était prévu comme l'un des 21 chantiers inscrits au plan de transport (Ville de Montréal, 2008, p. 18). Pour le REM, sa forme finale proposée par la CDPQ ne pouvait pas être prévue en 2008. Par contre, le projet permet de compléter deux chantiers prévus à l'époque, soit la réalisation d'une navette ferroviaire entre le centre-ville et l'Aéroport de Montréal ainsi que l'augmentation de la capacité de transport en commun dans le corridor Pont Champlain-Bonaventure (Ville de Montréal, 2008, pp. 18-19). Dans le PMAD, les projets y sont inscrits moins précisément, alors que le plan mentionne seulement « le prolongement du métro » et la réalisation d'une « navette aéroportuaire » (CMM, 2012, p. 136).

La revue de littérature réalisée a permis d'illustrer que le développement de projets de transport collectif sur rail (train léger et tramway) favorise généralement une augmentation de l'usage de ces modes ainsi que des modes actifs. Ils permettent aussi à plus long terme une réduction du nombre moyen de déplacements effectués en voiture pour les ménages à proximité de ces nouveaux corridors. Une densification et une diversification des usages des sols à proximité des stations sont toutefois essentielles pour aller chercher l'effet multiplicateur de ces projets (Ewing & Hamidi, 2014). Néanmoins, si ces projets sont un pas dans la bonne direction, il est moins certain que ceux-ci permettent à eux seuls de réduire le nombre absolu de déplacements réalisés en voiture à l'échelle métropolitaine ou encore de réduire les niveaux de congestion. Il est toutefois possible que l'influence de ces projets permette de ralentir la croissance de l'usage de la voiture comme à Portland (Ewing & Hamidi, 2014) et de ralentir la croissance des volumes de véhicules dans les corridors autoroutiers directement influencés par ces projets comme ce fut le cas pour le système de train léger à Denver (Bhattacharjee & Goetz, 2012).

5.6.2 Les projets d'augmentation de la capacité routière

Tout comme pour les projets de transport collectif, il est nécessaire de valider si ces projets étaient inscrits dans les documents de planification. Pour la région de Québec, le plan de mobilité durable ne mentionne pas le 3^e lien et indique : « A priori, il n'y a pas lieu d'augmenter la capacité autoroutière dans la région. Il n'est pas nécessaire non plus de réduire le nombre de voies d'autoroute. » (Ville de Québec, 2011, p. 86). La Ville recommande plutôt de transformer certains tronçons autoroutiers en boulevards urbains (p. 87). Au niveau métropolitain, le PMAD ne mentionne pas spécifiquement le 3^e lien, mais titre une section « Des investissements routiers qui participeront également à la mobilité durable de la région. » en appuyant par la suite les projets d'augmentation de la capacité routière prévus par le ministère des Transports en soulignant que l'automobile demeurera le mode de déplacement principal dans la région (CMQ, 2013, p. 141).

Dans la région de Montréal, le plan de transport de Montréal ne mentionne pas le prolongement de l'autoroute 19, celui-ci n'étant pas situé sur le territoire de la ville. Il est de plus souligné que « Montréal ne vise pas l'augmentation de la capacité routière donnant accès à l'île... » (Ville de Montréal, 2008, p. 128), la Ville souhaitant plutôt repenser le partage de l'espace de façon à favoriser les modes actifs et collectifs. Toutefois, le plan propose tout de même le prolongement et le raccordement de plusieurs segments routiers artériels principalement aux extrémités est et ouest de l'île (p. 137). Au niveau métropolitain, le PMAD comprend des éléments contradictoires. Ainsi, dans un encadré sur l'aménagement, le transport et la santé publique, il est indiqué que « Parallèlement à l'augmentation de l'offre de transport collectif, une politique de non-expansion du réseau autoroutier urbain pour empêcher le trafic induit contribue aussi au transfert modal vers le transport collectif... » (CMM, 2012, p. 83). Pourtant, il y est indiqué plus loin dans le plan que « Tout comme pour les réseaux de transport en commun, des investissements importants sur le réseau autoroutier seront donc nécessaires pour le maintenir et le développer. » (p. 138). L'énoncé est suivi d'un tableau listant quatre projets de prolongement ou parachèvement d'autoroute (incluant l'A-19), deux projets d'ajouts de voies de circulation et de nombreux projets de réfection et d'optimisation (Tableau 27, p. 139).

Tel qu'il a été illustré sommairement dans la revue de littérature, il est largement démontré de façon théorique et empirique que l'ajout de capacité routière (incluant un nouveau lien routier) ne permette pas de réduire les enjeux de congestion en plus favorise un type de développement

urbanistique orienté sur l'automobile. Dans le cas du 3^e lien, douze experts consultés par le *Journal de Québec* ont d'ailleurs confirmé que le projet ne sera pas une exception à ce qui a été observé ailleurs (S. Martin, 2017). Sur la page dédiée au projet, le Ministère des Transports du Québec (2019f) indique pourtant que celui-ci permettra de « Réduire la congestion aux heures de pointe, favoriser l'utilisation du transport collectif et optimiser le transport de marchandises ». Le transport collectif serait ainsi favorisé par l'inclusion d'une voie réservée aux autobus, au covoiturage et aux véhicules électriques. À noter que le rapport de l'analyse multicritères sur lequel s'est appuyé le ministre des Transports pour identifier le corridor et le choix d'un tunnel (plutôt qu'un pont) n'a pas été rendu publique à la date de publication du présent article (juillet 2020) (Radio-Canada, 2019a). De plus, des arguments économiques et environnementaux ont aussi été avancés par le ministre de l'Environnement qui soulignait qu'en contribuant au développement économique de la région le projet s'inscrirait dans une perspective de développement durable qui permettra de lutter contre les changements climatiques (Porter, 2019).

Les justifications du prolongement de l'autoroute 19 dans la région de Montréal ne sont pas très différentes de celles pour le 3^e lien et permettent aussi de souligner la résilience de la dépendance à l'automobile au sein des institutions. En effet, le ministère des Transports est forcé par le Bureau d'audiences publiques sur l'environnement (BAPE) en 2014 de réaliser une analyse plus approfondie entre des scénarios d'autoroute à deux voies et ceux de boulevards urbains notamment parce que « [La commission d'enquête] estime que, dans la foulée du virage énoncé dans ses documents de planification, le Ministère doit accorder plus de place aux modes de transport actif et collectif et orienter stratégiquement ses actions vers cet objectif. » (BAPE, 2015, p. 126). Dans son analyse comparative subséquente, le ministère conclut toutefois que le choix d'un boulevard urbain aurait multiplié les intersections à feux et aurait ralenti la circulation, réduisant ainsi la capacité routière à un point qui « ... ne permet pas d'atteindre les niveaux de service acceptables. » (MDDELCC, 2018, p. 9). Une telle conclusion confirme la difficulté pour l'appareil gouvernemental de sortir d'un paradigme de planification traditionnelle des transports où l'optimisation des flux de véhicules guide les décisions. En somme, si les documents d'évaluation ont permis de démontrer qu'une amélioration de ce corridor était nécessaire, notamment afin de bonifier les services de transport collectif (BAPE, 2015), nous contestons, au regard de la littérature établie, le potentiel du projet dans sa forme finale choisie de contribuer à l'atteinte des objectifs des documents de planification. De plus, en choisissant une autoroute qui double la

capacité automobile actuelle, il demeure difficile d'imaginer comment il sera possible « ...de favoriser le transfert modal et de réduire les coûts environnementaux et économiques liés à la congestion routière » tel qu'avancé par Ministère des Transports du Québec (2018) dans son annonce du projet. En effet, à titre d'exemple, Bhattacharjee and Goetz (2012, p. 268) soulignaient que la demande induite générée par l'augmentation de la capacité des autoroutes inter-états en même temps que le développement du réseau de train léger de Denver était l'un des facteurs ayant contribué à l'incapacité du train léger à réduire l'équilibre de congestion sur ces mêmes autoroutes.

5.6.3 Évolution des dépenses en transport routier vs transport collectif

Comme il n'est pas possible d'évaluer l'ensemble des projets d'infrastructures routières et d'infrastructures de transport collectif, un indicateur est proposé pour évaluer les priorités gouvernementales : la part des investissements dans le réseau routier versus celle dans les infrastructures de transport collectif. Ces investissements sont inscrits annuellement au Plan québécois des infrastructures (PQI) et, selon une compilation effectuée pour le PQI 2018-2028, 69% des investissements en transport sont dirigés vers le développement et le maintien du réseau routier et 31% vers les infrastructures de transport collectif (L'Alliance TRANSIT, 2018). Dans la mise à jour 2019-2029 du PQI survenue un an après l'entrée en vigueur de la politique de mobilité durable, la proportion des investissements est passée à 73% pour le réseau routier et à 27% pour le transport collectif (L'Alliance TRANSIT, 2019).

5.6.4 Le cas de l'électrification des transports

Le gouvernement provincial a adopté en 2015, avant l'adoption de sa Politique plus englobante de mobilité durable, une vaste stratégie d'électrification des transports (Ministère des Transports du Québec, 2015b). L'électricité québécoise étant produite à 99% depuis des sources hydriques renouvelables (Ministère des Transports du Québec, 2015b), l'électrification des transports est présentée comme un choix judicieux pour la province. Ses objectifs sont la réduction des émissions de GES du secteur des transports, la réduction de la dépendance aux énergies fossiles et le développement économique. La stratégie vise d'une part les transports collectifs et le transport de marchandises. Elle vise d'autre part la transformation du parc de voitures particulières *via* un ensemble de mesures pour favoriser l'achat de véhicules électriques et leur utilisation. Un rabais à l'achat de véhicules personnels 100% électriques et hybrides rechargeables neufs pouvant atteindre

8000 dollars canadiens est offert depuis 2012 (Gouvernement du Québec, 2019b). Depuis mai 2019, s'ajoute un rabais de 5000 dollars canadiens du gouvernement du Canada (Gouvernement du Canada, 2019c). Un soutien financier est aussi offert pour l'installation de bornes de recharge à domicile et l'usage de l'automobile est encouragé par l'accès aux voies réservées et l'accès sans frais aux ponts à péage (Ministère des Transports du Québec, 2022). Pour le Gouvernement du Québec, la somme des rabais octroyés totalisait 280 millions de dollars canadiens pour la période allant de 2012 à avril 2019 (Transition Énergétique Québec, 2019).

S'il peut être convenu que l'électrification du parc de véhicules fait partie des solutions pour réduire certains impacts de l'automobilité, la stratégie dans sa forme actuelle et le message envoyé par le gouvernement à travers les efforts et les sommes qui sont déployés sont questionnés, notamment à l'égard des objectifs des documents de planification. En ne s'attardant qu'à la Politique de mobilité durable, il apparaît improbable que l'encouragement à l'achat et à l'utilisation des voitures électriques privées permette de contribuer à l'atteinte des cibles de réduction de la part modale de l'auto solo (C-4), à la réduction des temps de déplacement (C-2) et à la réduction des dépenses des ménages en transport (C-10). En somme, nous argumentons que dans sa forme actuelle, la stratégie d'électrification des transports encourage plutôt la poursuite d'un modèle de développement du système de mobilité basé sur la possession et l'utilisation de l'automobile, contribuant à entretenir la dépendance sociétale à l'automobile. Cette incohérence de la stratégie québécoise d'électrification des transports privés avec les objectifs de mobilité durable pourrait être considérée comme un « transport taboo », un terme proposé par Gössling and Cohen (2014) pour identifier ce qui semble présentement intouchable en matière de politique de transport.

5.7 Conclusion

L'approche d'analyse en trois perspectives proposée dans le présent article visait à déterminer si les mobilités automobiles sont en déclin au Québec et si ce déclin s'accompagne d'une transformation des mécanismes de planification des transports et de l'aménagement du territoire. L'approche était appliquée à la province ainsi qu'à ses deux régions métropolitaines, Montréal et Québec. La première perspective d'analyse a permis d'illustrer que le Québec ne semble pas avoir vécu le phénomène de « peak-car » observé aux États-Unis, en Australie et dans plusieurs pays européens. En effet, l'utilisation de l'automobile et la motorisation ont continué d'augmenter dans

la province et aux échelles métropolitaines dans les deux dernières décennies, soutenues par une croissance importante dans les milieux suburbains de Montréal et Québec en dépit d'une croissance de l'usage des transports collectifs et du vélo dans les cœurs urbains.

La deuxième perspective d'analyse a permis tout d'abord de révéler une reconnaissance inégale des enjeux liés à la dépendance à l'automobile et à la croissance des mobilités automobiles (usage et possession) par les autorités planificatrices. La reconnaissance explicite de ces enjeux décroît avec l'augmentation de l'échelle de planification, étant ainsi plus présente au niveau des plans de transport et de mobilité municipaux, qu'au niveau des PMAD et qu'au sein de la Politique de mobilité durable. Paradoxalement, les cibles les plus ambitieuses de *réduction* de l'utilisation et de la possession automobiles sont identifiées dans la Politique provinciale de mobilité durable. Les plans municipaux et les PMAD se limitent à des cibles d'augmentation des usages (parts modales ou achalandage) des modes actifs et collectifs. Ce paradoxe est particulièrement frappant pour le Plan de transport de la Ville de Montréal qui place la réduction de la dépendance à l'automobile au cœur de sa vision, mais qui ne fixe aucun objectif direct de réduction des mobilités automobiles. Sur une note plus rassurante, les cinq documents font le lien entre le développement urbain des dernières décennies et l'utilisation accrue de l'automobile et l'augmentation de la motorisation. Ils indiquent aussi qu'une planification intégrée de ces deux composantes est essentielle pour atteindre les objectifs de mobilité durable.

La troisième perspective a permis de mettre en relief les principaux projets d'infrastructures de transport avec les visions et objectifs des documents de planification. Tout d'abord, à l'exception du projet de troisième lien routier entre les rives nord et sud de la région de Québec, tous les projets étaient inscrits (quoique partiellement pour le REM) dans les PMAD et dans les plans municipaux. Par la suite, en s'appuyant sur la littérature existante, il peut être avancé que les projets de transport collectif (Ligne bleue, REM, RSTC) sont alignés avec les visions des documents de planification et devraient permettre de contribuer à l'atteinte de certaines des cibles fixées. Pour aller chercher les effets multiplicateurs de ces projets, ceux-ci devront être accompagnés d'une planification intégrée du développement urbain dans leurs corridors respectifs. Force est toutefois de constater qu'il est peu probable que ces projets, à eux seuls, puissent permettre une réduction absolue des mobilités automobiles. Il importe néanmoins de rappeler que ces projets de transport collectif, à l'instar d'autres projets documentés dans le monde, ont le potentiel de générer un large éventail de bénéfices sociaux, environnementaux et économiques découlant de l'augmentation de

l'accessibilité, de leur influence sur le développement urbain et de leur capacité à ralentir la croissance des mobilités automobiles.

Finalement, il est estimé, au regard de la littérature, que les projets autoroutiers (3^e lien et A-19) ne sont pas alignés avec les visions des documents de planification et ne contribueront pas à l'atteinte de presque l'ensemble des objectifs des documents de planification. L'augmentation de la capacité autoroutière de ces projets risque d'induire une demande automobile à court et à long terme qui pourrait compromettre les gains attendus des projets de transport collectif prévus pour chacune des régions. Il est donc d'autant plus étonnant et incohérent de constater la présence du prolongement de l'A-19 dans le PMAD de Montréal. De plus, les promesses d'inclusion de voies réservées au transport collectif dans les deux projets afin de les qualifier de projets de « mobilité durable » peuvent être associées à une stratégie visant à leur conférer une acceptabilité sociale et environnementale plutôt qu'à un réel désir de planifier autrement la mobilité. De façon générale, ces arguments environnementaux s'ajoutent aux arguments de développement économique qui sont typiques d'une résistance politique et des institutions à un changement de paradigme de mobilité. Une situation décrite par Newman and Kenworthy (2015b, p. 143) qui soulignent la difficulté pour une ville (dans le cas présent, une province) de se sortir d'un paradigme de développement basé sur le réseau routier où les nouveaux projets routiers sont justifiés sur le plan d'économie de temps, de carburant et autres bénéfices pour les communautés. Une situation à laquelle s'ajoute le contexte d'une agence gouvernementale (ici, le ministère des Transports) dédiée presque exclusivement au développement routier et offrant aux politiciens et décideurs des évaluations biaisées en faveur du développement automobile (Newman & Kenworthy, 2015b, p. 144).

En somme, la poursuite de la croissance des mobilités automobiles, l'absence d'objectifs et d'outils de réduction de la place de l'automobile dans la majorité des documents de planification et la poursuite simultanée de projets d'infrastructures aux effets opposés illustrent toute la difficulté à mettre en œuvre un changement de paradigme de mobilité qui puisse réellement inverser les tendances actuelles. Les difficultés pour le gouvernement de réaliser pleinement ce changement de paradigme par la mise en application d'une politique ambitieuse de mobilité durable adoptée en avril 2018 soulignent l'impact politique de la dépendance à l'automobile. Cette situation au Québec revient à confirmer ce que suggérait Dupuy dans une entrevue récente pour la revue *Flux* (G. Dupuy & Gallez, 2018, p. 107), c'est-à-dire que la dépendance à l'automobile serait « ...

surtout un problème qui se pose à toutes les politiques publiques qui se prétendent vertueuses dans la régulation des mobilités. Je dirais que c'est un problème politique ».

CHAPTER 6 ARTICLE 2: CAR OWNERSHIP AND THE BUILT ENVIRONMENT: A SPATIAL MODELLING APPROACH

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ABSTRACT

Car ownership is linked to higher car use, which leads to important environmental, social and health consequences. As car ownership keeps increasing in most countries, it remains relevant to examine what factors and policies can help contain this growth. This paper uses an advanced spatial econometric modelling framework to investigate spatial dependences in household car ownership rates measured at fine geographical scales using administrative data of registered vehicles and census data of household counts for the island of Montréal, Canada. The use of a finer level of spatial resolution allows for the use of more explanatory variables than previous aggregate models of car ownership. Theoretical considerations and formal testing suggested the choice of the Spatial Durbin Error Model (SDEM) as an appropriate modelling option. The final model specification includes sociodemographic and built environment variables supported by theory and achieves a Nagelkerke Pseudo- R^2 of 0.93. Despite the inclusion of those variables the spatial linear models with and without lagged explanatory variables still exhibit residual spatial dependence. This indicates the presence of unobserved autocorrelated factors influencing car ownership rates. Model results indicate that sociodemographic variables explain much of the variance, but that built environment characteristics, including transit level of service and local commercial accessibility (e.g., to grocery stores) are strongly and negatively associated with neighborhood car ownership rates. Comparison of estimates between the SDEM and a non-spatial model indicates that failing to control for spatial dependence leads to an overestimation of the strength of the direct influence of built environment variables.

Keywords: Car Ownership, Spatial Modelling, Built environment, Accessibility.

6.1 Introduction

Cars are ubiquitous in most societies as they offer their users freedom of movement over vast distances. However, their extensive use by a large share of the population is now widely acknowledged to be a leading cause of greenhouse gas emissions responsible for the current climate crisis (IPCC, 2014). It is also linked to negative health impacts through road fatalities and injuries, air pollution, and stress (Nieuwenhuijsen, Bastiaanssen, Sersli, Waygood, & Khreis, 2019; The World Bank, 2014). Car ownership itself is not necessarily perceived as an issue despite the extensive evidence that it is positively associated with higher use of cars and reduced use of other modes (e.g. Dieleman et al., 2002; Eluru, Pinjari, et al., 2010; Sioui et al., 2013; Sun et al., 2014).

Car ownership has been increasing steadily in most countries over the last decades, though there is evidence of a saturation point (S. C. Davis & Boundy, 2019). In Canada, the number of cars has been increasing 1.8 times faster than the population since 2000. This holds true even in large urban centers. As an example, the number of non-commercial vehicles per 1000 adults on the Island of Montréal increased by 10 % (from 413 to 455) between 2000 and 2018 (Laviolette et al., 2020). This shows how relevant it remains to refine our understanding of car ownership.

Most recent research on the subject has been conducted using disaggregate models where the modelling unit is the household (see the work of Anowar, Eluru, et al. (2014) for a comprehensive review). While those methods allow the researcher to gain insightful knowledge of the mechanism shaping household decisions, they must rely on expensive travel surveys of sometimes small sample sizes, and thus often need complementary survey data from aggregate level datasets. Survey data with sparse spatial distribution could be problematic for example when trying to assess the impact of localized changes in transportation infrastructure or accessibility because there might not be enough observations in the zone of influence of those changes. Furthermore, not all regions and cities have access to such detailed travel surveys. Despite some limitations in the interpretability of the data, aggregate modelling can rely on publicly available administrative data or census data where almost all registered vehicles in the studied region can be accounted for. Car ownership rates can thus be estimated at various geographical scales, allowing for a more precise analysis of its spatial distribution. A high spatial resolution where the values are aggregated within

small geographical units can be useful to investigate the spatial dependence shaping the phenomenon being analyzed.

One measure of spatial dependence is positive spatial autocorrelation which happens when units that are close to each other present similar values of the investigated variable (Haining, 2001). This generally means that standard linear models cannot be used because doing this violates the assumptions of independence of observations and uncorrelated error terms. Spatial modelling methods are thus needed to account for and investigate those spatial interactions.

The main objective of this paper is to investigate the relationship between car ownership rates measured within small geographical units and various characteristics of the built environment relevant for transport and planning policy while controlling for spatial dependence.

The investigation starts by testing the hypothesis that the observed spatial correlation in car ownership rates observed at this spatial resolution is due not only to within-neighborhood sociodemographic and built environment characteristics, but also such characteristics in nearby neighborhoods (i.e., contextual effects). Additionally, because individual transportation decisions have been recognized to be influenced by social interactions (E. Dugundji, Páez, & Arentze, 2008; E. R. Dugundji et al., 2011), car ownership decisions of household within a zone could be influenced by the behaviour of other households within nearby zones (i.e., endogenous effects), thus potentially affecting the aggregate car ownership rates. In this study we consider built environment influences such as accessibility to local opportunities, transit and carsharing services. We then examine the impact of not controlling for spatial dependence arising from observed and unobserved factors. To achieve this, a modelling framework is proposed to identify a spatial model specification adequately suited for investigating these questions and to obtain robust estimates of the relationship between car ownership rates and built environment including accessibility. In this respect, aggregate models relying on data covering the entire region allows for precise analysis of the spatial distribution of car ownership and its influencing factors.

6.2 Literature review

Car ownership has been shown to relate to personal and built environment characteristics, and in some cases policy (Senbil et al., 2009). Age is found to influence car ownership, but not in a linear manner (Sun et al., 2014) and some cohorts seem more car-oriented (Sun, Waygood, & Huang,

2012). When modelled at the household level, income is a key determinant in car ownership with higher income associated with more cars owned even when neighborhood income variables are included instead of household level income (Anowar et al., 2016). This relationship might not be linear (Potoglou & Kanaroglou, 2008; Senbil et al., 2009). Household size has also been shown to positively influence car ownership (H. S. Kim & Kim, 2004) as well as household structure such as being a couple or having a child (Potoglou & Kanaroglou, 2008; Sun et al., 2014). The presence of children in the household is not necessarily associated with higher numbers of vehicles when other variables are accounted for (Bhat & Pulugurta, 1998).

In terms of built environment variables, higher residential density or higher mixed density are associated with lower propensity for households to own several cars (Bhat & Guo, 2007; Potoglou & Kanaroglou, 2008; Sun et al., 2014). Some have argued that when attitudes, travel preferences, and residential self-selection are accounted for, built environment variables may not be significant factors explaining car ownership (Xinyu Cao et al., 2007a), while others have shown that even when controlling for those factors, built environment variables remain significant (Bhat & Guo, 2007), even having direct effect on the household's car ownership decision (Van Acker et al., 2014).

Related to the built environment are the options provided through the transport network. The impact of transit on car ownership has also been frequently investigated, however with varying levels of precision. Some considered only the number of transit stops accessible within a threshold distance around the household (Potoglou & Kanaroglou, 2008), others added the number of kilometers of bus and rail line within that same buffer (Anowar et al., 2016). More precise measures describing transit level of service have also been included, showing that higher levels of service are associated with lower car ownership (Becker et al., 2017). A lesser investigated, but nonetheless influential variable on car ownership is the availability of onstreet and off-street parking in high-density areas, with higher parking availability of both types associated with higher car ownership levels (Z. Guo, 2013a, 2013b). This suggests that parking management policies (such as context-based limits) should be used in tandem with the provision of public transportation to reduce the need for car ownership (De Gruyter, Truong, & Taylor, 2020).

As discussed above, built environment features of neighboring areas may influence car ownership, but aggregated spatial modelling methods have rarely been employed to examine car ownership.

For example, S. Clark and Finley (2009) compared three spatial modelling methods (Spatial Error Model (SEM), Geographically Weighted Regression (GWR) and Hierarchical Bayesian Spatial Model) to examine the relationship between household car ownership and income across England and Wales using census data. The modelling unit was electoral wards, leading to a total of 1100 units across the country and the explanatory variables were simply population density and household net income. In another paper Clark (S. Clark, 2007) compared the SEM with GWR using the same two variables, but at a finer geographical scale, where a total of 8000 electoral wards across the country were used. In an exploratory study, Whelan et al. (Whelan et al., 2010) tested a range of model formulations (linear, log-linear, s-shaped functions such as logistic or Gompertz and GWR) to model the number of cars per adult at the Lower Layer Super Output Area (LSOA), a UK statistical unit with an average population of 1,500. Numerous sociodemographic variables were included (income, household structure, dwelling tenure, nationality) along with three policy relevant variables: accessibility by public transport, on-street parking permit cost and coverage, and a measure of local accessibility to amenities. They concluded that all three variables had the expected sign (negative impact on car ownership rates) and magnitude. Except for the GWR formulation, the other tested models by Whelan et al. did not account for spatial autocorrelation. Spatial interaction effects due to observed and unobserved factors have also been integrated in discrete choice models of household fleet composition by Paleti et al. (2013). Their results show that a distance-based spatial interaction effect between households is statistically significant, improves model fit and leads to elasticity estimates considerably higher in magnitude than the non-spatial model. This difference in magnitude could lead to very different policy effect forecasts, clearly indicating the need to incorporate spatial dependence when modelling car ownership. Despite this important finding, very few discrete choice models of car ownership in the literature have controlled for spatial dependence in such a way, most likely because of the very complex model estimation requirements. Examining spatial dependence effects is more easily conducted using aggregate models where the entire region is divided into zonal units and car ownership is measured using a continuous outcome variable such as the average number of vehicles per household. A regression model incorporating spatial interaction effects could thus provide us with estimates of the relationship between the influencing factors and car ownership that are robust to the violation of assumption in regression arising from spatial dependence.

The review suggests that advanced state-of-the-art spatial modelling methods, such as the Spatial Durbin Model (SDM) or Spatial Durbin Error Model (SDEM) as suggested by Lesage (LeSage, 2014; LeSage & Pace, 2009) have not been used to model car ownership. Furthermore, previous aggregate car ownership models have been conducted using large geographical units. The smallest reported unit used was the UK's Lower Layer Super Output Area (LSOA) (Whelan et al., 2010) and in the US, the Transport Analysis Zone (Holtzclaw et al., 2002). The current paper makes use of administrative data provided by the Province of Québec's (Canada) car registration authority (the SAAQ), to model car ownership at a very fine geographical scale using state-of-the-art spatial modelling methods. This allows the use of several sociodemographic and built environment variables to explain local variation in household car ownership rates for the objective of examining the effect of spatial dependence.

As discussed above, various influences have been found on car ownership levels, but the variables considered in spatially aggregated studies have been limited. In this study, the finer grained spatial level allows inclusion of built environment influences at levels that better reflect short walking distances that are key for car free (or reduced car) life.

6.3 Methods

6.3.1 Theoretical considerations for spatial modelling of car ownership

Several reasons are attributed to the presence of spatial dependence where two cases close to each other have similar values (positive spatial autocorrelation) (Haining, 2001). Three reasons are of high relevance in understanding why car ownerships exhibit spatial dependence. A first reason is spatial continuity, where the modelling units of measurement is smaller than the scale at which the phenomenon varies. In the present case, the modelling unit is the Dissemination Area (DA) of the Canadian census where, on the Island of Montréal, 95 % of units have a land area between 0.02 and 0.61 square kilometers. The boundaries defined by Statistic Canada for those areas are not specifically designed to model car ownership rates. This means that the size of the modelling unit can be smaller than the scale at which car ownership varies in space.

The second is that the spatial autocorrelation of the process being studied depends on the spatial relationship of observed and unobserved influencing factors. The car ownership rate measured within a spatial unit (e.g., census tract) is an aggregation of household behaviours (i.e., the choice

of owning one or more cars). As detailed in the previous section, this behaviour is influenced by (typically observed) individual and household characteristics (e.g., income, composition, age, education or race) as well as attitudes and lifestyle preferences (usually unobserved). The distribution of those population characteristics across a region, when measured within statistical units, is rarely random and tends to follow spatial distributions that could be the results of forced or self-selection of individuals into specific neighborhoods that fit their preferences or economic constraints. Built environment characteristics such as density, diversity and the type of dwellings are also influencing factors in household car ownership decisions all of which, when measured within spatial units, are likely to exhibit specific patterns of spatial dependence, most likely arising from spatial continuity.

A third important reason leading to spatial dependence is spatial spillover where car ownership levels in one spatial unit might be influenced by conditions in that unit, as described in the previous paragraph, but also conditions in neighboring units. This could be a result of social norms and interactions between individuals where, for example, car ownership decisions by those within one zone are affected by decisions of individuals within neighboring zones (endogenous effects) (Goetzke & Weinberger, 2012). Spatial spillover could also be due to the influence of exogenous conditions in neighboring units. For car ownership, those conditions can be the sociodemographic characteristics of the neighboring zones and, more importantly, the characteristics of the built environment such as density, diversity of land-use, design of the streets, presence of local commercial, service or employment opportunities and accessibility to mobility resources such as highways, transit, on-street and off-street parking, carsharing and bikesharing.

Those different explanations for spatial dependence can be modelled by the inclusion of three main types of spatial interactions terms in a regression (Elhorst, 2010). Consider a situation where no spatial spillover is taking place and all the known influencing factors of the process being studied are measured. In such a case, a linear regression model with no spatial interaction term could be sufficient to explain all observed spatial dependence in the dependent variable, leaving no residual spatial correlations, thus respecting the assumption of independent error terms. In reality, it is very likely that one or more influencing factors will be unobserved. Modelling the presence of unobserved spatially correlated variables is commonly achieved by adding a spatial autoregressive coefficient in the error term to reflect the dependence in the regression residuals. A model with only this effect is called the Spatial Error model (SEM) and is defined by the following equation:

$$y = X_i\beta + u \quad (6.1)$$

$$u = \lambda W + \varepsilon \quad (6.2)$$

Where, using vector notation, for n spatial units W is an $n \times n$ matrix where the non-null elements represent spatial units that are connected to each other, β is $k \times 1$ vector of coefficients, λ denotes the average strength of the spatial correlation in the errors and ε a vector of independently and identically distributed error terms.

The second type of interaction terms allows for the inclusion of endogenous effects arising from social interactions between household and individuals of adjacent zones. Such processes would be modelled through a simultaneous autoregressive model (SAR) where a spatial lag vector is added to the standard linear model that reflects the average value of the neighboring regions' car ownership rates in explaining a region's own car ownership level. The equation for the SAR models takes the following form:

$$y = \rho Wy + X\beta + \varepsilon \quad (6.3)$$

Where the parameter ρ represents the strength of the spatial dependence.

The third interaction includes the exogenous (or contextual) spatial spillover effect described above. This process is modelled by a model referred to as the SLX (spatial lag of X s), which adds the term $WX\theta$ where θ is the vector of $k \times 1$ coefficient vector of the lagged X variables to the standard linear model:

$$Y = X\beta + WX\theta + \varepsilon \quad (6.4)$$

While these three spatial models each include one type of spatial interaction, the contemporary approach to spatial modelling suggests testing more complex models involving two spatial interaction terms (Elhorst, 2010). These models are first the SACSAR model (also called the Kelejian-Prucha) which have a spatially lagged dependent variable (WY) and spatially autocorrelated error term ($W\varepsilon$). Then the Spatial Durbin Model (SDM), advocated by LeSage and Pace (2009), includes a lagged dependent variable (WY) and spatially lagged explanatory variables (WX). Finally, the Spatial Durbin Error Model (SDEM) suggested by LeSage (2014) as a good

option for applied work, is a model with a spatially autocorrelated error term (λW) and spatially lagged independent variables (WX).

Not properly modelling those different types of spatial interactions could lead to regression coefficients that are biased and inconsistent.

6.3.1.1 Model specification for small-scale aggregate modelling of car ownership

The challenge of determining what model to use is to identify which of these possible specifications is best suited to examine the various reasons for the presence of spatial dependence. In their book LeSage and Pace (2009) and in a later paper LeSage (2014) make the case that the use of the SACSAR model has too many drawbacks for applied work and thus can be ruled out. They suggest that for most empirical work, only two configurations are left as starting points: the SDM and the SDEM. Elhorst (2010), referring to Lesage and Pace's (2009) book, indicates that the SDM will offer unbiased coefficient estimates even if the true data-generating process is any of the other models (SAR, SEM, SDEM or SACSAR models). Despite this, empirically testing to determine which of the SDEM or SDM model would be best suited to model the studied phenomenon is not trivial because these two models are not nested. LeSage (2014) suggests choosing either of those configurations should be based on strong theoretical basis as to the nature of the spatial spillover effects influencing the outcome being studied.

Both models include explicit accounting of contextual neighboring influences through the inclusion of lagged exogenous variables (the X_s). Those lagged variables are usually the average values of the neighbors defined according to the spatial weight matrix. As described above, such influence is likely to be happening in the case of car ownership rates modelled at fine geographical scale. As described by LeSage (2014), exogenous neighborhood effects are considered local spillover effects because there is no feedback mechanism involved. For example, if density increases in zone i , it might only affect car ownership rates in the zones that are first-order neighbors of zone i .

From a theoretical perspective, the main question left to ask in order to support the selection of either the SDEM or the SDM is whether some endogenous effects could be taking place. As described above, the support for the inclusion of such effect comes from the hypothesis that people's car ownership decision would be influenced by car ownership decisions of their

neighbors. This also requires the assumption that “the neighborhood” is considered to be a valid social reference group when it comes to consumption and transport related decisions. Goetzke and Weinberger (2012)’s work bring some evidence to this by trying to differentiate between contextual and endogenous effects in car ownership decisions using New York City data. Car ownership rates are first modelled at the block group level, and then in a second step, the estimated values are used as input in a binomial probit model of household car ownership. The endogenous and contextual effects being measured are thus between individual households and their immediate spatial surrounding, i.e., the block group of the US Census within which the observed households are located (zones that are very close in size to the Dissemination Area (DA) of the Canadian census used in the current paper). The credibility of that assumption of “the neighborhood” as a valid social reference group lies in the scale Goetzke and Weinberger consider for defining the neighborhood. The block group, like the DA, represents the very streets on which people live. Seeing your neighbor’s cars (or lack of) sitting in their driveway or parked on the street or discussing with your immediate neighbors could affect your own decision. Their paper produced some evidence to support that hypothesis.

In the present case, the modelling unit is the Canadian Dissemination Area (DA) and the “neighborhood” is defined as either the contiguous DA or as the K-nearest DAs (the spatial weight matrix selection methodology is described in the next section). In Montréal’s most central areas, selecting the 30 nearest neighborhoods corresponds roughly to a neighborhood scale of a 12-15 minute walk. In more suburban areas, this area is larger due to lower density. While it cannot completely be ruled out, our hypothesis is that the endogenous effect is unlikely at this scale. People’s decisions are influenced by social norms, such as how their neighbors behave (J. M. Nolan, Schultz, Cialdini, Goldstein, & Griskevicius, 2008). However, a household’s decision about how many cars to own (which could be extended to types) is unlikely to be meaningfully affected by the decisions of people living 4-8 streets away (10-15 minutes). Evidence from the study of neighborhood networks shows that they rapidly decrease after the first intersection (Grannis, 2009). In other words, the spatial scale of the current analysis would favor the use of the Spatial Durbin Error Model (SDEM) over the SDM. The SDEM also allows for controlling spatial dependence arising for unobserved influencing factors that are spatially correlated such as measures of off-street or on-street parking or the attitudes and preferences of people in each DA.

For these reasons, the SDEM serves well the objective of investigating the magnitude of the association between car ownership and the built environment at the current scale.

Another consideration supporting this choice is the ease of interpretation of the direct, indirect and total effects. Interpreting those effects is more straightforward for the SDEM than in the case of the SDM. One can simply interpret the regression level coefficients (β_k and θ_k for the lagged exogenous variables): the direct effect is the average influence of the independent variables of zone i on the dependent variable of zone i (β_k). The indirect effect is the average influence of the independent variables of neighboring zones (where the neighboring regions are defined by the row-standardized W matrix, θ_k). This also makes the comparison between the OLS, SLX and SDEM coefficients valid (Elhorst, 2010, p. 21), which is an objective of the current paper. On the other hand, the interpretation of the SDM effects relies on simulated direct, indirect and total impacts that are more complex and less intuitive since it has to account for feedback endogenous effects (e.g., Unit A $\rightarrow$ Unit B $\rightarrow$ Unit C $\rightarrow$ Unit A) propagating through the studied region.

A final critical element supporting the choice of the SDEM over the SDM in the current analysis is the inclusion of accessibility variables (sum of transport/commercial opportunities) measured within walking-distance buffers around the centroid of each zone. This method of calculation is common in disaggregate models and offers a very precise estimation of the influence of accessibility using realistic walkable connectivity. It is also more consistent across the region than relying on the number of opportunities within zones of varying size or within varying number of zones, depending on how the spatial weight matrix is specified. However, it implies that the calculation of those variables relies on elements that are not strictly contained within the boundaries of each zone (e.g., the sum of the number of bus stops within 400 m walking buffers of the centroid of zone i would contain some stops from zone i , but also stops located within neighboring zones). For this very reason, those explanatory variables should not be lagged because they already account for neighborhood effects and doing so would result in multiple counting, leading to biased coefficients. While it is possible to choose not to lag some specific exogenous variables, it is not possible to withdraw those variables from the feedback mechanism at play when a lag on the dependent variable is included, such as is the case for the SDM. This would result in multiple counting of the same effects that could strongly bias the entire regression results.

With exogenous variables being lagged while others are not, the SDEM takes the following form:

$$Y = X\beta + WX\theta + Z\nu + u \quad (6.5)$$

$$u = \lambda W + \varepsilon$$

Where X is the vector of independent variables that are lagged and Z the vector of independent variables that are not lagged for the reasons described above. β are the estimated direct coefficients of the explanatory variables that will be lagged, θ the indirect coefficients of those variables and ν the coefficients of the variables which are not lagged.

6.3.2 Modelling framework

To examine the hypothesis that the built environment, the transit level of service, and carsharing availability explain part of the spatial dependence and variance in car ownership levels, a cross-sectional spatial modelling framework is proposed. The framework draws extensively from the recent spatial econometric literature and follows closely the procedure described by Elhorst (2010). Elhorst's framework is a mixture of the modern *general-to-specific* model specification search strategy recommended by LeSage and Pace (2009) and the more classical *specific-to-general* strategy set forth by Anselin (1988).

After a proper analysis of the spatial distribution of household car ownership rates and test for spatial autocorrelation using Global Moran's I test, a linear regression model (OLS) with various sets of potential sociodemographic explanatory variables was run. Anselin (1988)'s Lagrange Multiplier tests were used to check if the OLS model should be rejected in favor of either the spatial-lag model (SAR) or the spatial error model (SEM). As both tests were significant, the SDEM was selected over the SDM for theoretical considerations detailed in the previous sections. Likelihood ratio tests were then conducted to see if this more complex model could be reduced to either the SLX or the SEM. The chosen specification was then tested with varying neighboring structures. LeSage (2014)'s fifth principle was used and only simple spatial weight matrices were tested. The selection procedure was based on Stakhovych and Bijmolt (2009) recommendation that goodness-of-fit measures and information criteria were good methods to identify a matrix very close to the true specification, especially when the spatial parameter value is high. This sensitivity analysis is also important because Stakhovych and Bijmolt (2009)'s findings also indicate that with high values of the spatial parameters (ρ or λ) the regression coefficients could be very sensitive to the weight matrix. While Bayesian model probability was suggested by LeSage and

Pace (2009, p. 162) as able to identify the true specification among very similar matrices, it was deemed unnecessary to try to find *the* best possible matrix since similar matrices will be highly correlated due to common elements (LeSage & Pace, 2014). Queen's contiguity matrix, K-nearest neighbors (where K = 10 to 40, by steps of 5 are tested) as well as a matrix of neighbors below threshold distances of 800, 1000, 1200, 1400 and 1600 m were tested. At this step, the optimal model specification has been confirmed. Candidates for built environment variables (Table 6.1) were added all at the same time. The objective of adding explanatory variables in two steps was to test if car ownership spatial dependence could be explained only with the inclusion of SD variables versus also considering the effect of BE variables. The test procedure for model specification was run again to see if the addition of the built environment variables brought a change to the model specification. Then, each variable was removed one at a time to test if its presence offered a significant improvement to the model fit. Model fit was assessed using Akaike Information Criterion (AIC) values and likelihood ratio test. This step was repeated until no variable could be removed without decreasing significantly the fit of the model.

Spatial dependence analysis and weighting schemes were conducted using the *spdep* package in R and spatial models were estimated using the package *spatialreg* (Bivand, 2019, 2020).

6.3.3 Study area

The region for the current analysis is the Island of Montréal, Québec, Canada. It is a subregion of the Greater Montréal Area (GMA) and it contains the City of Montréal as well as 15 other municipalities. According to the 2016 Canadian Census, the island has a population of 1,942,000 with an average population density of 3,889 persons/km² (Statistics Canada, 2017). In 2016, the transit system had three components, a metro system of four lines and 68 stations (64 located on the Island), a bus system of 218 lines and six lines of commuter train converging toward the Central Business District. The modelling unit for the analysis is the Dissemination Area (DA). It is the smallest standard geographical unit for which all census variables are available. This spatial unit is smaller than the US Census Tract, covers all of Canada and averages a population of 400 to 700 people based on previous census. The boundaries of the DA are those of the 2016 census. There is a total of 3202 DA on the Island of Montréal among which 3156 (no missing values in 2016) are considered for the analysis. The unpopulated DAs are mainly park and industrial areas which are not relevant for an analysis of residential car ownership.

6.3.4 Data sources

Vehicle data. The number of residential registered vehicles for 2016 aggregated at the Dissemination Area (DA) were obtained from the Société d'assurance automobile du Québec (SAAQ), the government authority regulating the use of motor vehicles in the province of Québec.

Census variables. A set of sociodemographic variables was obtained from the 2016 Canadian Census at the DA level using University of Toronto's CHASS Data Centre.

Built environment and accessibility. The land-use dataset was obtained from the Communauté Métropolitaine de Montréal (CMM) for the year 2016. The GTFS for 2016 were extracted from Transitfeeds.com. The dataset of carsharing stations was obtained from Communauto, the only station based carsharing company operating in Montréal. The commercial opportunities were extracted from the Enhanced Point of Interest dataset obtained from DMTI Spatial. The specific extraction procedure can be supplied on demand by the authors. OpenStreetMap's road and pedestrian network was used for the calculation of walking accessibility buffers.

All datasets were integrated in a geospatial database in PostgreSQL, using PostGIS spatial extension.

6.3.5 Preparing the variables

Dependent variable: The number of vehicles per household was used as the dependent variable. It was obtained by dividing the total number of residential cars and light trucks registered within a DA by the number of private dwellings occupied by residents. It was selected over the number of vehicles per adult because vehicles are mainly household level decisions linked to household disposable income. One limitation of the dataset is that small business owners or people being provided with a company car and who are using these cars also for their personal use are not accounted for since these vehicles are registered as commercial. This would not be a problem if the proportion of such vehicles was distributed homogenously in the region, but this is unlikely to be the case. One assumption is that higher income households are more likely to have vehicles registered this way. Figure 6.1 shows a map of the distribution of the number of vehicles/dwelling unit, assuming one household by dwelling in the studied region.

Explanatory variables: All potential sociodemographic and built environment variables (selected based on prior research) are listed in Table 6.1. The land-use mix entropy within each DA is estimated following the method described by (Cervero & Kockelman, 1997) considering five land-use categories: residential, commercial, offices, leisure and/or parks, and institutional.

For maximum precision, accessibility to transit and to commercial opportunities were measured as cumulative opportunities within a buffer of space accessible by foot below a threshold distance. Using QGIS's Network Analysis tool with OSM network accessible by foot (thus including park trails and other pedestrian "shortcuts"), polygons covering the space delimited by a network distance of 400 m and 800 m around the centroid of each DA were calculated. Those distances correspond respectively to about 5 and 10 minutes of walking at a normal pace. Following tests of association, the 400 m threshold was used for the number of bus stops and a measure of transit level of service: the frequency * direction * bus lines over a period of 24 hours. The 800 m buffer was used for the presence of a metro station (binary variable), the number of grocery stores, the number of carsharing vehicles and the presence of at least one carsharing station (again following tests of association for the different thresholds).

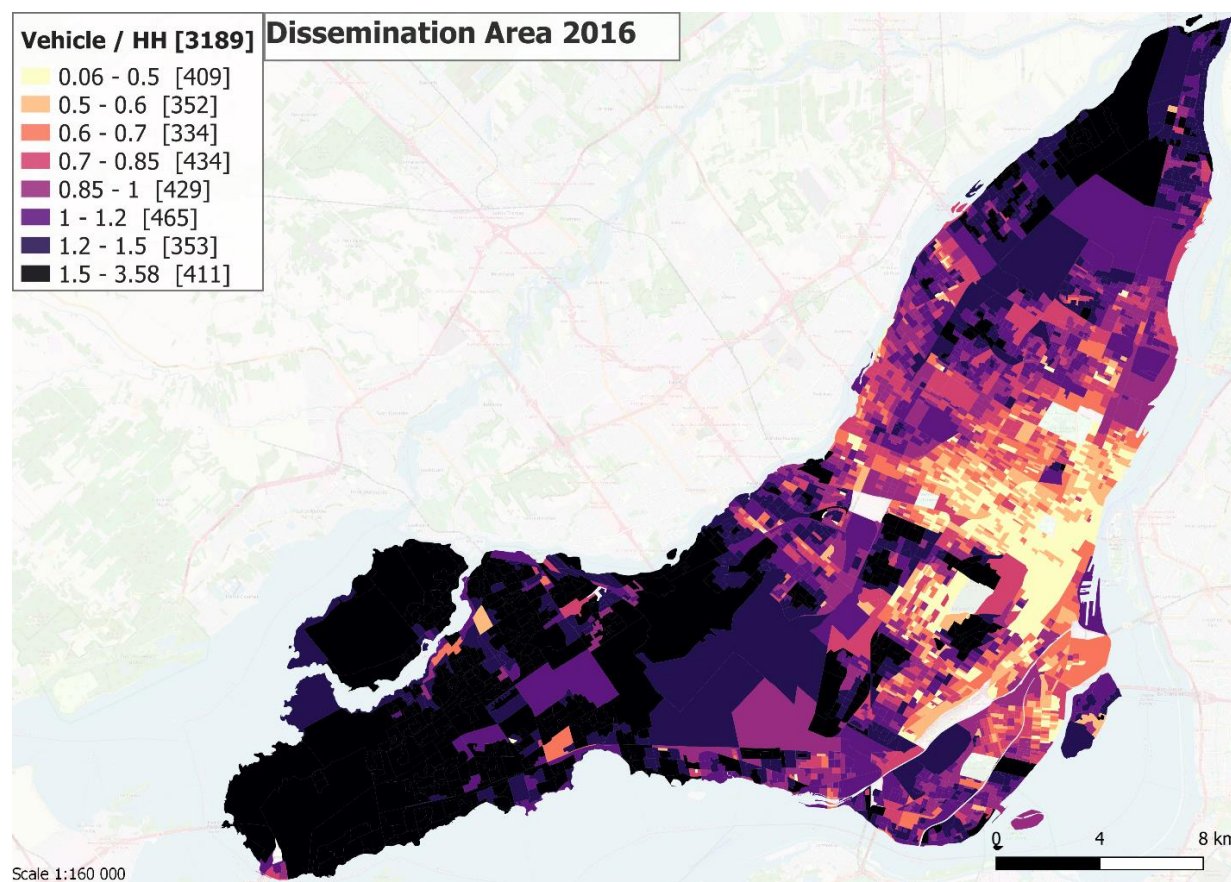


Figure 6.1 Distribution of vehicles per household on the Island of Montréal at the 2016 dissemination area (DA) level. In the legend, the value between brackets [] indicates the number of DAs.

Table 6.1 Descriptive statistics of dependent variables and potential explanatory variables

Region: Island of Montréal						
n = 3156 Dissemination Area (DA)	Mean	Std.Dev	Min	Max	Skew.	Kurt.
DA Land area [km ²]	0.15	0.58	0.01	16.00	15.07	289.94
Dependent variable						
Vehicles / household	0.942	0.425	0.11	2.788	0.706	-0.025
Sociodemographic variables						
INCOME						
% of HH with tot. Income < 50k CAD	0.456	0.176	0	0.935	-0.32	-0.369
HH Median After-tax income	52966	24419	11440	283904	3	16
Log (HH Median After-tax income)	10.802	0.368	9.345	12.556	0.749	1.726
HOUSEHOLD						
HH avg. Size	2.284	0.471	1.241	4.367	0.492	-0.222
% of single-pers. HH	0.359	0.147	0	0.812	-0.034	-0.488
% of HH with child	0.374	0.148	0	0.800	0.062	-0.689
AGE						
Average age	40.34	5.44	23.40	79.80	1.84	7.40
% of pop. aged 20-34 yo	0.230	0.097	0.000	0.684	1.261	1.846
% of pop. aged 65 of above	0.161	0.093	0.016	0.944	2.554	11.188
DWELLINGS						
% of detached house	0.154	0.287	0	1	2.004	2.695
% of homeowners	0.429	0.284	0	1	0.657	-0.624
Built environment variables						
HH density [HH/km ²]	4888	4396	14	81004	4.53	50.50
Log (HH density)	8.13	0.95	2.66	11.30	-0.95	2.08
Entropy 5 categories	0.26	0.22	0.00	0.97	0.56	-0.61
Accessibility to transit, carsharing stations and commercial opportunities						
Nb. of bus stops, WD 400 m	7.24	4.71	0	29	0.67	0.45
Bus frequency, WD 400 m [busline*direction*trips over 24 h]	295	215	0	1893	1.20	2.61
Metro stations, WD 800 m (binary)	0.226	0.419	0	1	1.31	-0.29
Carsharing stations, WD 800 m (binary)	0.56	0.50	0	1	-0.24	-1.94
Nb. of carsharing cars, WD 800 m	5.74	9.60	0	65	2.52	7.21
Grocery stores, WD 800 m	5.08	5.81	0.00	37.00	1.99	4.95

Note: WD = Walk distance buffer

While the land area of the dissemination areas is not a potential variable, its presence in the table shows a highly positively skewed distribution due to a small number of very large areas. In fact, 97.8 % of DAs are smaller than the mean plus one standard deviation and the Q1, Median and Q3

values are respectively 0.038, 0.063 and 0.124 km². The log-transform of two highly positively skewed distributions (HH Median After-tax income and HH density) are shown because the transformed variables are used in the models. As the sample size is large (> 300), formal normality test are not recommended (H.-Y. Kim, 2013). Visual inspection alongside absolute values for skewness (≤ 2) and of Kurtosis (≤ 7) indicate that most non-binary variables follow a symmetric normal distribution with the exception of the number of carsharing stations and the percentage of the population aged 65 or above.

6.4 Results

Moran's I for the dependent variable (and the null model) shows significant autocorrelation with a value of 0.70 with a row-standardized matrix of 30 nearest neighbors. The value increases to 0.78 when selecting 10 nearest neighbors and goes down to 0.67 when 50 are considered. This indicates that closer neighbors exhibit higher correlation, but the value remains high as the number of neighbors increases.

6.4.1 OLS Models with sociodemographic variables

Following the preliminary steps above which confirmed an important spatial correlation in car ownership rates, several OLS models were estimated with different combinations of variables, one for each sociodemographic subcategory (Table 6.1). Two sets were retained for further analysis, because as we move through the identification process of the spatial model specification, the set of variables offering the best fit to the data might change. Set A contained four variables: % of households with total income of less than \$50,000 CAD, % of detached houses, % of households with a child, and average age. Set B contained five variables: the logarithm of the household median after-tax income, the % of homeowners, % of households with a child, the % of the population aged 20-34, and the % of the population aged 65 or above. In the OLS formulation, Set A with four variables appears to explain more variance showing better model fit ($R^2 = 0.8664$, AIC = -2788.5) then set B with five variables ($R^2 = 0.8411$, AIC = -2227.4) and has a lower residuals autocorrelation (Set A: Moran's I = 0.283, Set B: Moran's I = 0.36), thus explaining on average across the region more spatial dependence. For both models however, the studentized Breush-Pagan test values were highly significant indicating important heteroscedasticity.

6.4.2 Spatial Models Results

The LM-Tests for spatial error and spatial lag were conducted on the two OLS models. In both cases, regular and robust tests were all significant at a p -value < 0.0001 clearly indicating that OLS models must be rejected. All test results are reported in Appendix 1. As explained by Golgher and Voss (2016), since all four tests are significant, it doesn't provide us with clear information on which specification (Lag error or lag dependent variable) should be prioritised based on the data generating process.

Following the procedure and theoretical considerations described in the methodology section, a Spatial Durbin Error Model (SDEM) with lagged exogenous variables and a lag on the error term was estimated for both sets of sociodemographic explanatory variables. Likelihood ratio tests with simpler models (SEM and SLX) were significant, indicating that both models should not be reduced to a model with only one spatial interaction term.

Furthermore, contrary to the OLS formulation, the SDEM specification results indicated that Set B with five variables (M2b: $\lambda = 0.874$, LL = 2293, AIC = -4560 and Nagelkerke pseudo R^2 of 0.924) presents a better fit to the data than Set A with four variables (M2a: $\lambda = 0.831$, LL = 2232, AIC = -4441 and Nagelkerke pseudo R^2 of 0.921). This was also the case for the SEM, SAR and SDM specifications. Furthermore, this result holds even when removing either one of the age group variables of Set B. Set B was thus used for the next steps as it offers a better fit to the data when spatial interactions are incorporated.

A first sensitivity analysis for the spatial weight matrix for the SDEM indicates that the structure of 30 nearest neighbors offered the best model fit when only SD variables are included. This step will be repeated on the final formulation of the model.

6.4.2.1 Adding built environment and accessibility explanatory variables

In a first formulation (M3b.1), the following variables were added all at once to the Set B of sociodemographic variables: two variables measured within each DA: the logarithm of household density and the entropy for five land-use categories, and four accessibility variables measured by within walking-distance buffer around the centroid of each DA: the sum of bus stops (400 m), the presence of a metro station (800 m), the sum of local and chain grocery stores (800 m) and the sum of carsharing vehicles within (800 m).

As previously explained, it does not make much sense to have a lagged values of those variables as the walking distance buffers already captured neighboring influences. These four variables form the vector Z in equation (4).

In the first formulation, only the number of carsharing vehicles within an 800 m walking distance radius had a non-significant direct impact. The model was run again (M3b.2), replacing the variable by a dummy variable representing the presence of one or more carsharing stations also within 800 m. This showed a marginal model fit improvement (AIC for M3b.1: -4788.5 vs M3b.2: -4793.8), the dummy carsharing variable was now significant at $p < 0.05$ and there was no change in any other variable sign or significance. This could indicate that the *presence* of carsharing services in the vicinity is important, not the *number* of stations within reach. A third formulation was run to test if replacing the number of bus stops within 400 m by a measure of transit level-of-service (the sum of bus line * direction * trips over 24 h accessible at the stops within a 400 m buffer) would improve the fit of the model and better capture the influence of transit on household car ownership rates. This third model formulation (M3b.3) showed a fit improvement (AIC, M3b.2: -4793.8 vs M3b.3: -4821.4) possibly indicating that considering the level-of-service in addition to the accessibility to bus stops better captures the impact on car ownership rates. . A lower value of the λ parameter regulating the strength of the spatial dependence in the error term is also observed (λ , M3b.2: 0.774 vs M3b.3: 0.767) which indicates that more spatial dependence is explained by the included explanatory variables.

6.4.2.2 Validating the neighboring matrix W

Following Stakhovych and Bijmolt (2009) recommendations, information criterion (AIC) and log-likelihood values were compared for various neighbouring structures for this final SDEM specification. Confirming the previous results, a matrix of 30 to 50 nearest neighbours offers the best model fit and thus, 30 was selected over larger numbers for simplicity (results of the sensitivity analysis are reported in the Appendix 1).

6.4.2.3 Final Model Results for OLS, SLX and SDEM

The results for the final SDEM specification are presented in Table 6.2 alongside results for OLS and SLX models. Likelihood ratio tests with the simpler SEM (lagged error term only) and SLX (lagged explanatory variables only) models confirmed that the SDEM is still the best specification.

Multicollinearity was assessed using the Variance inflation factor (VIF). The average VIF is 2.67 for the included variables and no individual values are above five, (Dormann et al., 2013; A. Field, Miles, & Field, 2012, p. 293). The highest VIF values are for the log-transform *HH Median After-tax income* (4.21) and the *% of homeowners* (4.25). A model without this last variable was tested. The model offered poorer model fit and the changes in the coefficients of BE and accessibility variables were marginal. Thus the original model was retained. VIF values for the final model are reported in Appendix 1 alongside the matrix of zero-order correlations between variables.

Additionally, the observed spatial spillover and the inconclusivity of the Lagrange Multiplier tests indicate that the presence of social interactions between modelling units (DA) cannot be ruled out. For this reason, the Spatial Durbin Model (SDM) was also run for this final model specification (M3b.3) and the results are available in Appendix 1. The first observation is that the model fits are very similar with the Loglikelihood for the SDEM at 2432 and for SDM at 2451 and Nagelkerke Pseudo R^2 are 0.9305 (SDEM) and 0.9314 (SDM). The second observation is that the strength of the spatial parameters are also very similar. The parameter lambda for the SDEM is 0.767 and the rho for the SDM is 0.696. With both models being so close to each other, LeSage (2014) indicates that Bayesian posterior model probabilities are needed to identify the true data generating process. For the considerations described in the methodology section (interpretability of results, issues of double counting for the SDM and theoretical considerations of scale in the social interactions influencing car ownership decisions), the SDEM approach was the preferred model here and results are further analyzed.

Table 6.2 Results for the final OLS, SLX and SDEM specification for final variable selection.

DV = vehicles / 100 households		OLS			SLX			SDEM		
N = 3156		β Coeff.	SE	p	β Coeff.	SE	p	β Coeff.	SE	p
DIRECT EFFECTS	(Intercept)	-114.2	15.0	***	336.8	26.4	***	111.0	60.9	NS
	log(HH Median After-tax income)	20.7	1.36	***	41.90	1.57	***	40.21	1.43	***
	% of home owner	43.1	1.77	***	25.65	1.77	***	27.05	1.62	***
	% of HH with child	81.6	3.09	***	49.84	3.64	***	50.87	3.30	***
	% of pop. aged 20-34 yo	22.6	5.00	***	32.76	5.39	***	32.95	4.91	***
	% of pop. aged 65 of above	47.2	4.09	***	40.29	4.02	***	40.65	3.67	***
	Log (HH density)	-7.3	0.44	***	-4.00	0.41	***	-4.29	0.38	***
	Entropy 5 categories	-12.8	1.34	***	-7.90	1.21	***	-8.13	1.12	***
	Daily bus frequency, WD 400 m	-1.33	0.13	***	-1.06	0.12	***	-0.87	0.13	***
	Metro stations, WD 800m (0/1)	-4.74	0.73	***	-3.94	0.66	***	-2.89	0.81	**
	NB of grocery, WD 800m	-0.77	0.05	***	-0.35	0.05	***	-0.30	0.08	**
	Carsharing station, WD 800m (0/1)	-10.15	0.67	***	-3.24	0.65	***	-1.79	0.74	0.02
INDIRECT EFFECTS	log(HH Median After-tax income)	-			-51.84	2.85	***	-36.67	5.47	***
	% of home owner	-			33.33	4.38	***	34.81	9.05	**
	% OF HH with child	-			33.88	5.89	***	42.85	12.27	**
	% of pop. aged 20-34 yo	-			17.45	10.4	0.09	-12.05	19.99	0.55
	% of pop. aged 65 of above	-			45.26	10.3	***	32.87	19.66	0.09
	log(HH density)	-			-20.33	1.37	***	-10.75	2.32	***
	Entropy 5 categories	-			-34.40	4.45	***	-10.34	7.77	0.18
λ parameter in the error term		-			-			0.7671		***
Moran's I Test for residuals, KN30		0.225	SD = 51	***	0.154	SD = 35	***	-0.003	SD=-.54	NS
Nagelkerke Pseudo R2		0.896	# params. = 14		0.920	# params. = 20		0.931	# params. = 21	
Log-likelihood		1801	AIC = -3577		2215	AIC = -4391		2432	AIC = -4821	
Breush-Pagan Test		38.687	DF = 11	***	42.92	DF = 18	**	41.78	DF = 18	*
Likelihood Ratio Test: SLX / OLS		LR Ratio = 828.23, df = 7, p-value < 2.2e-16								
Likelihood Ratio Test: SDEM / SLX		LR Ratio = 432.57, df = 1, p-value < 2.2e-16								
Likelihood Ratio Test: SDEM / SEM		LR Ratio = 66.501, df = 7, p-value = 7.5e-12								

Note: * p <= 0.01, ** p <= 0.001, *** p <= 0.0001; The DV has been multiplied by 100 to ease the interpretation of aggregate coefficients.

6.4.2.4 Model results: controlling for spatial dependence

The first observation is that moving from the OLS to the SLX leads to an improvement in model fit as illustrated by the likelihood ratio and the reduction in AIC values, the latter controlling for the addition of the seven new parameters to be estimated. There is also a reduction in residual spatial dependence illustrated by a lower Moran's I statistics for the residuals. This is a first indication that some of the observed spatial dependence in car ownership rates across the study area could be arising from contextual spillover effects within the 30 nearest neighbors. However, Moran's test value remains significant (0.154) after controlling for those contextual effects, hinting at the presence of other sources of spatial dependence.

The results of the likelihood ratio (LR) test between the SDEM and SEM (note that only the LR test results are included in Table 6.2, not the coefficient and other model statistics of the SEM) indicate that the contextual spillover effects are present even when controlling for spatial dependence from unobserved factors. The LR ratio test between the SDEM and SLX and the high and statistically significant value of the spatial error parameter (λ) confirms the importance of controlling for residual spatial dependence that could arise from unobserved factors. Controlling for both types of spatial dependence results in a superior model fit and uncorrelated SDEM residuals.

One caveat is that despite adding numerous explanatory variables supported by previous research and taking into consideration spatial autocorrelation through the error term and exogenous variables, the Breusch-Pagan Test indicates heteroskedasticity. This is an important limitation because the use of a maximum likelihood estimator is inconsistent in the presence of heteroskedastic disturbance (Kelejian & Prucha, 2010). To palliate this, Kelejian and Prucha (2010) have developed a generalized form of the Generalized Method of Moments (GMM) estimator that allows for heteroskedastic innovation. The method has been implemented in the *sphet* package made available in R by Piras (2010). The final SDEM specification was thus run again using the function of this package and the results showed minor differences in some of the coefficient estimates. However, all variables had the same sign and the same three indirect effects were not significant (entropy, % aged 20-34 and % aged 65 plus). The λ parameter is also very

similar with a value of 0.752 (vs 0.767 for Maximum Likelihood). To respect space limitations, the results of this robust heteroskedasticity model are included in the Appendix 1.

Results reported in Table 6.2 show that direct effect of variables included have statistically significant coefficients and all have the expected sign, except possibly for the % of pop. aged 20-34 across all three models. Three lagged variables are not significant for the SDEM: *Entropy 5 categories*, *% of pop. aged 20-34*, and *% of pop. aged 65 plus*, suggesting that the population age of neighboring areas might not be associated with car ownership within a DA and that the degree of land-use mix beyond each region's border has no indirect influence beyond what is already captured by other included BE variables (i.e., lagged household density and the buffer-based accessibility measures such as bus level-of-service within 400 m or the number of grocery stores within 800 m).

An important observation is the considerable difference in coefficient estimates between the OLS model and the SLX/SDEM due to the inclusion of statistically significant lagged explanatory variables. As for the difference between SLX and SDEM, SD variables are consistent between the two specifications. However, BE and accessibility factors show larger differences between estimates indicating that choosing the wrong model and not accounting for unobserved spatial autocorrelation could bias coefficients and lead to under or over estimated effects.

6.4.2.5 Relationship between the built environment and accessibility characteristics on car ownership rate when controlling for spatial dependence

To avoid possible limitations regarding interpretation of coefficients of aggregated values, sociodemographic characteristics were only used as control variables and are not discussed further as our main purpose is to examine what influences car ownership that could be addressed by city policies. To some extent, one could argue that policies could influence the percentage of households of different types through housing policy, but our focus here is on the transport and land-use influences. As mentioned earlier, with the possible exception of the age variables, all other variables show signs and magnitudes as expected, and thus serve their purpose well. It should be noted that the log-transformed income variable has a positive direct effect, but a negative indirect effect in both the SLX and SDEM. One possible and cautious explanation is the spatial distribution of income across the city where "islands" of wealth are surrounded by low and medium

income DAs and vice versa. In those situations, clusters of high disposable income might better support a greater number and diversity of local shops and services, thus decreasing the need to travel far. The relationship between neighborhood income and car ownership rates has also been shown to vary based on density (S. Clark, 2007; S. Clark & Finley, 2009) or proportion of commuters using public transit (Trendle, 2019). Studying spatial heterogeneity in the relationship between income and car ownership is, however, beyond the scope of the current paper.

To facilitate the appreciation of the relationship between the built environment and accessibility, it is good to keep in mind the distribution of the dependent variable. Across the 3156 Dissemination Areas of the Island of Montréal included in the models, the mean rate of car ownership is 94 vehicles / 100 households, with a standard deviation of 42. For the following paragraph, if no model is specifically mentioned, the coefficients discussed are those of the SDEM.

As expected, both direct and indirect effects of **density** are negatively associated with car ownership. However, interpreting density coefficient in the traditional sense of regression might not be advised because density is usually considered a proxy for a range of other characteristics less commonly observed (e.g., type of housing, parking availability, household composition). This means that it might not be density itself that is responsible for the lower level of car ownerships. Furthermore, it cannot be assumed that a change in density affects behaviour either, nor can it be inferred from the current method. If within a DA, an old gas station is replaced by a condominium tower with limited parking per units, households moving-in might own on average fewer vehicles than households already living in the area, thus lowering the average rate of the entire DA. Another reason may relate to higher population densities supporting a wider range of local services, i.e., the diversity in local options, that is not captured perfectly by our measures. All those possible reasons for why density is negatively associated with car ownership cannot be distinguished using the current framework.

Thus, a cautious interpretation is that in the current context, for two DAs identical in every aspect except density, the interpretation of the direct effect is that if unit A has a density 10 % higher than unit B, it is expected to have a lower car ownership rate, on average, by 0.43 vehicles / 100 households. The indirect effect is that if unit A is surrounded by neighboring DAs with an average household density 10 % higher than unit B then it is expected to have a car ownership rate lower

by 1.08 vehicles / 100 households. Both effects combined lead to a total effect of -1.51 vehicles / 100 households if a DA and its surroundings increase density by 10 %. Comparing this effect to the OLS estimate indicate that a model that does not control for spatial dependence could *underestimate* this effect.

Diversity is measured here using entropy for five categories of land-use (residential, commercial, leisure and park, offices and institutionnal). A value of 0 indicates that the DA contains only one land-use type (residential) and a value of 1 indicates an equal balance of the 5 land-use types. All else being equal, the direct effect interpretation is that the difference between those two situations is associated with car ownership rates lower by 8.13 vehicles / 100 households. If this seems high compare to other coefficients, changing the diversity of a neighborhood so that the entropy value goes from 0 to 1 is not very realistic. Nonetheless, the results are important as it shows that higher diversity could lead to lower rates of car ownership. However, increasing diversity might require changes to zoning laws in many cities. The entropy measured here is an imperfect measure, and further investigation is needed to assess what combination of land-use categories could support reduced need for car ownership. Results for diversity are consistent with the literature (Sun et al., 2014).

Bus accessibility and level-of-service

On average across the region, a DA that sees an increase of 100 daily bus trips accessible at bus stops within 400 m (5 minutes of walking) is associated with a -0.87 vehicles / 100 households. While this might not seem like much, it's important to understand how this unit is calculated and what kind of changes to bus level-of-service leads to an increase of 100 units of this variable. Across the Island of Montréal, the average DA has 7.25 bus stops within 400 m and the average sum of bus trips over 24 hours at those bus stops is 295. If one DA is within range of one bus line, with buses running in both directions every 20 minutes for 16 hours per day, the value of this bus level-of-service variable will be:

$$Bus\ LOS = 1\ line * 2\ directions * \frac{3\ trips}{hour} * \frac{16\ hours\ of\ service}{day} = 96\ line - dir. - trips \quad (6.6)$$

With this example it becomes easier to interpret the coefficient estimate. Thus, on average in our sample, there are roughly three such lines accessible. If the transit agency was to add three trips / hour on this line in both directions (in this case, reducing the headway from 20 to 10 minutes), this would be associated with a reduction of $96/100 * -0.87 = -0.84$ vehicles per 100 households for *all* DAs with centroids located less than 400 minutes away from the stops of that bus line. Comparing the OLS and the SDEM coefficient indicates that not controlling for spatial dependence could result in slightly *overestimating* this effect.

Accessibility to a metro station

In the current equilibrium of the studied area, a DA with access to a Metro station within 800 m of walking distance (~ 10 minutes at an average walking speed) can expect to have 2.9 vehicles fewer per 100 households compared to a DA identical on all other aspects, but without metro access. It is important to remain cautious in forecasting the impact of adding a metro line using cross-sectional models because such massive infrastructure projects can have complex endogenous effects between built environment, travel behaviour and residential self-selection. For example, the opening of a metro line could spur investments in real estate development in the catchment area of that line, leading to an increase in density and diversity, but also a change in the *type* of housing (the latter of these is not captured in our data). The increased accessibility and changes in housing and land-use could also lead to important aggregate changes in sociodemographic characteristics arising from population movements (e.g., HHs with a preference for transit moving in close to the new line, lower-income population being forced out, etc.). Like other BE characteristics, comparing the OLS and the SDEM coefficients indicates that not controlling for spatial dependence results in an *overestimation* of the association between the presence of a metro station and car ownership.

Station-based carsharing services

Assuming that carsharing is not susceptible to the same complex endogenous effects as metro stations, it is safer to interpret the changes in car ownership rates arising from an increase in accessibility to carsharing vehicles. Holding everything else constant, the SDEM results indicate that adding one station (containing one or more vehicles) within 800 m (10-minute walk) of DAs

which *had previously no access*, we could expect a reduction of -1.8 vehicles / 100 households. While other methods are needed to assess the *causality* of the relationship (i.e., are such stations located where people have low access to cars, or is the effect of having such service allowing households to avoid ownership), the results obtained here are an indication that having access to station-based carsharing services could allow more households to live with fewer cars. The change could come from self-selection or behavioural change.

Comparing the OLS and SDEM estimated coefficients in Table 6.2 shows that this variable is one of the most susceptible to controlling for spatial dependence. Failing to do so results in an important *overestimation* of the effect of carsharing on household vehicle ownership rates.

Local accessibility to grocery stores

The final variable of interest tries to capture the influence of having grocery stores within walking distance. In dense urban neighborhoods, grocery stores do not only consist of large superstores, but can include a myriad of smaller grocery stores. The hypothesis behind the inclusion of this variable was that as the number of local grocery stores increases, it is more likely that one of the stores will satisfy people's needs without a car. The exact behavioural mechanism at play cannot be inferred with the current aggregate cross-sectional framework, but results obtained here indicate that from a policy standpoint, increasing access to grocery stores should be further investigated as a possible means to support lower car ownership rates. Across the studied area, the results indicate that an increase of one grocery stores within 800 m of walking-distance is associated with a value -0.3 veh / 100 HH. This might not seem like much, but it's important to understand that one additional grocery store can influence behaviours in several dissemination areas located in its vicinity. Finally, comparing the OLS with the SDEM estimates indicates that without controlling for spatial dependence, this variable would be *overestimated*.

6.5 Discussion and conclusion

The relationship between household car ownership rates and built environment characteristics are examined in this paper using spatial econometric models that investigate spatial dependence at small geographical units (~ 400-700 people) by combining census data with administrative data on registered vehicles. The fine resolution used here (i.e., the Dissemination Area (DA) of the

Canadian census) allows for the use of more explanatory variables than previous aggregate models of car ownership. The final formulation produces a Nagelkerke pseudo- R^2 of 0.93 with coefficients that are robust to the presence of strong spatial dependence. Results indicate that across all model specifications, built environment characteristics (density, diversity), access to metro stations, bus level-of-service and station-based carsharing services along with accessibility to local commercial opportunities (grocery stores) are negatively associated with car ownership rates. This confirms previous findings from discrete choice modelling. This also suggests that interventions improving access and level of service of public transportation and accessibility to local opportunities could lead to lower levels of car needs and therefore ownership. This agrees with past research indicating that households with fewer vehicles tend to travel less by car in terms of trips and travel distances (e.g., Sioui et al., 2013; Sun et al., 2014), supporting the idea that reducing the need for car ownership could lead to reduced car use.

Using zonal aggregate data is very useful to investigate the precise spatial distribution of car ownership rates and investigate possible sources of spatial dependence and thus adequately control for it. This spatial correlation is something that household level (disaggregate) data may misrepresent due to sparse sampling in space. A key finding of the paper comes from comparison of coefficient estimates of Ordinary least-square model and the Spatial Durbin Error Model (SDEM) for policy-relevant built environment and accessibility characteristics. The results suggest that not controlling for spatial dependence leads to an *overestimation* of the direct effect coefficient of all those characteristics, except density. On the other hand, when considering direct and indirect effects of density in the SDEM specification seems to indicate that the ordinary regression *underestimates* its effect. Additionally, the influence of income (unlike other SD variables considered), also appears to depend on context.

As for the investigation of sources of spatial dependence, the model inference confirmed that part of it arises from the spatial distribution of sociodemographic and built environment characteristics. Furthermore, testing model specifications with lagged explanatory variables (SLX, SDEM) shows that contextual neighborhood effects also play a role in explaining car ownership spatial dependence. However, the set of included explanatory variables measured within each modelling unit (the DA) and within the larger neighborhood (30 nearest neighbors) could not explain all the

spatial correlation still observed in the regression residuals. While the SDEM can produce unbiased coefficient estimates by including a lagged error term that leaves the residuals of the final model clean, the process illustrates that some important spatially correlated variables are currently omitted. Alternatively, some of this unexplained spatial dependence could also arise from social interactions between households of neighboring modelling units. The high similarity in the goodness-of-fit and the strength of the spatial interaction terms between the SDEM (Table 6.2) and the SDM (Appendix 1) indicate that this possibility could not be ruled out.

Indeed, there is evidence in previous research of social interaction effects in individual and household transportation decisions (E. Dugundji et al., 2008; E. R. Dugundji et al., 2011), including for car ownership decisions (Goetzke & Weinberger, 2012), however those neighborhood interactions most likely fade quickly with distance (Grannis, 2009). As such, the assumption within the current framework was that households within one modelling unit (DA) are unlikely to be influenced by the number of cars owned by households living 10-15 walking-minutes away (30 modelling units). Overall, the findings illustrate the importance in future research on car ownership to adequately control for spatial dependence from contextual spillover effects and from unobserved factors, confirming previous findings (Goetzke & Weinberger, 2012; Paleti et al., 2013).

As with all such research, further improvements can be made. The first and most important limitation comes from the aggregate nature of the data and modelling framework. Despite the small size of the modelling unit, the current framework cannot capture the underlying process of household car ownership decisions. While the influence of environmental factors can be assessed on the sum of individual behaviour (car ownership rates), controlling for sociodemographic characteristics in the current modelling framework relies on aggregate population measures. This is highly limiting and requires distributional assumptions for those variables that might not be realistic, and thus limit the interpretation of results for those variables.

A second limitation of our findings is that the buffer-based walking-distance accessibility measures were calculated from the centroid of each Dissemination Area, and despite their small size in most of the city, might not adequately capture the real accessibility experienced by individual households.

An important technical limitation is the presence of heteroscedasticity in the final model specifications, spatial or not, potentially leading to biased coefficients. A potential cause is irregular areal partitioning and variation in population counts of the Dissemination Areas. However, the results of an estimation procedure for the SDEM that is robust to heteroskedasticity (the Generalized Method of Moment or GMM estimator) showed minor differences in coefficient estimates, but no change to any variable sign and significance thresholds.

Potential omitted variables whose effects might not be captured by the included variables are: 1) some measures of on-street and off-street parking supply which have been shown by Z. Guo (2013b) to influence car ownership above and beyond the typical income and household characteristics variables; 2) attitudes toward cars, travel and lifestyle where people of similar thinking tend to cluster in the same neighborhoods (Van Acker et al., 2014); 3) some measure of job accessibility by transit, by car, by bicycle or some possible combinations of those; 4) some measure of employment location relative to each modelled Dissemination Area; 5) the diversity in shop types; 6) the type and design of infrastructure (e.g., restricting or facilitating high mobility); and 7) the diversity in housing options. Techniques and data to readily investigate their potential influence should be explored further. Another important avenue for future research is to expand the current work and the work of Goetzke and Weinberger (2012) to investigate the potential effects of neighborhood social interactions on household car ownership decisions. This should be conducted at a scale at which such interaction are most likely taking place (i.e., the street and street block) using a mixture of household-level data and finely aggregate measures of car ownership.

Additionally, investigating the effect of spatial dependence on car ownership should also consider spatial modelling methods that allow for spatial variation in the strength of the relationship between influencing factors (e.g., income) and car ownership such as geographically weighted regression (GWR) or through the inclusion of spatial regime in the modelling framework. Other spatial resolution(s) should also be tested to assess if the observed impacts of included variables are likely to change, thus leading to different policy recommendations. It would also be highly relevant to validate the results obtained with similar data from other cities and other countries.

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6.7 Author contributions

The authors confirm contribution to the paper as follows: study conception and design: Laviolette, Morency, Waygood, and Goulias; data collection: Laviolette; analysis and interpretation of results: Laviolette, Morency, Waygood, Goulias; draft manuscript preparation: Laviolette, Waygood, Morency, and Goulias. All authors reviewed the results and approved the final version of the manuscript.

Table 6.4 M1 (OLS): Set B of sociodemographic variables only with Lagrange Multiplier Test results

M1, Set B - OLS										
				St. Coeff			Pearson's			
				Coeff. (B)	SE	(β)	t value	Pr(> t)	r	VIF
(Intercept)				0.065						
LOG(HH income)	Median	After-tax		0.1826	0.016	0.158	11.14	< 2e-16***	.800	3.98
% of home owner				0.6459	0.02	0.432	31.54	< 2e-16***	.823	3.70
% of HH with child				1.1669	0.035	0.408	33.27	< 2e-16***	.745	2.97
% of pop. aged 20-34 yo				-0.223	0.059	-0.051	-3.79	0.000153	-.645	3.56
% of pop. aged 65 of above				0.5217	0.049	0.115	10.54	< 2e-16***	.196	2.33
n				3156		# p	5			
Loglike				1120.7		AIC	-2227.4			
R²				0.8405		Res. SE	0.1698			
F (4,3150)				3319, p-value < 2.2e-16						
Std. Breusch-Pagan Test				49.407		, df = 5, p-value = 1.832e-9				
Moran's I for residuals				0.3591		, SD = 81.731, p-value < 2.2e-16				
Lagrange Multiplier Tests				W: k-nearest 30						
LMerr = 6582.8, df = 1, p-value < 2.2e-16										
LMlag = 2020.3, df = 1, p-value < 2.2e-16										
RLMerr = 5264.9, df = 1, p-value < 2.2e-16										
RLMlag = 702.32, df = 1, p-value < 2.2e-16										
SARMA = 7285.2, df = 2, p-value < 2.2e-16										

Table 6.5 Lagrange Multiplier Tests for final model specification (M3b.3)

Lagrange Multiplier Tests: Final Variable selection (M3.b.3)	
W: k-nearest 30	LMerr = 2577.7, df = 1, p-value < 2.2e-16
	LMlag = 847.97, df = 1, p-value < 2.2e-16
	RLMerr = 2068.5, df = 1, p-value < 2.2e-16
	RLMlag = 338.8, df = 1, p-value < 2.2e-16
	SARMA = 2916.5, df = 2, p-value < 2.2e-16
W: Queen	LMerr = 788.2, df = 1, p-value < 2.2e-16
	LMlag = 636.59, df = 1, p-value < 2.2e-16
	RLMerr = 325.44, df = 1, p-value < 2.2e-16
	RLMlag = 173.83, df = 1, p-value < 2.2e-16
	SARMA = 962.03, df = 2, p-value < 2.2e-16

Table 6.6 Zero-order correlation matrix of candidate explanatory variables and the dependent variable (VEH/HH)

3156 DAs. Island of Montréal.	LOG(HH median after-tax income)	% of HH with tot. income < \$ 50 k	HH average size	% of single-pers. HH	% of HH with child	Average age	% of pop. aged 20-34 years old	% of pop. aged 65 of above	% of detached house	% of homeowner	log (HH density)	Entropy 5 categories	Nb. of transit stops, WD 400 m	Bus level-of-service, WD 400	Metro stations, WD 800 m (0/1)	Carsharing stations, WD 800 m	Grocery stores, WD 800 m	VEHICLE / HH
LOG (HH median after-tax income)		-0.946	0.658	-0.749	0.597	0.113	-0.474	0.069	0.675	0.843	-0.606	-0.082	-0.450	-0.404	-0.249	-0.369	-0.339	0.798
% of HH with tot. income < 50 k CAD			-0.599	0.708	-0.534	-0.143	0.434	-0.078	-0.680	-0.874	0.608	0.062	0.440	0.403	0.234	0.379	0.336	-0.791
HH average size				-0.936	0.948	-0.191	-0.522	-0.094	0.567	0.576	-0.522	-0.167	-0.473	-0.353	-0.333	-0.304	-0.505	0.744
% of single-pers. HH					-0.907	0.124	0.503	0.078	-0.631	-0.668	0.572	0.182	0.497	0.390	0.323	0.351	0.516	-0.803
% of HH with child						-0.179	-0.601	-0.095	0.515	0.517	-0.511	-0.193	-0.501	-0.365	-0.403	-0.386	-0.542	0.745
Average age							-0.509	0.944	0.173	0.266	-0.240	0.167	-0.154	-0.098	-0.133	-0.242	-0.161	0.222
% of pop. aged 20-34 years old								-0.537	-0.394	-0.494	0.506	0.059	0.490	0.353	0.486	0.495	0.488	-0.645
% of pop. aged 65 of above									0.119	0.190	-0.200	0.156	-0.163	-0.067	-0.154	-0.228	-0.189	0.196
% of detached house										0.756	-0.641	-0.057	-0.428	-0.375	-0.255	-0.368	-0.463	0.776
% of homeowner											-0.663	-0.022	-0.466	-0.400	-0.269	-0.408	-0.418	0.823
log (HH density)												-0.303	0.460	0.393	0.323	0.478	0.472	-0.731
Entropy 5 categories													0.114	0.113	0.093	0.044	0.055	-0.098
Nb. of transit stops, WD 400 m														0.733	0.440	0.465	0.484	-0.615
Bus level-of-service, WD 400															0.303	0.370	0.341	-0.513
Metro stations, WD 800 m (0/1)																0.470	0.460	-0.458
Carsharing stations, WD 800 m																	0.468	-0.580
Grocery stores, WD 800 m																		-0.623

Note: Variables with BLUE background are those retained for the final model.

Table 6.7 Sensitivity analysis of the final SDEM (M3b.3) to Queen, K-nearest neighbors and distance thresholds spatial weight matrix specifications.

	Moran's I	SDEM			
	VEH / HH	λ	Log-likelihood	AIC	*Relative Likelihood
Queen	0.779	0.499	2229.1	-4416.2	0.00
KNN 5	0.772	0.504	2248.2	-4454.4	0.00
KNN 10	0.755	0.618	2329.8	-4617.6	0.00
KNN 15	0.742	0.684	2398.2	-4754.4	0.00
KNN 20	0.727	0.718	2420.4	-4798.7	0.00
KNN 25	0.713	0.748	2427.2	-4812.3	0.00
KNN 30	0.702	0.767	2431.7	-4821.4	0.03
KNN 35	0.692	0.780	2435.4	-4828.9	0.17
KNN 40	0.685	0.791	2438.7	-4835.4	0.86
KNN 45	0.678	0.799	2439.5	-4836.9	0.79
KNN 50	0.672	0.816	2439.0	-4836.0	1.00
DIST. 400	0.694	0.425	2061.3	-4080.7	0.00
DIST.800	0.715	0.736	2298.7	-4555.5	0.00
DIST.1200	0.682	0.841	2369.4	-4696.8	0.01
DIST.1600	0.657	0.895	2379.3	-4716.6	1.00
DIST.2000	0.633	0.931	2345.7	-4649.0	0.00
DIST.2400	0.614	0.915	2323.3	-4604.6	0.00
DIST.2800	0.599	0.868	2304.3	-4566.6	0.00
DIST.3200	0.588	0.888	2296.9	-4551.8	0.00
DIST.3600	0.579	0.891	2287.2	-4532.4	0.00
DIST.4000	0.571	0.902	2273.2	-4504.4	0.00

Note: KNN = K-nearest neighbours Dist = Distance threshold. *The relative likelihood is measured as $\exp((AIC_{min} - AIC_i)/2)$. Where the results indicate the probability of model *i* relative to the model with the minimum AIC value to minimize information loss (see Burnham (2004) for detailed explanation).

Table 6.8 Alternative model specification for the M3b.3: Simulated impacts for the Spatial Durbin Model (SDM) with W : K-Nearest Neighbors, $K = 30$

SDM	Rho	0.6963				n	3156			
	Loglike	2451				# para.	21			
	AIC	-4861								
					-					
	AIC (SLX)	-4391	AIC (SAR)	4322.1						
	Nagelkerke Pseudo R2	0.931								
	Std. Breusch-Pagan Test									
	Spatial Hausman Test	-								
	LM Test for residual autocorrelation	Test value: 0.0959, p-value: 0.757								
LR Test: SDM / SLX		LR Ratio: 472.03, df = 1, p-value < 2.2e-16								
LR Test: SDM / SAR		LR Ratio: 552.78, df = 7, p-value < 2.2e-16								
Simulated mean Coeff. Estimates and SE. Iterations = 100										
DV: VEH / 100 HH		DE	p ²	SE	IE	p ²	SE	TE	p ²	SE
Direct Variables	log(HH Median After-tax income)	43.24	***	1.25	95.79	***	12.20	139.03	***	12.78
	% of homeowners	26.39	***	1.34	58.39	***	7.09	84.78	***	7.63
	% of HH with child	51.21	***	3.15	113.33	***	14.89	164.54	***	16.54
	% of pop. aged 20-34 yo	32.96	***	4.98	73.01	***	14.36	105.97	***	18.54
	% of pop. aged 65 of above	41.09	***	3.38	90.90	***	12.90	131.99	***	14.97
	log(HH density)	-4.19	***	0.37	-9.30	***	1.49	-13.49	***	1.77
	Entropy 5 categories	-8.17	***	1.11	-18.10	***	3.29	-26.27	***	4.19
	Bus level-of-service, WD 400 m ¹	-0.85	***	0.11	-1.89	***	0.34	-2.75	***	0.42
	Metro stations, WD 800 m (binary)	-2.52	***	0.61	-5.55	**	1.46	-8.07	***	2.01
	NB of grocery stores, WD 800 m	-0.18	***	0.05	-0.39	**	0.10	-0.56	***	0.14
Carsharing station, WD 800 m (binary)	-1.80	*	0.69	-4.01	0.02	1.68	-5.81	0.01	2.34	
LAG Variables	LAG: log(HH Median After-tax income)	-44.98	***	2.55	-99.56	***	13.13	-	***	14.36
	LAG: % of homeowners	-8.43	0.06	4.50	-19.16	0.08	11.00	-27.58	0.07	15.42
	LAG: % OF HH with child	-24.75	**	6.38	-55.41	*	18.48	-80.16	*	24.52
	LAG: % of pop. aged 20-34 yo	-14.85	0.11	9.25	-33.52	0.14	22.61	-48.37	0.13	31.66
	LAG: % of pop. aged 65 of above	-13.00	0.20	10.14	-29.72	0.23	24.60	-42.72	0.22	34.57
	LAG: log(HH density)	-1.47	0.30	1.42	-3.12	0.32	3.10	-4.59	0.31	4.52
	LAG: Entropy 5 categories	1.92	0.66	4.36	4.56	0.65	10.12	6.48	0.65	14.45

Note: DE = Direct effect, IE = Indirect effect, TE = Total effect. ¹The variable is calculated by summing the number of busline * direction * trips over 24 h / 100 accessible at stops within 400 m of walking-distance from the centroid of each dissemination area. ² p-values are simulated; * p <= 0.01, ** p <= 0.001, *** p <= 0.0001

Final SDEM Specification using the GMM estimator robust to the presence of heteroscedasticity of unknown form

Table 6.9 SDEM for final model M3b.3 estimated using the Generalized Spatial 2 stage least square procedure (GS2SLS) to obtain an efficient and consistent GM estimator for λ that is robust to the presence of heteroskedasticity of unknown form in the disturbance.

M3b.3, SDEM with W: K-nearest 30, Using the GS2SLS procedure of the sphet Package (Piras, 2010)					
	n	3156			
	# para.	21			
	Nagelkerke Pseudo R2	0.916			
	Lamda (λ)	0.767, SE = 0.037, t-stats = 20.7, p < 2.2e-16			
	Moran's I for GS2SLS SDEM Res., kn30	0.2034, SD = 46.462, p-value < 2.2e-16			
		Coeff. (B)	SE	t stats	Pr(> t)
Direct IMPACT	(Intercept)	132.926	61.589	2.16	0.0309
	log(HH Median After-tax income)	40.138	1.751	22.92	***
	% of homeowners	27.153	2.345	11.58	***
	% of HH with child	50.810	3.827	13.28	***
	% of pop. aged 20-34 yo	32.819	5.164	6.36	***
	% of pop. aged 65 of above	40.515	5.618	7.21	***
	log(HH density)	-4.291	0.499	-8.61	***
	Entropy 5 categories	-8.191	1.139	-7.19	***
	Bus level-of-service, WD 400 m*	-0.872	0.112	-7.80	***
	Metro stations, WD 800 m (binary)	-2.985	0.667	-4.47	***
	NB of grocery stores, WD 800 m	-0.308	0.082	-3.74	**
	Carsharing station, WD 800 m (binary)	-1.880	0.805	-2.34	0.0195
Indirect IMPACT	LAG: log(HH Median After-tax income)	-37.891	5.476	-6.92	***
	LAG: % of homeowners	35.365	8.841	4.00	**
	LAG: % OF HH with child	42.001	13.068	3.21	*
	LAG: % of pop. aged 20-34 yo	-11.979	20.232	-0.59	0.554
	LAG: % of pop. aged 65 of above	26.386	18.175	1.45	0.147
	LAG: log(HH density)	-11.486	2.892	-3.97	**
	LAG: Entropy 5 categories	-12.724	9.711	-1.31	0.190

Note: * p <= 0.01, ** p <= 0.001, *** p <= 0.0001

CHAPTER 7 ARTICLE 3: A KILOMETER OR A MILE? DOES BUFFER SIZE MATTER WHEN IT COMES TO CAR OWNERSHIP?

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HIGHLIGHTS

- Uses Gradient Boosting Machines to explore the effect of built environment on car ownership.
- Systematically investigate the impact of buffer sizes used to compute BE variables.
- Density, diversity, and design have consistent impacts across tested buffer sizes.
- Accessibility variables are very sensitive to buffer sizes selected.
- Threshold effects on car ownership are observed when small buffer sizes are used.
- Results provide insights for planning neighborhoods to support low car living.

ABSTRACT

When modelling car ownership, the scale at which built environment (BE) and accessibility indicators are measured are often overlooked. Most existing research use “fixed neighborhood” (zonal) or “sliding neighborhoods” (buffers around households) of the same distance (e.g., 1-km or 1 mile) to estimate the impact of various neighborhood features. However, it is likely that 1) different features have different ranges of influence on behaviour and 2) that the impact of some variables is highly scale-sensitive. Our study builds a series of Gradient Boosting Machines decision trees and uses partial dependence plots to examine potential threshold effects of various built environment characteristics and accessibility to resources when measured at different scales. Household-specific walking-distance buffers ranging from 400 to 1600 m are tested. Results indicate that BE measures of population density, land-use diversity, and design have consistent impacts across the tested buffer sizes and show mostly linear relationships with the probability of households being fully motorized below or above a threshold value. Accessibility to transit,

bikesharing, carsharing, and local amenities, however, appear very sensitive to the size of the neighborhood. Their relative influence within the models and the shape of their partial dependence function can change drastically as buffer sizes vary. Furthermore, smaller buffers (≤ 800 m) for accessibility measures exhibit clear threshold effects on car ownership, suggesting that shorter distances have more influence on car ownership. Further research is needed to validate the observed access distances and how many of each opportunity type are necessary for a significant impact on household car ownership decisions.

Keywords: Car ownership; Accessibility; Built environment; Machine learning; Gradient Boosting Machines; distance thresholds

7.1 Introduction

Car ownership is connected to various environmental, social, and economic problems (Gärling & Steg, 2007) and many cities are looking to decrease the number of cars on their roads by reducing car ownership needs, which in turn is expected to reduce car use since having fewer cars is associated with fewer car trips and fewer vehicle-kilometers travelled (VKT) (Sioui et al., 2013; von Behren, Bönisch, Niklas, & Chlond, 2020). One means that has attracted much attention over the years is by transforming the built environment features known to be key determinants of travel behaviour (Ewing & Cervero, 2010). Despite the wide variety of models proposed to study car ownership relationship with built environment characteristics, accessibility, and travel behaviour (Anowar, Eluru, et al., 2014) there are still questions to be answered. One relates to the distance thresholds necessary for a characteristic to have an effect and the possibility that different characteristics of the built environment (BE) have different “ranges of influence”. For example, it is common in many studies to use either a fixed neighborhood definition (e.g., census boundaries or TAZ) or, more recently, “sliding” neighborhood such as circular buffers or network distance buffers (“network bands”) with the same distance or access time (e.g., 1-km, 1-mile, or 10 min) for all BE and accessibility variables. This goes against logic suggesting that the range of influence of a metro station would likely be larger than that of a bus stop for example.

In other words, what “neighborhood” definition should be adopted and how large should that neighborhood be? When changes in the size and shape of spatial boundaries of neighborhoods lead to different relationships between variables, this is known in geography as the modifiable areal unit problem (MAUP) (Lloyd, 2014). Despite the wide literature analyzing built environment’s

impact on travel behaviour, there has been limited empirical research specifically investigating the effect of neighborhood definition and scale in transportation studies (Gehrke & Wang, 2020).

Some of those studies investigated the impact of shape and scale on active travel behaviour (A. Clark & Scott, 2013; Mitra & Buliung, 2012), travel mode choice (Gehrke & Clifton, 2014; Gehrke & Wang, 2020; M. Zhang & Kukadia, 2005), VKT (Hong, Shen, & Zhang, 2014) as well as residential location choice (J. Y. Guo & Bhat, 2007), most concluding that neighborhood scale and definition influence the magnitude, sign and significance of the coefficients. Such impacts are likely affecting policy recommendations.

However, to the best of our knowledge, while the issue of scale has been acknowledged in some car ownership modelling studies (Bhat & Guo, 2007), none has specifically investigated the issue despite car ownership being recognized as a key element of travel behaviour (Anowar, Eluru, et al., 2014; Van Acker & Witlox, 2010). Our current study tries to fill this gap by first investigating how the relationship between car ownership and BE attributes (density, design, diversity and accessibility measures to mobility resources and local amenities) can vary when calculated within different neighborhood scale.

Second, we also investigate another important issue when modelling the effect of built environment on travel behaviour: the presence of possible thresholds effects (or “non-linear” effects). Those non-linear effects can be problematic and lead to inconsistent findings by over or underestimating the effect of a certain features when the modelling method assumes linear relationships.

The analysis is conducted by building a series of models using a machine learning algorithm known as Gradient Boosting Machines (GBM) decision trees. This modelling method has been selected over more traditional models (e.g., binary, multinomial logistic regressions) for three primary reasons. First, it is a non-parametric method that is robust to the presence of multicollinearity (Hastie et al., 2009, ch. 10), an important issue when incorporating several features of the built environment in a single model. This follows J. Y. Guo and Bhat (2007)’s future research recommendation to “examine the appropriate neighbourhood scale of analysis while avoiding the effects of multicollinearity”. The second reason is the ability of GBM decision-trees to investigate non-linear relationships by producing partial dependence plots (W. Zhang et al., 2020). These plots show how the outcome variable varies as a function of one explanatory

variable, accounting for the average effect of all other variables in the model. And finally, the method also produces a ranking of the most relevant explanatory variables, which is important when trying to assess which built environment features policies should target to have the greatest impact on travel related decisions.

7.2 Literature review

7.2.1 Car ownership modelling methods

Car ownership has been demonstrated to be a critical variable influencing travel related decisions and long-term household decisions such as residential location. It also plays a key role in the relationship between the built environment and various aspects of travel behaviour. For these reasons, it has been an important transportation research topic. Anowar, Eluru, et al. (2014) have conducted the most recent and extensive review of traditional car ownership modelling framework at a disaggregate level. They classified the modelling framework into four categories: exogenous static, exogenous dynamic, endogenous static and endogenous dynamic. The first category is the most relevant to the current analysis. It includes the simplest vehicle representation: the number (and sometimes types) of vehicles owned by households at one point in time while considering that the vehicle ownership decision is independent from other decisions. For this type of modelling, standard discrete choice models have been considered, such as the binary logit and multinomial logistic model (MNL), the nested logit, the ordered logit or probit models. More advance discrete choice models accounting for heterogeneity in the population have also increasingly been used such as latent class MNL (S. H. Kim & Mokhtarian, 2018) or latent class ordered logit models (Anowar, Yasmin, et al., 2014). At the time of their study, machine learning methods were only starting to be used in travel behaviour research. Since the publication of their review however, their use has been vastly expanded. Car ownership has been modelled using, for example, neural network (Basu & Ferreira, 2020), random forest (Sabouri et al., 2020), support vector machines (Paredes et al., 2017) and gradient boosting decisions trees (W. Zhang et al., 2020). Paredes et al. (2017) compared MNL to five machine learning methods (gradient boosting decision trees, decision tree classifier, support vector machines (SVM) and random Forest) on the same dataset. They concluded that MNL offers more theoretical insights and can outperform or equal ML methods in prediction accuracy when the dataset is not pre-processed to take full advantage of the

machine learning algorithms. Adequate pre-processing of the data for ML methods, however, leads to accuracy up to 10% better than MNL, but at the cost of losing interpretability. In their comparison, MNL and Gradient Boosting decision trees (xgboost) lead to the same accuracy when the dataset prepared for MNL was used. Basu and Ferreira (2020) did a similar comparison and concluded that Neural Networks outperformed the ordered logit, MNL and the other ML methods in terms of prediction and generalization capabilities. The author still relied on the MNL to get insight into the effect of the independent variable on household car ownership decisions. We note however that in both comparative papers, the authors did not use interpretability tools available to some ML methods such as the relative influence of predictors and the partial dependence plots. Both tools are used in the current paper to assess the direction of influence, non-linearity of the relationship and relative influence of each built environment and sociodemographic variable.

7.2.2 Variables investigated in car ownership modelling

However, while Anowar, Eluru, et al. (2014) and recent comparison of traditional discrete choice and machine learning methods (Basu & Ferreira, 2020; Paredes et al., 2017) focus on modelling frameworks no published review of factors influencing car ownership similar to those found for travel behaviour (e.g., Ewing & Cervero, 2010). Three broad categories of factors are often included in car ownership modelling: 1) socio-demographics, including income, household composition and lifecycles, occupation status, driver's licensing, and more; 2) attitudes, including environment and travel related attitudes in attempts to control for residential self-selection (Xinyu Cao et al., 2009; Mokhtarian & Cao, 2008; van Wee & Cao, 2022) and 3) built environment characteristics (BE). This third category is of high interest to planners and policy makers and usually includes one or more of the following: density (residential, employment), diversity (entropy or other land-use diversity index), design (average block size, intersections, streets, highways, or bikeways), transit availability (proximity/presence of a rail station and bus stops), diverse destinations by various modes (car, walking, transit) and distance to CBD or local centers. On rare occasions, studies included commute related variables such as distance, time or generalized cost for household members (Bhat & Guo, 2007) or parking availability (Z. Guo, 2013a; Yin, Shao, & Wang, 2018).

7.2.3 The issue of scale in built environment variable measurement

Despite the wide range of included variables and modelling methods, one important aspect has received much less attention: what is the appropriate range of influence for disparate features of the BE? Further, is there an influence of the number of such feature (e.g., does one grocery store/metro station within a certain distance has the same influence as 2 or 3) or a threshold value beyond or below which there is no more measurable impact on household decisions? Drawing reliable conclusions on the direction and magnitude of the influence of built environment characteristics requires determining the right scale and methods of measurement for each one. In the travel behaviour literature, this issue is more broadly discussed as a spatial scale problem, the well-known modifiable areal unit problem (MAUP). The problem has two components, zoning and scale effects (Lloyd, 2014). The presence of scale effect indicates that there is an observed sensibility to changes in the scale of the measurement unit for a given feature. The zoning effects refers to the many ways to define the spatial boundaries of units used to aggregate each variable. Both effects were empirically observed in previous studies investigating relationships between built environment and travel behaviour (A. Clark & Scott, 2013; Gehrke & Clifton, 2014; Gehrke & Wang, 2020; Hong et al., 2014; Mitra & Buliung, 2012; M. Zhang & Kukadia, 2005). The effects were observed by comparing the magnitude, signs, and significance of variables at various scales and zonal systems using different modelling methods (binomial and multinomial logistic regression, Bayesian hierarchical models). All those studies also observed slight differences in model fit using various indices, without clear conclusion however on which scale and zone types to use.

Gehrke and Wang (2020) summarises that in travel behaviour research, two types of measurement methods have been used for capturing the impact of BE: fixed and sliding geographical units. The former refers to non-overlapping zonal systems such as administrative, statistical, or artificial zones (e.g., transport analysis zones). The latter refers to using household specific “buffers” where boundaries are set by pre-defined distances or time values (e.g., 1 km, 10 min). The easiest way to calculate those buffers is by using Euclidean distances, which results in circular buffers that do not consider any natural or artificial barriers. A more realistic approach consists of computing network distance buffers where each point on the boundary can be reached within the same time or distance value, thus accounting for street network connectivity. This concept, termed “network bands” by

J. Y. Guo and Bhat (2007), is argued to be conceptually and methodologically more appealing because it is the closest to representing how individuals might perceive their neighborhoods. Despite its superiority, Gehrke and Wang (2020) indicate that, likely due to data availability and calculation requirements, it is the least common method of measurement in the travel behaviour literature. For matter of concision and following recommendations by Gehrke and Wang (2020) and J. Y. Guo and Bhat (2007), the current study only investigates the effect of scale when using network distance buffers.

As previously stated, no studies specifically investigating neighborhood definition (zoning) and scale effects on household car ownership decisions could be found. Table 7.1 presents a summary of built environment characteristics along with measurement scale and method found in a none-exhaustive list of car ownership related research. Most reviewed studies using disaggregate models use fixed neighborhoods (zones) to compute aggregate measures. While there has been a recent effort to address spatial dependence arising from such aggregation using multilevel models (X. Q. Wang et al., 2018), it is far from clear if those pre-defined units adequately represent the “neighborhoods”. Several authors have attempted to address this issue by calculating household specific “sliding” neighborhoods using circular or network-distance buffers. However, as observed in Table 7.1, the distance thresholds used for these calculations are commonly used distances in travel behaviour research (500 m, 1 km, half a mile, etc.) and are very rarely justified by reference to empirical findings. Some studies provided no details about the scale of estimation of built environment variables included in their models (e.g., Anowar, Yasmin, et al., 2014; Moeckel & Yang, 2016). Only a few studies mentioned testing different buffer or zone size for some of their included variable estimation without much explanation on why a certain distance was selected for the final models (Anowar et al., 2016; Bhat et al., 2009; J. Cao & Cao, 2014; Jiang et al., 2017). In summary, these examples show the extent of the problem any researcher looking to model car ownership is facing and for any policy maker who wishes to support car-free and car-light lifestyles. While the issue might not be critical for modelling BE characteristics considered proxies for other things (e.g., density, street network design) it is of particular interest when computing local accessibility to amenities or mobility resources. Indeed, if different buffer sizes or neighborhood scales are considered, are these leading to different results that might affect policy recommendations?

Table 7.1 Summary of zones and buffer size used in car ownership modelling. Non-exhaustive list of 19 studies.

		Transport Analysis Zones (TAZ), Census Tract, “Neighborhood” or other zones	Buffers (R: radius or N: network) around HH
		n Studies	n Studies
Density	Residential	12 (Ding & Cao, 2019), (Potoglou & Kanaroglou, 2008), (Zegras, 2010), (Ding, Wang, et al., 2018), (Z. Guo, 2013a), (Bhat et al., 2009), (Bhat & Guo, 2007), (Anowar et al., 2016), (X. Q. Wang et al., 2018), (Caulfield, 2011), (Moeckel & Yang, 2016), (Xinyu Cao et al., 2019)	4 R-500 m: (Jiang et al., 2017) R-800 m: (X. Huang et al., 2017), (S. Li & Zhao, 2017) N-0.25, 0.5, 1 Miles: (J. Cao & Cao, 2014)
	Job	7 (Ding & Cao, 2019), (Z. Guo, 2013a), (Ding, Wang, et al., 2018), (Bhat et al., 2009), (Bhat & Guo, 2007), (Moeckel & Yang, 2016), (Xinyu Cao et al., 2019)	0 -
	Mix density / Job-Housing Balance	4 (Potoglou & Kanaroglou, 2008), (Jiang et al., 2017), (Xinyu Cao et al., 2019), (S. Li & Zhao, 2017)	0 -
Diversity	Entropy	4 (Ding & Cao, 2019), (Ding, Wang, et al., 2018), (Anowar et al., 2016) ^a , (X. Q. Wang et al., 2018)	3 R-500 m: (Potoglou & Kanaroglou, 2008) R-800 m: (S. Li & Zhao, 2017) ^b N-0.25, 0.5, 1 Mile: (J. Cao & Cao, 2014)
	Diversity Index	3 (Van Acker & Witlox, 2010), (Zegras, 2010), (Bhat & Guo, 2007)	3 R-500 m: (Z. Guo, 2013a) R-1 mile: (Bhat et al., 2009) R-1 km: (Jiang et al., 2017)

Notes: R-XXXm = Radius of X distance from HH; N-XXX = Network distance from HH; For accessibility and distance to center measures, the measures included in the “zone” column indicates that they were calculated from the zonal centroid and not from precise household location.

^a It was not entirely clear from the paper what scale of measurement was used.

^b S. Li and Zhao (2017) calculated buffers radius from the center of the selected “neighborhoods”, with no indication on the size of those “neighborhoods”

Table 7.1 Summary of zones and buffer size used in car ownership modelling. Non-exhaustive list of 19 studies (continued)

	Transport Analysis Zones (TAZ), Census Tract, “Neighborhood” or other zones	Buffers (R: radius or N: network) around HH
	n Studies	n
Design		
Avg. Block Size / Block Density	4 (Ding & Cao, 2019), (Ding, Wang, et al., 2018), (Bhat & Guo, 2007), (Bhat et al., 2009)	0 -
Intersection Density	2 (X. Q. Wang et al., 2018), (Yin et al., 2018),	2 R-800 m: (X. Huang et al., 2017) N-0.25, 0.5 & 1 mile: (J. Cao & Cao, 2014)
Bikeway Density	1 (Bhat & Guo, 2007)	2 R-0.25, 1 & 5 miles: (Bhat et al., 2009) R-500 m: (Jiang et al., 2017) ^c
Road / Highway Density	2 (Bhat & Guo, 2007), (Bhat et al., 2009)	3 R-0.25, 1 & 5 miles: (Bhat et al., 2009) R-500 & 1000 m: (Jiang et al., 2017) ³ R-800 m: (X. Huang et al., 2017)
Access to Transit		
Rail/BRT	2 Dummy: (Ding & Cao, 2019) Distance from zone: (Zegras, 2010)	6 Dummy, R-500 m: (Jiang et al., 2017) Dummy, R-800 m: (X. Huang et al., 2017) Dummy, R-1000 m : (Jiang et al., 2017) Network distance from HH: (Z. Guo, 2013a), (J. Cao & Cao, 2014) Metro lines length, R-600 m: (Anowar et al., 2016)
Bus	2 Transit stops density: (X. Q. Wang et al., 2018), (Yin et al., 2018)	
Accessibility		
Local (amenities, retail, services)	0 -	4 NB/Density of retail within R-500 m: (Potoglou & Kanaroglou, 2008), (Jiang et al., 2017), within R-800 m: (X. Huang et al., 2017). Nb of groceries & restaurant, R-800 m: (S. Li & Zhao, 2017)

Note: ³ Jiang et al. (2017) tested 500 m and 1000 m but retained only 500 m for the street-design characteristics factor analysis, indicating that the 1000 m radius did not produce coherent results.

Table 7.1 Summary of zones and buffer size used in car ownership modelling. Non-exhaustive list of 19 studies (continued)

	Transport Analysis Zones (TAZ), Census Tract, “Neighborhood” or other zones	Buffers (R: radius or N: network) around HH
	n Studies	n studies
Accessibility (continued)		
By car	3 NB people within 15 min from Census Tract: (Van Acker & Witlox, 2010) TAZ-to-TAZ Ratio of car/transit access: (Zegras, 2010) TAZ-to-TAZ Employment, shopping and recreational: (Bhat & Guo, 2007)	
By transit	1 TAZ-to-TAZ Employment, shopping and recreational: (Bhat & Guo, 2007)	1 Job accessibility in 30 min from HH: (J. Cao & Cao, 2014)
Distance to center	(From zone centroid)	(From home address)
CBD / Center	7 Euclidean: (Ding & Cao, 2019), (Zegras, 2010), (Ding, Wang, et al., 2018), (X. Q. Wang et al., 2018), (S. Li & Zhao, 2017) Network: (Van Acker & Witlox, 2010), (Yin et al., 2018)	3 Euclidean: (Jiang et al., 2017), (Xinyu Cao et al., 2019) Network: (X. Huang et al., 2017)
Second-order / other	1 To Nearest ring road: (S. Li & Zhao, 2017)	1 Euclidean: (Xinyu Cao et al., 2019)

7.2.4 Non-linear and thresholds effects of BE on travel behaviour

In addition to the issue of scale, there has been an increased focus on investigating non-linear and threshold effects of built environment characteristics on travel behaviour in recent years. It was identified as a key element in the complex relationship between travel behaviour and the built environment in a recent special issue of *Transportation Research Part D: Transport and Environment* (W. Zhang et al., 2021). As walking, cycling and active travel in general is more sensitive to subtle changes in built environment characteristics, many papers investigated non-linear effects specifically on those behaviours for various subpopulation or trip purposes. This has been done by analyzing partial dependence plots produced from gradient boosting decision trees (GBDT)(X. Huang et al., 2021; Liu et al., 2021; Yang et al., 2022), Random Forest (Cheng et al., 2020) or Generalized Additive Modelling (GAM)(Wali et al., 2021; Wu et al., 2021). Other methods such as simple bivariate plots (Elldér, Haugen, & Vilhelmson, 2020) or multilevel mixed-effect logit and linear models using ordered categories or quintiles for the independent variables have also been used (Eom & Cho, 2015; Koohsari et al., 2019). GBDT has also been applied to

investigate the non-linear and threshold effects on car mode choice or VKT (Ding, Cao, & Næss, 2018; Ding, Cao, & Wang, 2018; K. Wang & Wang, 2021) as well as transit ridership at metro stations (Ding, Cao, & Liu, 2019).

The same machine learning methods were also used to investigate threshold effects on vehicle ownership. For example, Sabouri et al. (2020) used random forest to investigate the effect of built environment and ride hailing service availability across the US on car ownership. Ding, Cao, Dong, Zhang, and Yang (2019) used GAM to assess the non-linearity of BE on electric bike ownership in China. W. Zhang et al. (2020) specifically investigated the non-linear relationship between household car ownership and variables describing regional accessibility, local accessibility, and transit access by applying Gradient Boosting Decision Trees. They used a 1280-respondents travel survey from Beijing and modelled the number of cars owned by each household as a count variable (0 to 4). They included the following density variables measured within a 1-km network distance buffer: population, street intersections, employment, retail, and services. They did not test alternative buffer-size and the buffers were constructed from the centroid of 26 neighborhoods where the surveyed households were located and not from the precise location of each household. Depending on the size of those neighborhoods, this might misestimate the true accessibility of the households, and thus the threshold effects they approximate. They also included variables for the shortest network distance to local and city center and to the nearest bus stop and metro station, once again, measured from the centroid of those 26 neighborhoods. They identified threshold effects for several of those variables by analyzing their respective partial dependence plots. However, as discussed, questions exist not only on what might be the appropriate buffer sizes to use, but also the quantity of the feature to consider. Their results will be compared to our own findings in the result section.

In summary, almost all studies confirmed the non-linearity effects of most if not all tested built environment attributes on various aspects of travel behaviour. However, it seems that none of the reported studies have investigated how threshold effects may vary when neighborhood scale used for measurement also varies. This appears to be an important gap in the literature that the present study tries to address.

7.3 Method

7.3.1 Data sources

7.3.1.1 Car ownership and household data

The main data source for this analysis is the 2018 Origin-Destination Travel Survey of the Greater Montréal Area (GMA), Québec, Canada. This is a telephone-based and web-based survey conducted every five years in the metropolitan area of Montréal to record the trips of about 4–5% of resident households over one fall weekday. The 2018 edition collected data from 73,421 households housing a population of 168,883. The survey is conducted using a stratified sampling and weighting method based on the 2016 Canadian Census to be representative of the population of the surveyed region. The dataset contains household-level variables, including precise geocoded coordinates, individual-level variables for all members of each surveyed household and trip information about every trip made on the day preceding the survey interview. In terms of car ownership information, only the number of private vehicles owned by each household is known.

7.3.1.2 Built environment, mobility resources and opportunities

Population density is computed using the 2016 Canadian Census population data using the smallest available statistical unit (Dissemination Block). The land-use dataset necessary to compute entropy measures of diversity was obtained from the Communauté Métropolitaine de Montréal for the year 2016. Metro stations and bus stop's location are extracted from the General Transit Feed Specification (GTFS) of the agencies operating in the region. The dataset of carsharing stations was obtained from Communauto and the bikesharing stations from BIXI. The commercial opportunities (grocery stores) were extracted from DMTI Spatial database. OpenStreetMap's road and pedestrian network was used for the calculation of walking accessibility buffers and road characteristics (e.g., intersection density). All datasets were integrated in a geospatial database in PostgreSQL, using the PostGIS spatial extension.

7.3.2 The study area

The region for the current analysis comprised three subregions of the GMA. The Island of Montréal and the suburbs of Laval and Longueuil. According to the 2016 Census, the study area has a total

population of 2.78 million within 1.21 million households, with an average population density of 2700 people per square km. In 2018, the transit system had three components, a metro system of four lines and 68 stations, a bus system of 348 lines and a commuter train system of six lines converging toward the CBD. The study area has 46,517 household observations in the 2018 OD Survey and is illustrated in Figure 7.1.

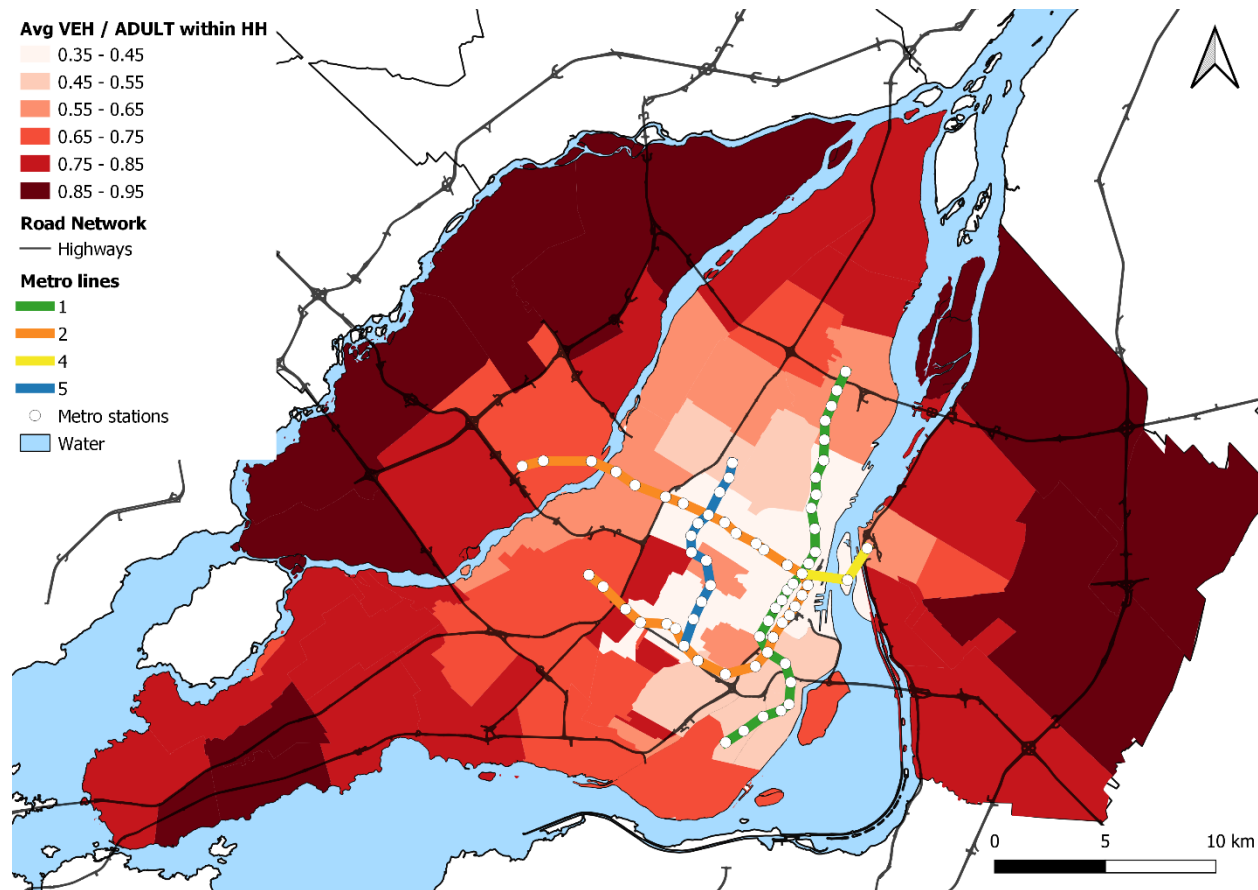


Figure 7.1 Map of the studied region with weighted average car ownership rates in vehicle per adult within households by municipal sectors

7.3.3 Preparing the variables

The built environment and accessibility variables considered were selected based on prior research listed in Table 7.1. To compute the variables, walking distance buffers are computed around each surveyed household using the exact coordinates derived from the geocoded household address. Walking distance buffers were selected over Euclidean distances as they are assumed to better reflect the true accessibility of households within their neighborhood. Buffers of seven different

distances - 400, 600, 800, 1000, 1200, 1400 and 1600 m – were constructed using QGIS's Network Analysis tool and PostGis's *ConcaveHull* function. The method offers much higher precision than other methods such as the buffer computed by W. Zhang et al. (2020) from the centroid of a limited number of neighborhoods. Examples of the seven buffer sizes are illustrated in Figure 7.2 for a central and suburban neighborhood. Street network configuration in suburban neighborhoods leads to smaller areas covered by walking distance buffers and lower accessibility compared to urban neighborhoods.

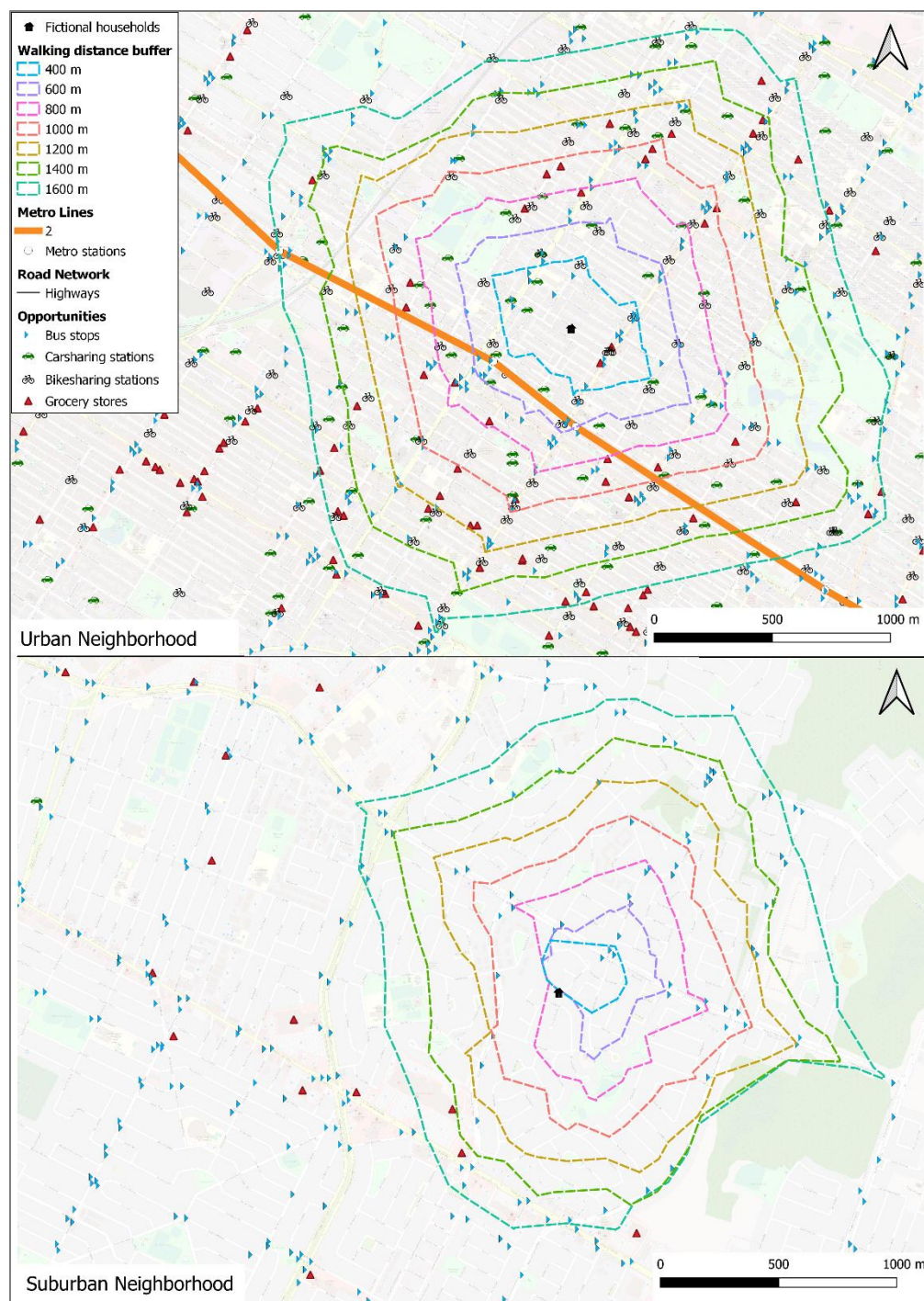


Figure 7.2 Walking distance buffers examples for central (top) and suburban (bottom) neighborhoods

Population density was computed by summing the fraction of the population of the Dissemination block of the 2016 Canadian Census intersecting each buffer's polygon and dividing by the buffer's total surface area. As a measure of diversity, the entropy was computed within each buffer

following the method described by Potoglou and Kanaroglou (2008) considering five land-use categories: residential, commercial, offices, leisure and/or parks, and institutional, excluding categories not considered relevant for travel behaviour (e.g., industrial, agricultural, vacant lots). To assess neighborhood design, two variables commonly used in travel behaviour research according to Ewing and Cervero (2010) and Stevens (2017)'s meta-analyses are intersection density and the percentage of four-ways intersections. The former is a proxy for street block size and the latter for street connectivity, both of which are recognized to be associated with travel behaviour according to both meta-analyses. To reduce the number of variables and capture the potential effect of both variables, they are combined to obtain four-ways intersection density within each buffer. Visual inspection on the map suggests that the indicator appears to be a good discriminant between North American traditional grid-style small-blocks neighborhoods (≥ 30 four-ways intersections per square km) and suburban style neighborhoods with curving streets forming loops, three-ways intersections and many cul-de-sac (≤ 15 four-ways intersections per square km) neighborhoods. The difference can be observed on Fig. 2 where the variable has a density of 72 four-ways intersection within the 1-km walking buffer while the suburban household has a value of 10.

Accessibility to mobility resources was computed by summing independently each of the following opportunities within each buffer for the seven selected distances: number of bus stops, number of metro stations, number of station-based carsharing vehicles, number of bikesharing stations.

Similarly, accessibility to local amenities was computed by summing the number of local and chain grocery stores. Accessibility to other amenities (pharmacies, daycare, primary schools) were tested but were later dropped because not contributing significantly to the models.

Sociodemographic (SD) control variables were selected based on prior research on car ownership and extracted directly from the OD survey data. Household income, the presence of at least one mobility-disabled person in the household, the average age of adults in the household, the age amplitude of household adults (maximum minus minimum age), the number of children (17 and below), the number of workers (the sum of part-time workers, full-time workers and students aged 18 or above) are included. The reason for including the age amplitude of household adults is to

capture the presence of two-generations households (e.g., two parents in their 60's and two children in their early 20's or two adults in their 50's with a parent in their 70's or 80's).

Descriptive statistics for sociodemographic variables and distance based built environment variables are presented in Table 7.2. Descriptive statistics for the built environment variables measured within buffers at various distances are presented in Table 7.3. Buffers of 600 m and 1400 m were not included to facilitate legibility but can be supplied upon request.

Table 7.2 Sociodemographics and distance-based built environment descriptive statistics for *1adultHH* and *2+adultsHH* subsamples

Variable	Description / Categories	<i>1adultHH</i>		<i>2+adultsHH</i>	
		n	%	n	%
Outcome	n observations	16 384		30 123	
Car ownership level	0 car	7 171	43.8%	3 199	10.6%
	< 1 car / adult	na	na	16 003	53.1%
	>= 1 car / adult	9 213	56.2%	10 921	36.3%
Socioeconomic characteristics		n	%	n	%
Disability within HH (%)	Yes	1 371	8%	1 942	6%
Nb actives	0	9 097	56%	6 665	22%
	1	7 287	44%	5 516	18%
	2+	na	na	17 942	60%
Nb of children (<= 17 yo)	0	15 282	93%	20 950	70%
	1	607	4%	3 697	12%
	2+	495	3%	5 476	18%
Income	< 30 000 CAD	5 092	31%	2 458	8%
	30 000 to 89999 CAD (REF)	6 483	40%	10 296	34%
	> 90 000 CAD	1 116	7%	10 251	34%
	Doesn't know / Refuse to answer	3 693	23%	7 118	24%
		Mean	Coeff. Var.	Mean	Coeff. Var.
Average age of HH adults (>= 18 years old)		59.7	29%	49.9	31%
Age amplitude of HH adults (Max adult age - Min adult age)		na	na	11.8	120%
Distance-based built environment characteristics					
Euclidean Distance to CBD [km]		8.88	62%	11.00	57%
Dist. To nearest metro station [m]		3 977	122%	5 858	103%

Note: na = not applicable.

Table 7.3 Descriptive statistics for buffer-based built environment variables

Variable		WD 400 m		WD 800 m		WD 1000 m		WD 1200 m		WD 1600 m	
		Mean	CV	Mean	CV	Mean	CV	Mean	CV	Mean	CV
1adultHH (n = 16384)	Pop. density [pers. / km2]	8 751	53%	7 576	47%	7 239	46%	6 984	45%	6 618	45%
	Entropy [0-1] 5 cat.	0.43	48%	0.55	29%	0.58	26%	0.60	24%	0.63	21%
	Density of 4-ways inters.	34.3	59%	28.6	54%	27.3	52%	26.5	51%	25.1	50%
	Nb of bus stops	8.5	61%	33.2	46%	51.0	44%	72.2	43%	125.1	43%
	Metro station (dummy)	0.09	322%	0.27	164%	0.33	142%	0.38	127%	0.46	108%
	Nb of carsharing veh.	1.6	197%	6.6	159%	10.0	154%	14.1	152%	23.9	147%
	Nb of bikesharing stations	1.0	170%	3.9	159%	6.1	157%	8.6	157%	14.9	155%
	Nb of grocery stores	1.3	155%	4.8	113%	7.3	105%	10.2	101%	17.4	96%
2+adultsHH (n = 30123)	Pop. density [pers. / km2]	7 194	61%	6 400	55%	6 148	54%	5 946	53%	5 640	53%
	Entropy [0-1] 5 cat.	0.35	58%	0.49	35%	0.52	30%	0.55	27%	0.59	23%
	Density of 4-ways inters.	29.3	69%	24.1	63%	22.9	62%	22.0	61%	20.8	60%
	Nb of bus stops	6.8	74%	27.9	55%	43.2	52%	61.6	51%	107.0	50%
	Metro station (dummy)	0.06	413%	0.18	210%	0.23	182%	0.27	163%	0.34	139%
	Nb of carsharing veh.	1.0	259%	4.3	205%	6.7	198%	9.3	195%	15.8	189%
	Nb of bikesharing stations	0.6	219%	2.4	205%	3.8	203%	5.4	202%	9.3	200%
	Nb of grocery stores	0.9	193%	3.5	141%	5.3	130%	7.5	124%	13.0	117%

7.3.4 Modelling Framework

To answer the research questions and obtain insights on what distance matters for each built environment characteristic, a machine learning algorithm, Gradient Boosting Machines (GBM)¹⁵, is applied to a series of submodels. GBM works by growing an ensemble of small decision trees where at each iteration, a new tree is fitted to the residuals of the current ensemble and added to the ensemble while leaving the previous trees unchanged (Hastie et al., 2009, ch. 10).

It uses the principles of gradient descent algorithm where parameters are changed iteratively in the direction of the gradient of the loss function. Friedman (2001) proposed a generalized boosting algorithm adaptable to any loss function, and thus applicable to regression and multiclassification problems. Friedman (2002) extended his framework by including stochastic gradient descent by sampling a fraction of the training sample, which reduces the chances of finding only a local minimum. One downside of GBM models is that they are prone to overfitting, which can inflate the impact of outliers and thus require cross-validations method to stop the search process before it happens. A 5-folds cross-validation is used for the present analysis.

An advantage of GBM decision-trees is that they require very little pre-processing of variables as they can handle different types of explanatory variables (continuous, categorical, count) easily and are able to handle missing values (Hastie et al., 2009). Furthermore, if the objective is prediction, high correlation between variables is not a problem because the algorithm will not choose a weak variable sharing a lot of variances with a stronger variable when splitting variables during the tree growing process. This is useful when exploring built environment characteristics influencing travel behaviour since many such variables tend to be highly correlated. However, if the objective is to understand the relationship between the predictors and the outcome, then collinearity between included variables might be a problem as the algorithm might select the variables that are the most relevant from a purely statistical point of view, but that might not be of high importance from a theoretical perspective or for policy decisions. This means a careful interpretation of the results in light of previous research is needed.

¹⁵ GBM is also known as Gradient tree boosting or gradient boosted regression trees (GBRT).

There are several open-sources libraries for gradient boosting applications. Two R packages were considered for the current analysis: *gbm* developed by Ridgeway (2020) and *xgboost* developed by Chen and He (2021). Both packages' algorithms are based on Friedman (2001, 2002)'s gradient boosting framework with minor variations for efficiency. After testing and comparing both packages, *xgboost* was selected for two reasons. First, its efficient algorithm and parallel computation offers quicker performance (Chen & Guestrin, 2016) than *gbm* which in the current context is important since dozens of models had to be run to test various buffer sizes for all the included built environment variables. Second, it offers more stochastic hyperparameters such as column subsampling which is not available in *gbm*. Boehmke and Greenwell (2020, ch. 12) suggests that this specific additional subsampling hyperparameter offers benefits in the presence of numerous correlated relevant predictors, which is the case here with the included built environment variables.

For binary outcomes, such as if a household owns at least one car (1) or none (0), the *xgboost* algorithm uses the negative loglikelihood function. For multiclassification problems, it uses the generalized loglikelihood function for multinomial outcomes (Chen & He, 2021). For more information about the detailed mathematical formulations behind the *xgboost* algorithm, see Chen and Guestrin (2016)'s paper.

7.3.4.1 Hyperparameters

GBM decision-trees are highly flexible due to the numerous hyperparameters that can be adjusted to the specific needs of the problem. The *xgboost* hyperparameters used in the current modelling framework are summarized in Table 7.4. The tested values were selected based on recent transportation applications of GBM (Ding, Cao, & Næss, 2018; W. Zhang et al., 2020) and suggestions from the general literature on GBM (Friedman, 2001; Hastie et al., 2009). A total of 120 combinations of hyperparameters are tested for each subsample (*1adultHH* and *2+adultsHH*) independently using a grid-search. For each subsample reference model, the combination that produces the lowest error rate on the test set is selected for the rest of the procedure.

Table 7.4 Description of hyperparameters and tested values

Hyperparameter	Description	Tested values
NB of trees (or iterations)	Total number of trees (iterations) in the gradient boosting ensemble.	Maximum set to 3000
Learning rate (or <i>shrinkage</i>)	Defines how fast the algorithm goes down the gradient of the loss function by scaling the contribution of each tree by this value.	0.01, 0.05, 0.1
Tree depth	Maximum number of splits in a single tree. Deeper trees allow for more interactions between variables.	3, 4, 5, 6, 7
Min. number of observations in node	Defines how many observations are needed for a split to be allowed.	10 et 15
Row subsampling	Fractions of rows to subsample at each iteration	0.5, 0.75, 1
Column subsampling	Fraction of columns to subsample at each tree (iteration)	0.8, 0.9, 1

Finally, to interpret the results and shed light on our research questions, two principal methods of analyzing GBM outputs are produced and compared at various steps of the general procedure described in the following section.

7.3.4.2 Relative influence of explanatory variables

When using GBM decision-trees, it is not possible to test the significance of each explanatory variable. However, Friedman (2001) extended an existing method of identifying the relative importance of each variable in a single decision to an ensemble of decision trees such as produced by GBM. Following the nomenclature used by Friedman, the influence of an explanatory variable j averaged over the ensemble of M trees (T_m) can be approximated by:

$$I_j^2 = \frac{1}{M} \sum_{m=1}^M \sum_{t=1}^{J-1} i_t^2 1(v_t = j) \quad (7.1)$$

Where the influence of variable j in each tree is computed by summing over the non-terminal nodes t (i.e., splits) of the J -terminal node of tree T when the current splitting variable v_t is the same as the variable j we are querying. This is multiplied by the empirical squared improvement i_t^2 resulting from this split. It is then common, as is the case in the R package `xgboost`, that the relative influence of each variable in the model are standardized to sum to 100%. Note that the

relative influence does not give any indication of the direction of influence of each variable on the outcome. For this, we turn to the partial dependence plots.

7.3.4.3 Partial dependence plot

Partial dependence plots (PDP) are a powerful visualization tool to investigate the non-linear relationship between explanatory variables and the response variable in GBM models. They show the average change in the outcome variable (or in the log-odds of the response variable in the case of a binary response) as we change the inspected explanatory variable, holding every other variable constant at their mean. While their relevance can be limited when there are strong interactions between explanatory variables, they can nonetheless provide useful insights on the effect of the most important variables in the model. These plots will be used to analyze the relationship between various BE attributes and household car ownership considering various buffer sizes.

7.3.5 General research framework

The main research objective is two-fold: 1) investigate what buffer size (distance) should be considered when computing BE variables for car ownership modelling and 2) identify thresholds effects of BE variables (i.e., how many of that variable) on household car ownership decision for various distances. A general procedure is proposed to examine those research questions using a series of GBM decision-trees. A 4-steps process is established and summarized in

Figure 7.3.

To understand the structural effect of the investigated BE characteristics on household car ownership decisions, the number of cars is normalized to household size by dividing the number of household cars by the number of adults (18 or above).

The outcome variable is then obtained by classifying each household within three distinct vehicle ownership status: no car, one or more cars shared by two or more adults (i.e., less than one car / adult) and full motorization (i.e., more than or equal to 1 car / adult). This approach takes out of the equation any ‘surplus’ vehicle that is unlikely to be explained by BE characteristics (an old car, a sports car, etc.). One caveat of this method is that households with only one adult cannot be classified in the middle category (less than one car / adult) and thus need to be modelled separately. For this reason, the OD survey sample is split between one adult households (*1adultHH*) and

multiple adults' households ($2+adultsHH$). For the $1adultHH$, the outcome variable takes a binary form (0: no car, 1: 1 or more car). This caveat however allows us to investigate and compare BE effects on single-adult and multiple adults' households. The GBM models are run using the *xgboost* R package and a training set containing 70% for each subsample. The remaining 30% of each subsample is used for computing prediction accuracy.

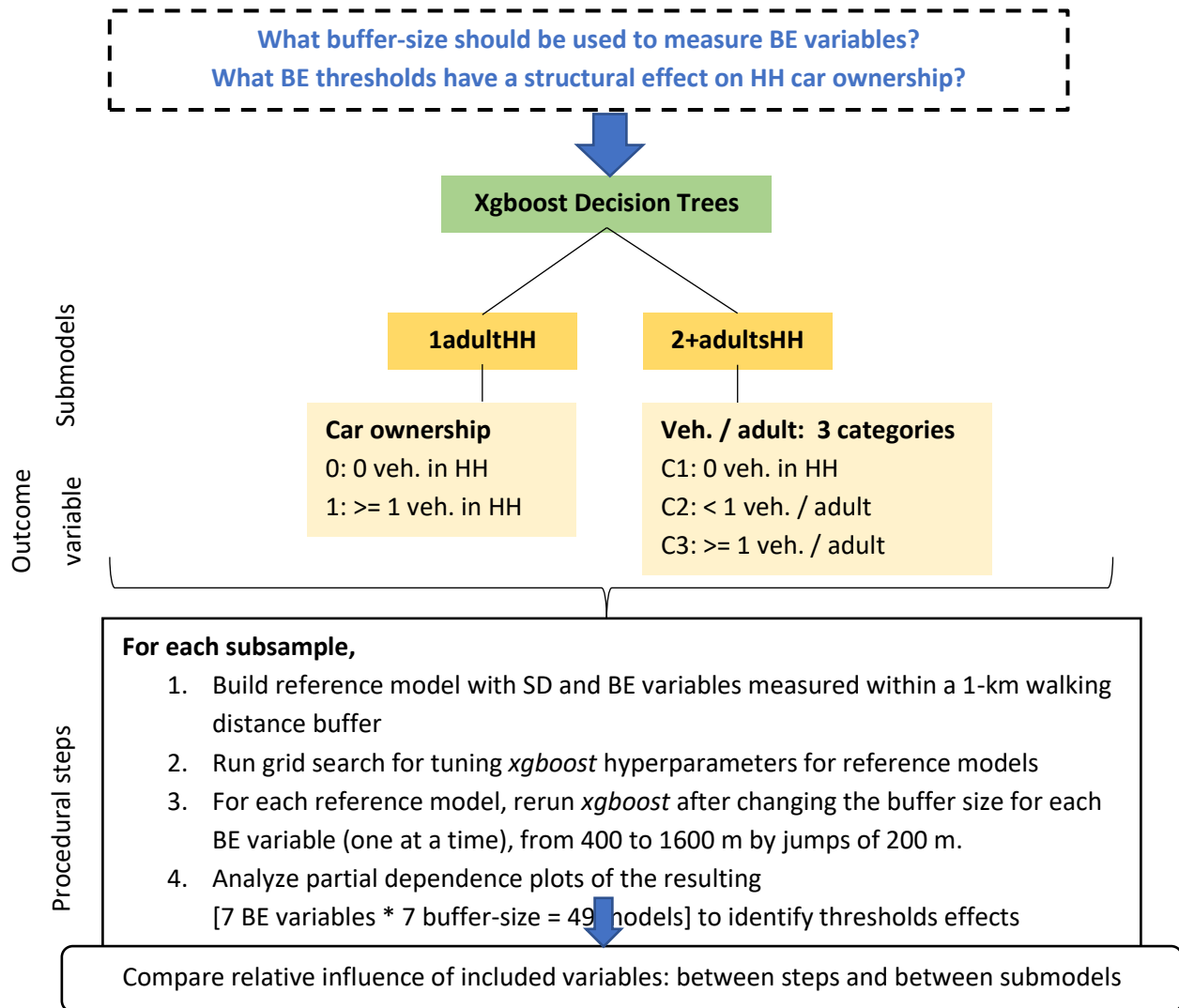


Figure 7.3 General framework to investigate research question

7.4 Results

7.4.1 Results of the reference models

In the first step of the general framework, a reference GBM model is run with candidate SD and BE variables for both subsamples. In these reference models, the buffer size for BE characteristics measurement is set to a 1-km walking distance. Model performance statistics and the relative influence (RI) of each explanatory variable are presented in Table 7.5 with the hyperparameters selected following the identification procedure using the grid search described in step 2.

The first observation is that the *2+adultsHH* model achieves a lower prediction accuracy (64.6%) than the *1adultHH* model (70.7%) which has one less outcome class. The dominant SD (and overall) variable for *1adultHH* is the dummy variable for low-income households (< 30 k CAD / year). For the *2+adultsHH*, the age variables (average age and age amplitudes of household adults) rank second and fourth in RI, for a combined influence of 20%. As categorical indicators are not permitted in the xgboost algorithm, the income was encoded as four dummy variables with the most represented category (30 k to 90 k CAD) as the reference category, and thus not included as one of the variables. The total relative influence of income is 26.3% for *1adultHH* and less than half of that for *2+adultsHH* (11.7%). For *1adultHH*, the RI of household income is comparable to the 31% obtained by W. Zhang et al. (2020) for their all-households model. One person in the household having some mobility disability is, unsurprisingly, more important in explaining car ownership status for *1adultHH* than for *2+adultsHH*. The number of active adults in the household - the sum of part-time and full-time workers and students (aged 18 or above) - has very low influence for *1adultHH* (1.5%), ranking 15th out of 16 variables. The variable plays a larger role in explaining car ownership status for *2+adultsHH* (6.6%, 5th). Interestingly, in both models, the number of children does not play an important role, ranking last and second to last with a RI of roughly 2%.

Despite disparities in SD variables ranking between subsamples, the combined relative influence of SD variables is very similar (44.8% for *1adultHH* and 43.2% for *2+adultsHH*) and offer less predictive power than the combined BE influence (55.25% and 56.8%). The ratio between SD and BE influence is the inverse of what was found by W. Zhang et al. (2020) where the combined RI was 62.4% for SD and 37.6% for BE. This could potentially be explained by the variables selected,

the method for buffer calculation (from neighborhood centroids) and by the nature of the outcome variable being modelled.

Population density, which is generally considered a proxy variable for various BE characteristics, ranks first among BE variables and respectively second and first for *1adultHH* and *2+adultsHH* overall with very similar relative influence (16.9% and 16.2%). The two other “traditional” built environment characteristics measured within walking-buffer, Entropy index and the density of 4-ways intersections, have moderate influence on both models, confirming that diversity and design are associated with household car ownership decisions.

Four included variables serve to capture the accessibility to mobility resources. In a first iteration of the models (results available upon request), accessibility to the metro network was measured with a binary variable indicating whether at least one metro station was located within a 1-km walking buffer distance around each household. In that form, the variable performed poorly, with a relative influence of <1% for both household subsamples. This was counter intuitive since the Metro network is the backbone of the Montréal transit system, running at high frequency from 5:30 AM to midnight every day. In the final iteration of the models (results presented in Table 7.5), accessibility to the metro network was measured as the shortest walking distance to the nearest metro station. In this form, the variable is the third most influential in both models, with a RI of 10.8% for *1adultHH* and 10.2% for *2+adultsHH*. Such results are considerably higher than the 2% found by W. Zhang et al. (2020) in the Beijing study where they also computed the variable as the network distance to the nearest station, but from the neighborhood centroid instead of from each household's precise location.

Accessibility to carsharing vehicles within walking distance is the 6th most important variable in both models with a RI of ~6.5%, indicating that the availability of this mobility service might be affecting car ownership decisions of nearby households. Accessibility to bus stops and to bike-sharing stations have lower influence in both models, with RIs around 3%. Finally, accessibility to local grocery stores seems to play a more important role in *1adultHH* car ownership decisions (RI = 6%) than multiple adults' households (RI = 3.9%). This result is intuitive since it is likely easier for a single adult household to go grocery shopping on foot than for larger households (i.e., the amount to carry would likely be less).

Table 7.5 Results of the reference GBM models (*xgboost* Decision Trees)

Household subsample		<i>1adultHH</i>		<i>2+adultsHH</i>	
Outcome		Car in HH (0 vs 1+)		Cars / adult (3 cat.)	
# Of outcome categories		2		3	
# Of observations in sub-sample		16384		30123	
Hyperparameters	# Of trees (iterations)	3000		3000	
	Loss function	Logloss		MNL logloss	
	Interaction depth	3		5	
	Shrinkage	0.01		0.01	
	Minimum observation at nodes	10		10	
	# Of cross-validation folds	5		5	
	Sample fraction	0.75		0.75	
	Column sample by tree	0.8		0.8	
Reference models (All BE variables at WD 1000 m)					
Results	Best iteration	773		985	
	Test logloss / mlogloss	0.557		0.752	
	Cross-validation prediction accuracy	70.79%		64.73%	
Buffer size		Rank	RI (%)	Rank	RI (%)
Sociodemographic (SD)					
Income: < 30 k CAD	-	1	18.5%	10	4.9%
Income: >= 90 k CAD	-	8	4.0%	7	6.3%
Income: unknown	-	9	3.8%	17	0.5%
Disabled pers. in HH (dummy)	-	4	8.3%	15	2.6%
Average age of HH adults	-	5	6.8%	4	9.8%
Adult age amplitude	-	-	-	2	10.3%
# actives(workers + 18+ students)	-	16	1.5%	5	6.6%
# of <= 17 years old	-	15	1.8%	16	2.2%
Total SD Influence		44.75%		43.19%	
Built environment (BE)					
Population density [pers./km²]	1-km WD	2	16.9%	1	16.2%
Entropy, 5 categories	1-km WD	12	3.0%	8	5.2%
4-way intersection density	1-km WD	13	2.9%	12	3.7%
Distance to CBD (km)	-	10	3.2%	9	5.1%
Min walking dist. to metro station	-	3	10.8%	3	10.2%
# of bus stops	1-km WD	14	2.8%	13	3.1%
# of carsharing vehicles	1-km WD	6	6.6%	6	6.4%
# of bikesharing stations	1-km WD	11	3.1%	14	3.0%
# of grocery stores	1-km WD	7	6.0%	11	3.9%
TOTAL BE Influence		55.25%		56.81%	

Note: RI = Relative influence; WD = walking distance.

7.4.2 Results of the buffer-size variation analysis

In the next step of the modelling framework (

Figure 7.3, Step 3), 49 GBM models for each subsample of households were computed, each varying the buffer-size of one of the seven BE variable, holding the distance of all other variables at a 1-km buffer. Figure 7.4 and Figure 7.5 illustrate how the relative influence of each variable within each model varies depending on the size of the walking distance buffers used for computation. Specifically, for both subsample models, the relative influence for the number of carsharing vehicles and the number of bike-sharing stations varies drastically between the smallest buffer (400 m) and the largest buffer (1600 m). The change is the most extreme for carsharing where it goes from the lowest RI (0.5%) at 400 m to the 5th (8.9%) at 1600 m for *1adultHH*, a 16.8-fold increase and from the 16th (1.1%) at 400 m to the 5th rank (7.6%) at 1600 m for the *2+adultsHH*, a 7-fold increase. One can argue that since those two variables are in absolute terms (number of opportunities) instead of relative terms (density of), larger buffers would exhibit more variability than smaller ones. However, other variables measured in absolute term such as number of bus stops and number of grocery stores do not show such drastic changes. Bus stops is even the second most consistent variable across buffer size after Entropy with a RI mean of 2.8% and 3.11% and standard deviation (between buffer size) of 0.71% and 0.44% respectively for *1adultHH* and *2+adultsHH*.

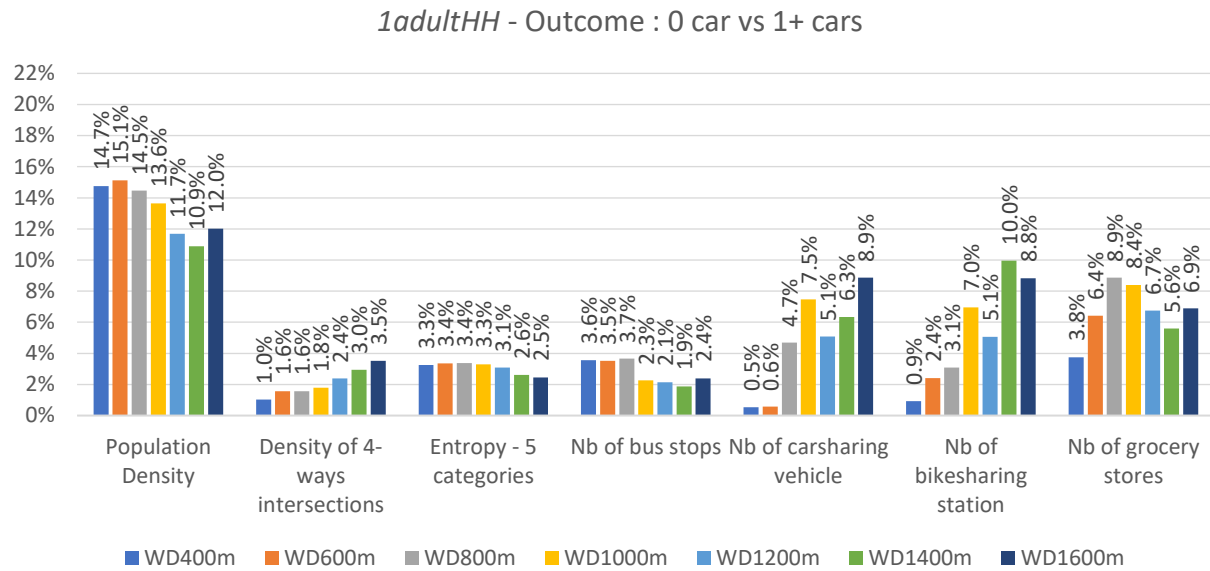


Figure 7.4 Relative influence of BE variables for *1adultHH* models for varying walking distance (WD) buffers

For *1adultHH*, the number of grocery stores shows a rising influence from 400 to 800 m, then a diminishing influence up to 1600 m while for *2+adultsHH* it simply shows a rising influence as the buffer grows wider. For both subsamples, the relative influence of population density diminishes when going from 400 to 1600 m. Neighborhood design measured with 4-ways intersection density shows the opposite trend: its influence increases steadily from 400 to 1600 m for the *1adultHH* models but exhibit a steady influence for *2+adultsHH*.

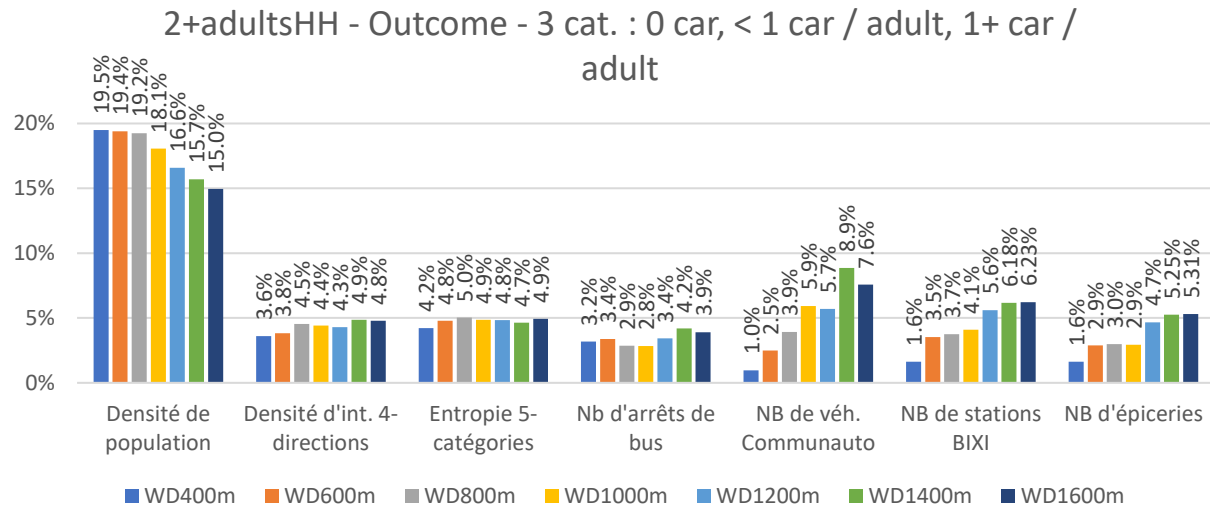


Figure 7.5 Relative influence of BE variables for 2+*adultsHH* models for varying walking distance (WD) buffers

While the relative influence of the variables included in Gradient Boosting decision trees are useful indicators, they do not provide information on the direction of influence of each variable. For this, partial dependence plots, as described in the methodology section, are produced for each continuous explanatory variable. For *1adultHH* binary outcome model, each curve shows the change in probability of having at least one car versus no car because of changes in the value of the investigated BE variable, holding every other variable constant at their means. For 2+*adultsHH*, three partial dependence curves are produced for each variable. Each curve represents the change in probability of belonging to one of the three possible outcome classes (no car, less than one car per adult and one or more car per adult) as the value of the investigated BE changes, holding every other variable constant at its mean. The probabilities for all three classes always sum to one. The absolute value of the probability depends on the interactions and specific distribution of the outcome of all variables included in the model. What matters is the difference between the maximum and minimum probabilities for a given variable and the shape of the distribution which could help identify threshold effects. To avoid risky interpretation of patterns based only on outliers, each partial dependence curve is shown for a distribution going from the 1st to the 99th percentiles of each variable for each subsample.

For distance-based built environment variables (**distance to CBD** and **walking distance to nearest metro station**), partial dependence plots (PDPs) are produced once for each subsample models and presented in Figure 7.6 and Figure 7.7.

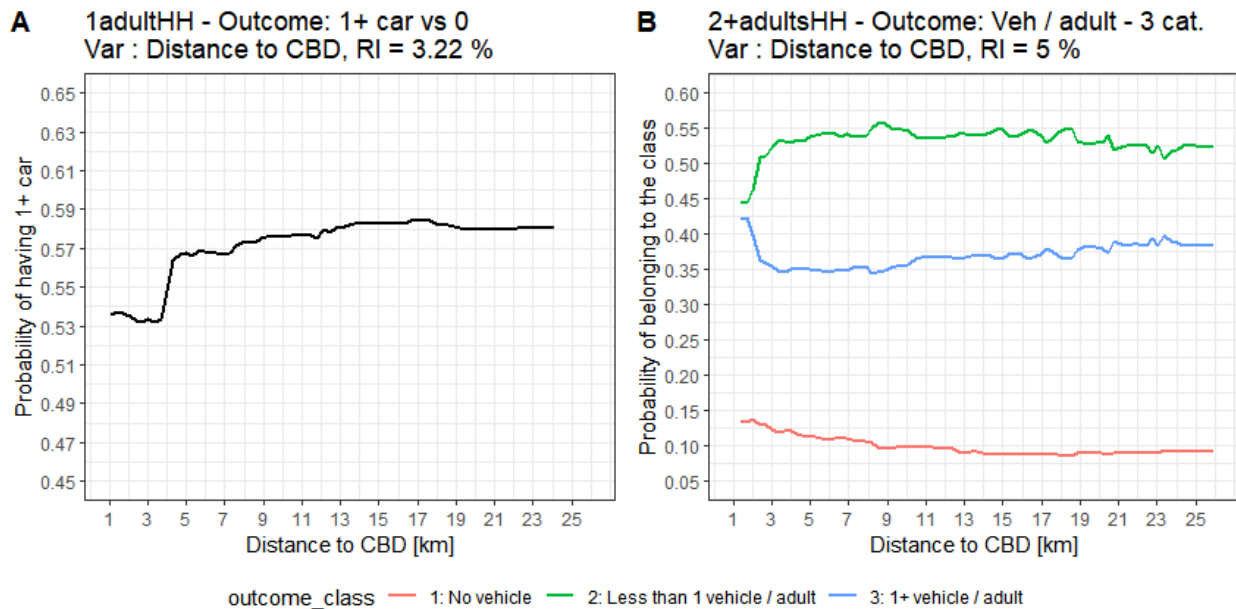


Figure 7.6 Partial dependence plots for the Euclidean distance to Montréal's central business district

Considering the **distance to CBD** for the *1adultHH* model (Figure 7.6, plot A), there seems to be a threshold effect between 3.5 and 4.5 km where the probability of being motorized rises sharply and then increases slowly up to 14 km. For *2+adultsHH* (Figure 7.6, plot B), the sharp rise is closer (between 2 and 3.5 km from the center) and only concerns the probability of being fully motorized versus sharing vehicles between household adults. This indicates that all else being equal, households very close to the center are less likely to need one vehicle per adult than those further away. The probability for *2+adultsHH* to have no vehicle (red curve in Figure 7.6, plot B) diminishes slightly and slowly up to 9 km from the CBD before staying stable as the distance keeps increasing.

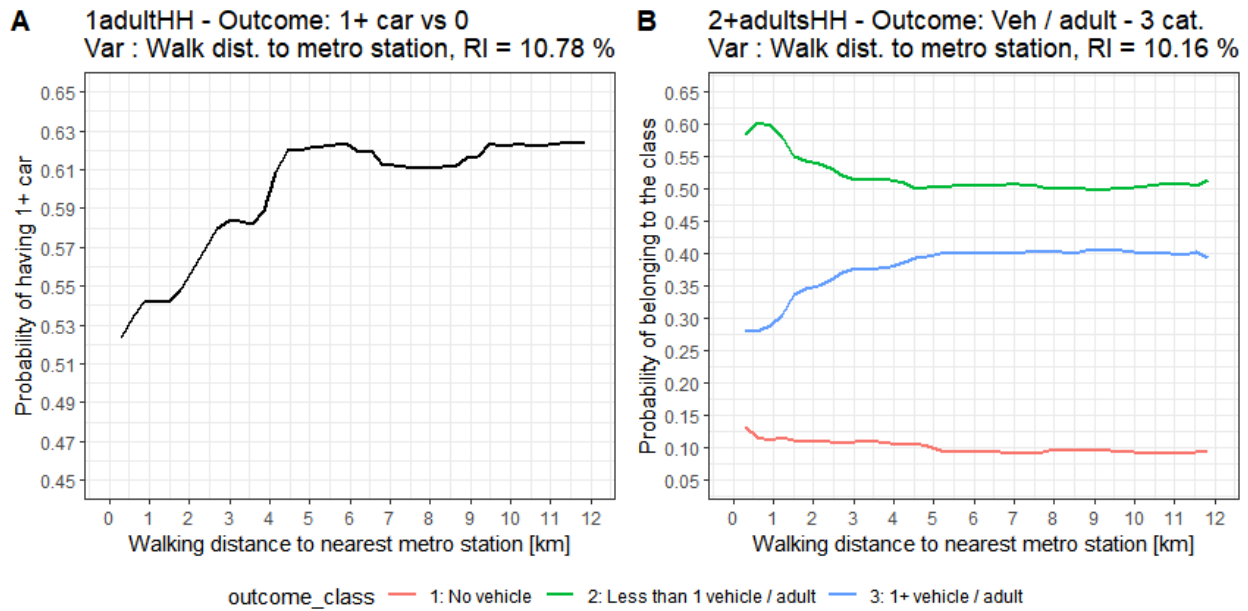


Figure 7.7 Partial dependence plots for the distance to the nearest metro station

Accessibility to the metro network seems to have a clear effect on *1adultHH* car ownership decisions. The PDP (Figure 7.7, plot A) shows three steady increases in the probability to own a car, followed by three plateaus. The first plateau goes from 800 m to 1500 m (or about 10 to 20 min of walking), a second one shows at around 3 km potentially representing a close catchment area where stations can be access easily by bus or by bike and a final one appears at 4.5 km potentially delimiting the overall area considered as the “central neighborhoods” of Montréal. For multiple adults' households (Figure 7.7, plot B), the probability of having one or more cars per adult (blue curve) increases steadily up to 6 km with a mirror decrease in the probability of having less than one car per adult (green curve), beyond which no changes in the probability of belonging to either class is observed. The probability of having no vehicle (red curve) slightly decrease as the distance to the nearest metro station increases from 500 m to 5–5.5 km.

For buffer-based variables the partial dependence curves for four of the seven tested buffer sizes for both subsamples are presented in Figure 7.8 to Figure 7.13 (curves for the three other tested distances – 600, 1000 and 1400 m – are not displayed for clarity but can be supplied upon request by the authors).

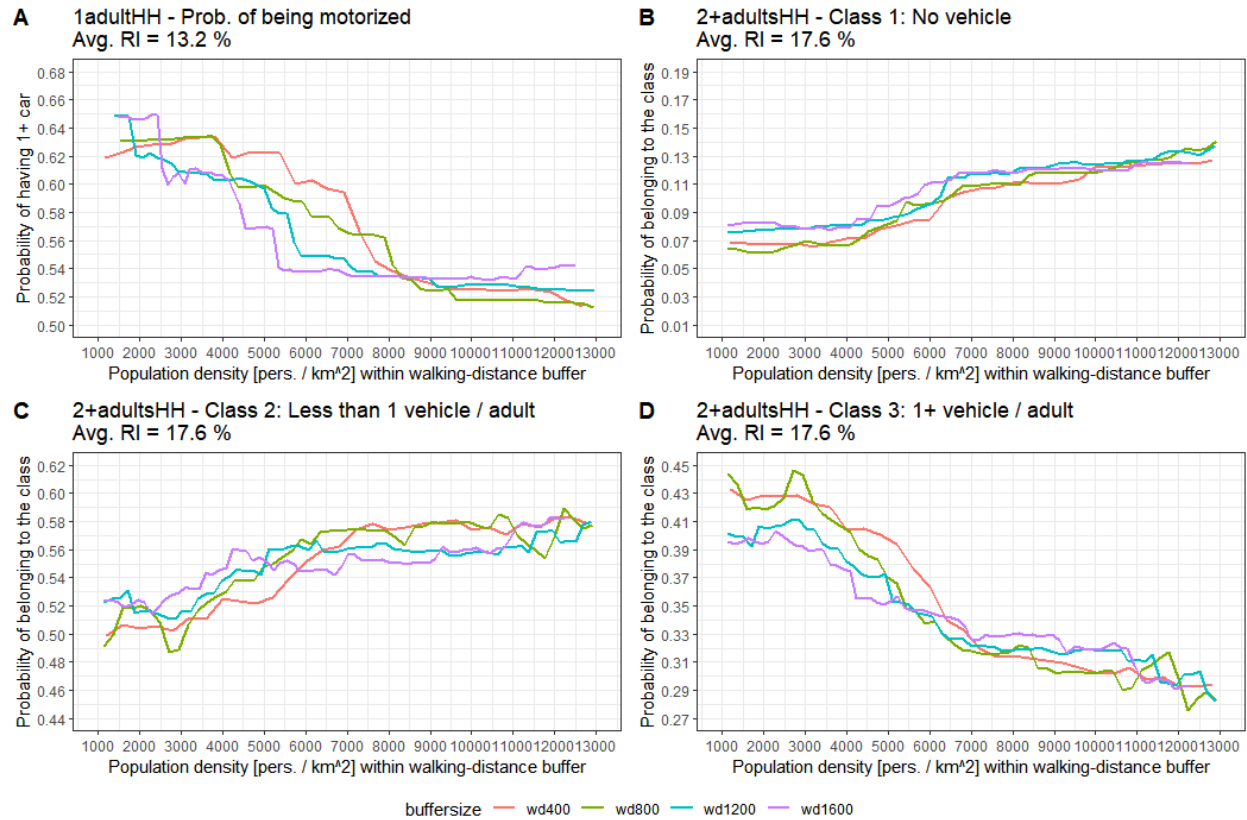


Figure 7.8 Partial dependence plots for population density

Figure 7.8 indicates that the probability of being fully motorized (one car per adult) decreases rather steadily as **population density** increases up to 8500 people per km squared for all buffer sizes except 1600 m for *1adultHH* (plot A) and up to 7000 people per km squared for *2+adultsHH* (plots B to D). Higher densities do not seem to further reduce car ownership probability for both subsamples. Smaller buffers exhibit more plateaus followed by sharper changes than larger buffers where density is smoothed out because it is averaged over larger areas.

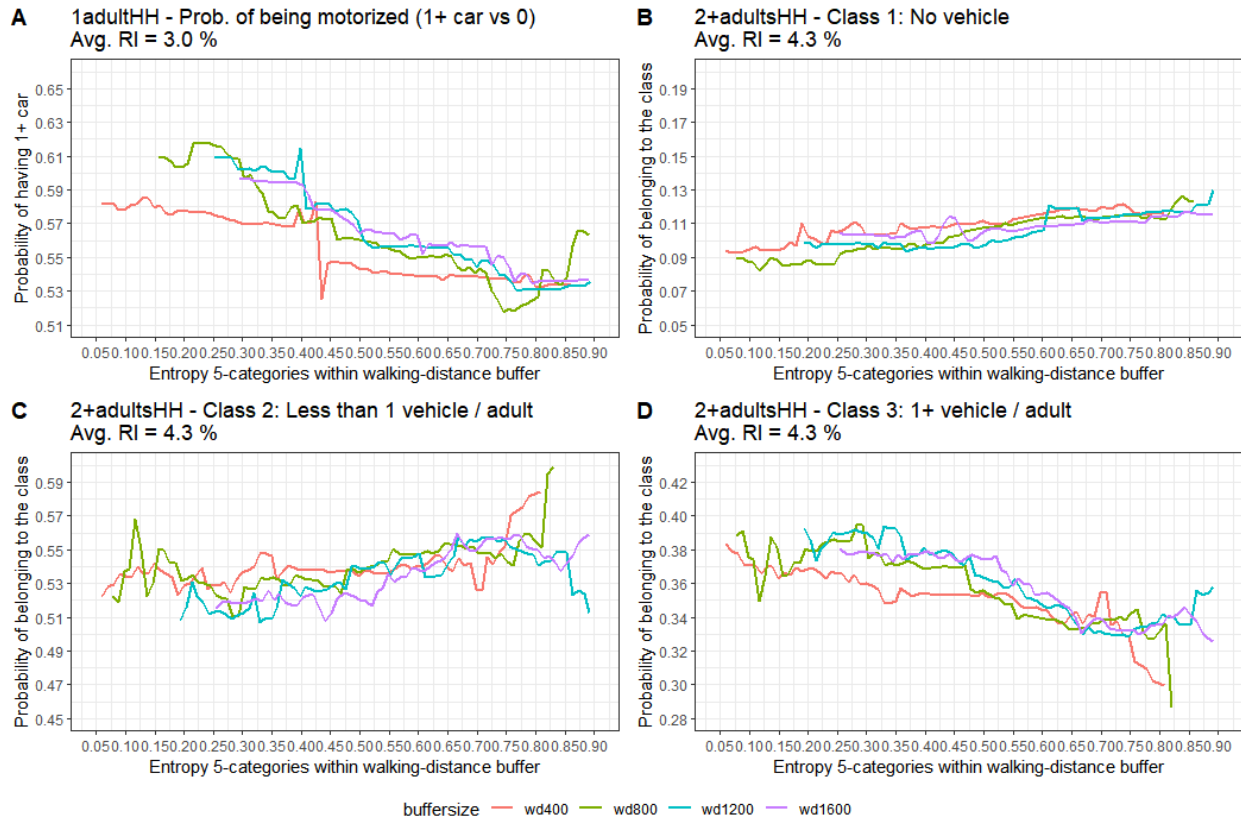


Figure 7.9 Partial dependence plots for Entropy index measured with 5 categories

For *1adultHH* (Figure 7.9, plot A), **entropy** shows a roughly negative linear relationship with the probability of owning a car for buffers of 800, 1200 and 1600 m. A sharp drop at an **entropy** value of 0.45 is observed for the smallest buffer (400 m). For *2+adultsHH* (Figure 7.9, plots B-D), the probability of having no vehicle or less than one vehicle per adult in the household increases as entropy increases from a value of 0.20 to a value of 0.75, for all buffer sizes consider. For *2+adultsHH*, the difference between the minimum and maximum probabilities for all three classes is larger for smaller buffers (≤ 800 m) than for larger buffers (≥ 1200 m). For *1adultHH* (Figure 7.9, plot A), **entropy** shows a roughly negative linear relationship with the probability of owning a car for buffers of 800, 1200 and 1600 m. A sharp drop at an entropy value of 0.45 is observed for the smallest buffer (400 m). For *2+adultsHH* (Figure 7.9, plots B to D), the probability of having no vehicle or less than one vehicle per adult in the household increases as entropy increases from a value of 0.20 to a value of 0.75, for all buffer sizes consider. For *2+adultsHH*, the difference between the minimum and maximum probabilities for all three classes is larger for smaller buffers (≤ 800 m) than for larger buffers (≥ 1200 m).

Access to bus stops is one of the variables that exhibit the highest variability in distributions as the buffer sizes changes from 400 m to 1600 m. Fast decrease in car ownership probabilities for both household subsamples are observed in Figure 7.10 for the smallest buffer (400 m) while for larger buffers, the curves are smoother and do not dig as deep. This could be an indication that smaller buffer sizes best capture threshold effects of bus accessibility on car ownership.

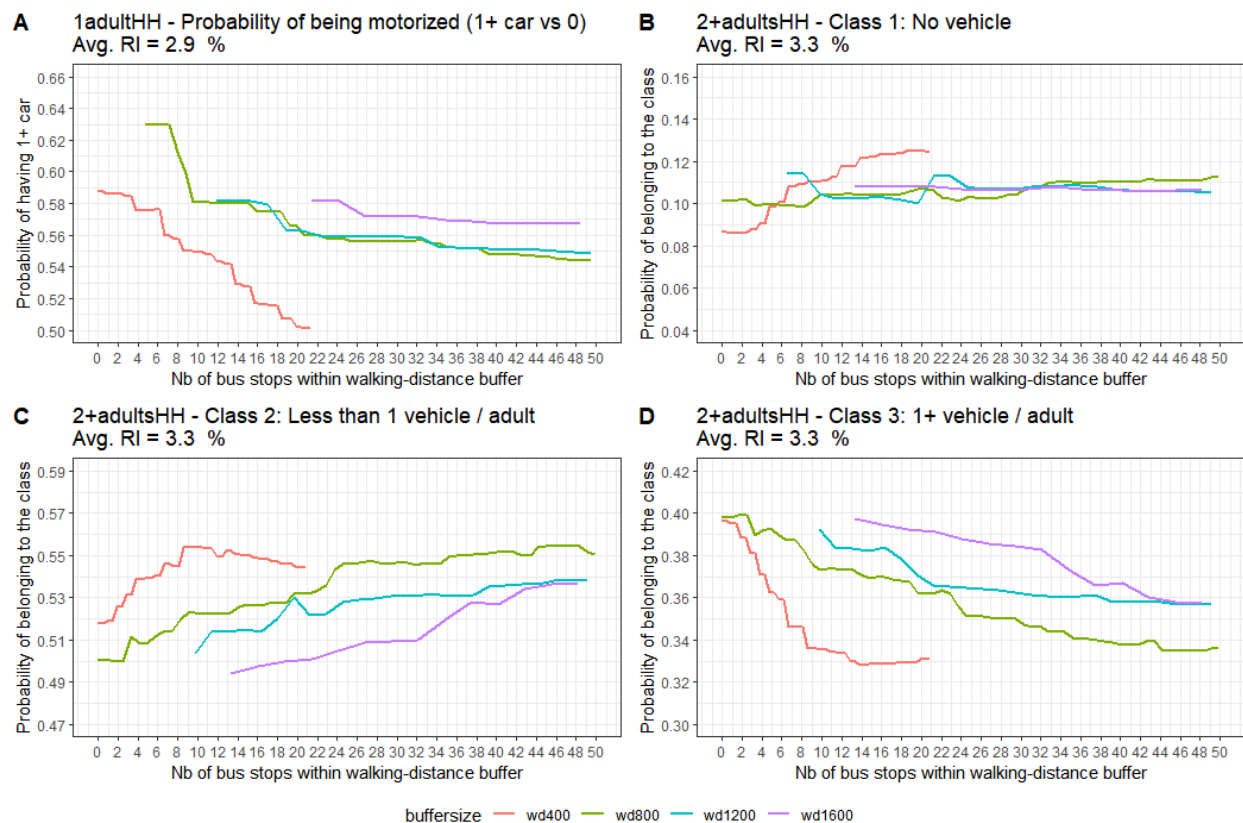


Figure 7.10 Partial dependence plots for the number of bus stops within buffer

For access to **carsharing** for *1adultHH* (Figure 7.11, plot A) the probability of having a car drops sharply for the 400, 800 and 1200 m buffer sizes when up to four station-based carsharing vehicles are available within walking distance. For 1600 m buffers, the lowest probability is reached at 8–9 vehicles. For *2+adultsHH* (Figure 7.11, plots B to D), the largest overall decline in car ownership probability is observed when a medium size buffer (800 m) is considered. For this buffer, the sharpest change is observed at two vehicles, the point at which the probability to be fully motorized (plot D) drops while the probability to share a vehicle (class 2, plot C) and to have no vehicle (class 1, plot B) increases in return. After this initial drop, a decline in probability of being fully motorized is observed for up to 20 vehicles. This seems to indicate that an increasingly larger

number of carsharing vehicles accessible within a 10-min walking radius allows more multiple adults' households to get by without every adult needing their own car.

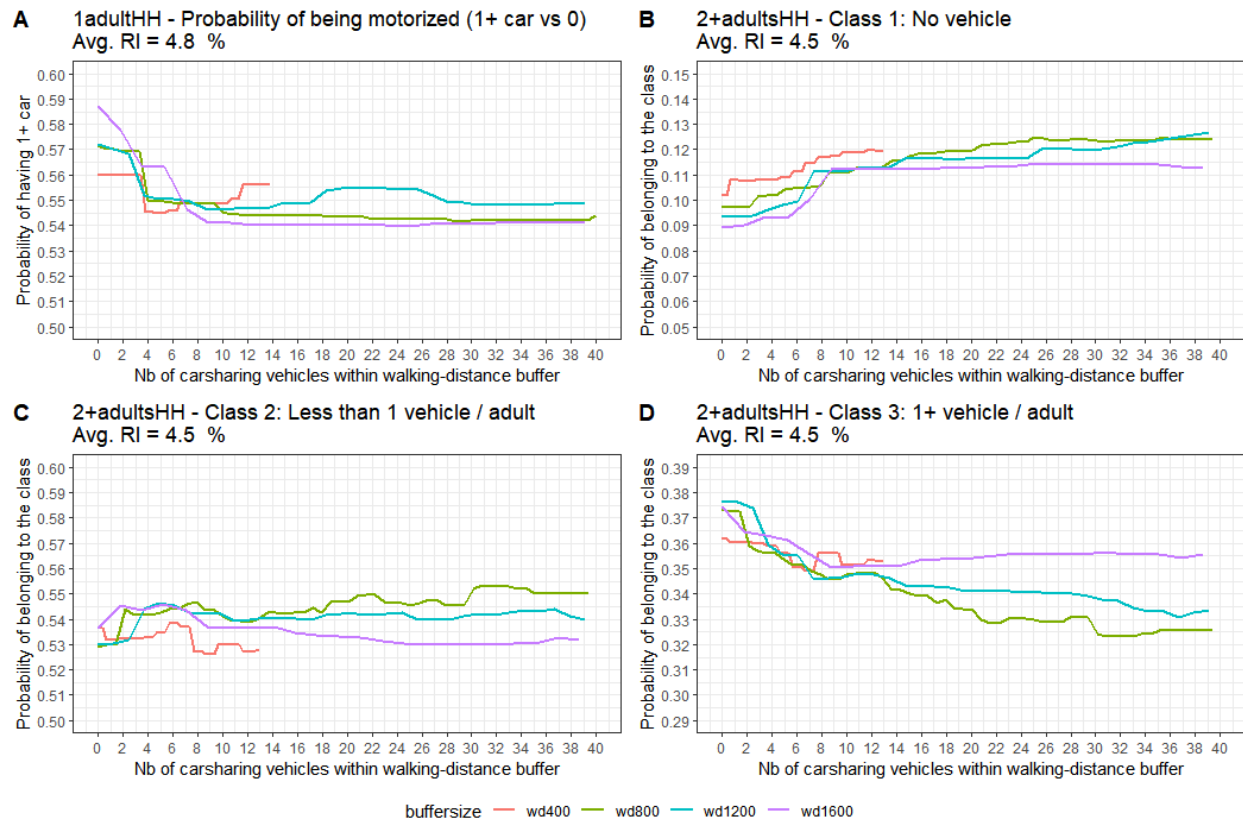


Figure 7.11 Partial dependence plots for the number of carsharing vehicles within buffer

For **bikesharing**, Figure 7.12 indicates that the availability of as little as 1–2 bikesharing stations within a short walking distance (≤ 800 m) and up to four stations when larger buffers are considered (≥ 1200 m) are associated with lower probability of car ownership compared to having access to no station for both subsamples. For 2+*adultsHH*, smaller buffers (400 m) exhibit a much sharper decrease in full motorization probability than larger buffers which seem to diminish the probability slowly as the number of bikesharing stations increases. A fair question to ask is: does the proximity to bikesharing service really have an impact on people's car ownership decision? From a purely statistical point of view, the RI of the variable for both models are low ($\sim 3\%$), but not negligible. It indicates that the xgboost algorithm selects the variable frequently for its good ability to reduce the loss function and predict the outcome. This is not synonym with causation. As the bikesharing stations are mostly located in the central neighborhoods, a possible hypothesis is that the variable acts as a proxy for other characteristics not currently captured by the included

variables. High constraints on on-street parking where bikesharing station density is high could be a possible factor (bikesharing stations are commonly installed on on-street parking spots in Montréal).

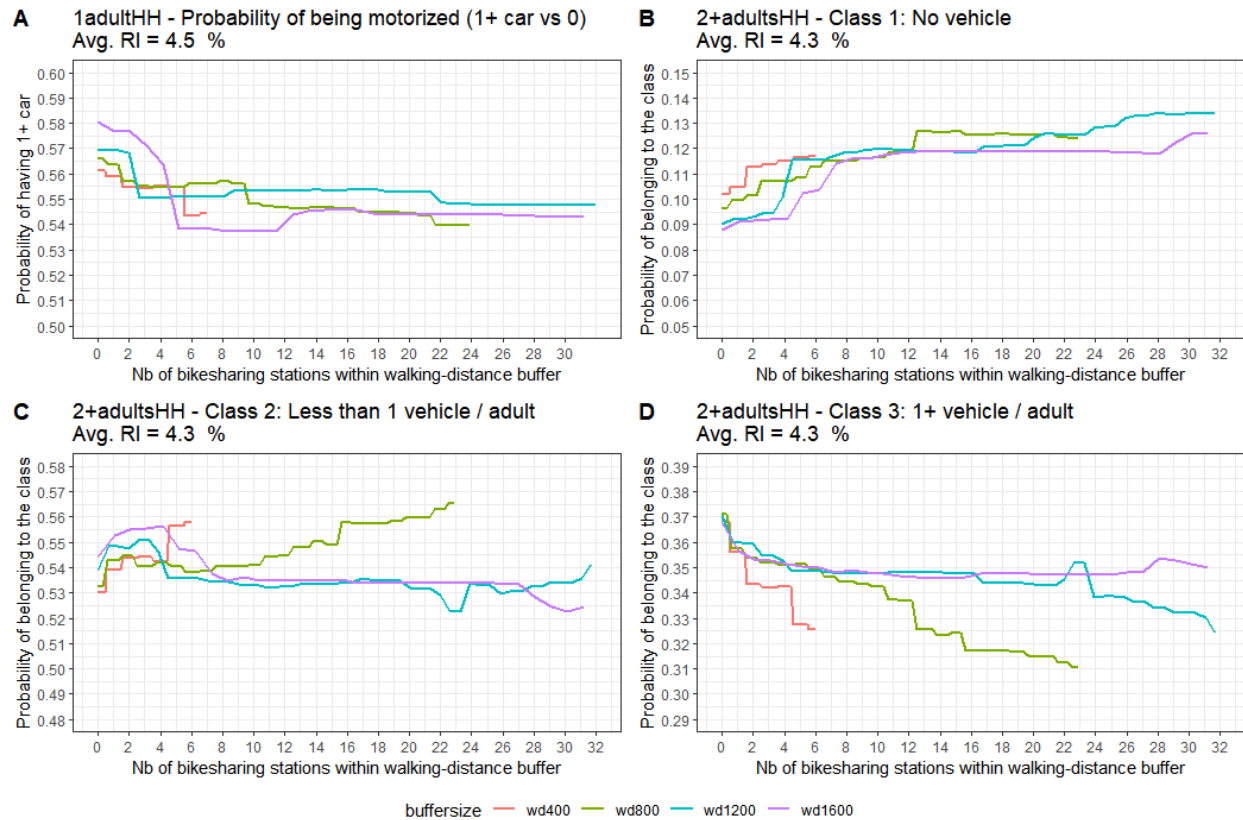


Figure 7.12 Partial dependence plots for the number of bikesharing stations within buffer

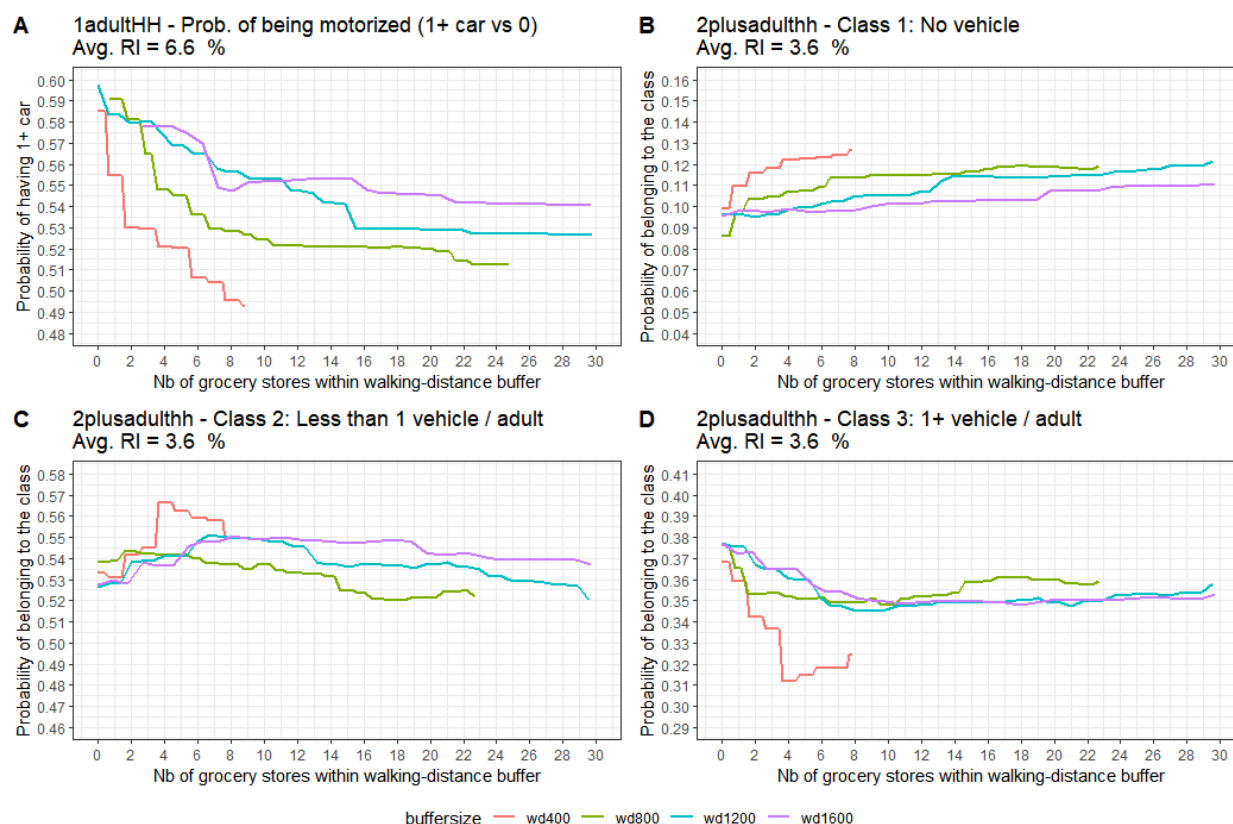


Figure 7.13 Partial dependence plots for number of local and chain grocery stores within buffer

Finally, in line with other accessibility variables analyzed (bus stops, bikesharing stations, carsharing vehicles), smaller buffer sizes (400 to 800 m) show fast dropping probability of car ownership when the number of accessible **grocery stores** rises (Figure 7.13). The relative influence of the variable, which affects the change in probability of being motorized, is higher for *1adultHH* than for *2+adultsHH* and thus the change in probabilities is higher in the *1adultHH* model. The grocery store variable includes large grocery stores but also small local fruits and vegetable stores which are very common in Montréal's central neighborhoods. Having access within a 5 or 10-min' walk (400 m and 800 m buffers) to up to several of those stores appears important for helping *1adultHH* to live car-free and, to a lesser extent, to avoid full motorization for *2+adultsHH*. For *1adultHH* (Figure 7.13, plot A), when short distances are considered (400 m), only two stores seem necessary to have a strong influence on car ownership probability. For *2+adultsHH* (Figure 7.13, plots B to D), the trends are not as clear, but having at least four stores within a very short distance (400 m) is associated with lower probability of full motorization (Plot D, more than or equal to one vehicle per adult). Furthermore, the variable can also be seen as a

proxy for accessibility to a wider range of retail opportunities usually located on the same commercial streets but not captured through included variables. The key findings for each BE variable are summarized in Table 7.6 for *1adultHH* and in Table 7.7 for *2+adultsHH*.

Table 7.6 Summary of results for *1adultHH* models

Variables	Relative Influence for the 7 tested buffer size			Key findings
<i>Buffer-based variables</i>	Mean	Min RI	Max RI	
Population density [people / km ²]	13.2%	1400 m 10.9%	600 m 15.1%	All buffer sizes perform well. A convergence in car ownership probability is observed at 8500 p. / km ² which is the lowest value for all buffers.
4-ways intersection density [4-ways int. / km ²]	2.1%	400 m 1.00%	1600 m 3.50%	Larger buffers (1200 and 1600 m) show the largest changes in car ownership probabilities. Plateaus of lowest probabilities are reached between 10 to 15 four-ways inters. / km ² .
Entropy 5-cat. [Entropy index 0-1]	3.1%	1600 m 2.50%	800 m 3.40%	Buffer size >= 800 m all perform well with linear decline in car ownership probabilities for entropy values between 0.25 to 0.75
NB of Bus stops	2.8%	1400 m 1.90%	800 m 3.70%	400 m buffer shows the fastest and largest decline in probability. Lowest probability of car ownership is reached at 20 bus stops within 400 m buffer.
NB of Carsharing vehicles	4.8%	400 m 0.50%	1600 m 8.90%	1600 m buffer shows the largest drop in probability. The lowest plateau is reached at 8 carsharing vehicles for this buffer. For smaller buffers (400, 800 and 1200 m), a sharp drop in car ownership probability is observed when 3-4 carsharing vehicles are within buffer. ^a
NB of bikesharing stations	5.3%	400 m 0.90%	1400 m 10.00%	1600 m buffer shows the largest drop in probability. Lowest plateau is reached at 5 bikesharing stations for this buffer. Smaller buffers (400, 800 and 1200 m) show smaller decline for up to 6 stations. *
Nb of grocery stores	6.7%	400 m 3.80%	800 m 8.90%	400 m buffer shows the fastest and largest decline in probability. Lowest probability of car ownership is reached at 8 grocery stores within 400 m buffer.
<i>Distance-based variables</i>	RI in reference model			
Distance (Euclidean) to CBD (km)		3.2%		Fastest increase in car ownership probability is observed between 3 and 5 km from CBD followed by a slow increase up to 14 km.
Walking distance to metro station		10.8%		Three linear increases in car ownership probabilities are observed: 0-800 m, 1.5 to 3 km and 3.8 to 4.5 km, each separated by a plateau. No significant change past 4.5 km.

Note: ^a The location of carsharing vehicles and bikesharing stations are mostly constrained within the central neighborhoods of the city of Montréal. This means that a much larger proportion of observed households have zero carsharing vehicles and/or bikesharing stations within smaller buffers (400 m) then within larger buffers (1600 m). This reduces the variance and explanatory power of smaller buffers for those variables within the models. In short, it can't be ruled out that closer is better.

Table 7.7 Summary of results for 2+adultsHH models

Variables	Relative Influence for the 7 tested buffer size			Key findings
	Mean	Min RI	Max RI	
<i>Buffer-based variables</i>				
Population density [people / km ²]	17.6%	1600 m 15.0%	400 m 19.5%	Results are consistent across buffer sizes. Changes in full motorization (↓), partial motorization (↑) and zero-car (↑) probabilities are observed for values up to 6500 to 8500 p. / km ² .
4-ways intersection density [4-ways int. / km ²]	4.8%	400 m 4.2%	800 m 5.0%	Results are consistent for buffers >= 800 m. Changes in car ownership status probabilities are observed for densities of 4-ways intersection [int. / km ²] between 0 and 8 and between 36 and 50 with no changes observed in between.
Entropy 5-cat. [Entropy index 0-1]	4.3%	400 m 3.6%	1200 m 4.9%	Results are consistent across buffer sizes. Slow linear decline in full motorization probabilities for entropy values between 0.25 to 0.80 with corresponding increase in zero-car and partial motorization probabilities.
NB of Bus stops	3.4%	1000 m 2.8%	1400 m 4.2%	400 m buffer shows the fastest and largest change in car ownership status probabilities. For this buffer, rapid changes in zero-car probability (↑) and full motorization probability (↓) are observed up to 14 stops. Partial motorization probability increases (↑) slowly up to 9-10 bus stops within buffer.
NB of Carsharing vehicles	5.1%	400 m 1.0%	1200 m 8.9%	800 m buffer shows the largest change in probabilities. For this buffer, changes in zero-car probability (↑) and full motorization probability (↓) are observed up to 20 carsharing vehicles within buffer. Partial motorization probability increases (↑) slowly up to 30 vehicles.
NB of bikesharing stations	4.4%	400 m 1.6%	1600 m 6.2%	800 m buffer shows the largest change in probabilities while 400 m shows the fastest change up to 6 bikesharing stations. For 800 m buffer, changes in zero-car and partial motorization probabilities (↑) and full motorization probability (↓) are observed for up to 12 to 16 stations.
Nb of grocery stores	3.7%	400 m 1.6%	1600 m 5.3%	400 m buffer shows the fastest and largest change in probabilities. Highest zero-car and partial motorization probabilities and lowest probabilities for full motorization are reached at 4 grocery stores within 400 m buffer.
<i>Distance-based variables</i>	RI in reference model			
Distance to CBD (km)	5.1%			Fast increase in full motorization probabilities and corresponding decline in partial motorization is observed between 1.5 and 3.5 km. Zero-car probability declines slowly up to 9 km.
WD to metro station	10.2%			Fast increase in full motorization probabilities and corresponding decline in partial motorization is observed between 0.5 and 5 km. Zero-car probability declines slowly up to 5 km.

Note: Zero-cars = class 1: No vehicle, Partial motorization = class 2: Less than 1 vehicle / adult, Full motorization = Class 3: 1+ vehicle / adult.

7.5 Discussion and conclusion

In this paper, we applied Gradient Boosting Machines (GBM) decision-trees to investigate how the scale of measurement of built environment (BE) variables affects their estimated relationship with household car ownership and to investigate potential threshold effects. To do so, variables of interest were computed within seven increasingly larger walking distance buffers (from 400 m to 1600 m by steps of 200 m) around each observed household of the Montréal 2018 Origin-Destination Survey (“network bands” concept). A series of GBM models were run for two subsamples of households: *1adultHH* and *2+adultsHH*, varying one buffer size for one variable at a time while keeping the other variables’ buffer at a reference value of 1 km. For both subsamples, the included BE variables have a higher cumulative relative influence than included sociodemographic (SD) variables. Results of the compared relative influence and the partial dependence plots of the three more “traditional” measures of the built environment (density, diversity, and design) are consistent across tested buffer sizes for both sub-models, indicating that those measures are not too sensitive to the distance selected for their measurement. This could be explained by their relative nature i.e., by being averaged over surface areas, and the fact that these are usually considered “proxy” measures of built environment. They also exhibit the most linear relationships of all variables with the probability of being fully motorized and can thus “safely” be used in logistic regression commonly used for modelling car ownership.

In contrast, accessibility measures to shared mobility resources (carsharing, bikesharing) and to local commercial amenities (grocery stores) all exhibit important changes to their relative influence within the models when the size of the buffer used for calculation changes gradually from 400 m to 1600 m. Furthermore, the partial dependence plots of those variables show clear threshold effects on the probability for both household types to be fully motorized when small buffers are used (≤ 800 m). In terms of accessibility to transit, access to a metro station (dummy) was the least important BE variable for both household types and for all tested buffer sizes. This does not mean that accessibility to the metro network does not affect people's car ownership decision, but rather that the method for computing the variable (a dummy within a buffer) might not be optimal to capture the true effect of the metro network. An alternative method of calculation was tested: the shortest walking distance to the nearest station. Measured this way, the variable

performed much better in the models, achieving a relative influence of about 10% for both models of household subsamples, second only to population density among included BE variables. This result serves as a caution to any researcher and practitioner looking to include rail accessibility in car ownership modelling: the accessibility calculation method matters.

The relative influence of accessibility to bus stops (the number within the buffer) was among the lowest for BE variables included ($\sim 3\%$) but was very consistent across tested buffer sizes. However, the shape of the partial dependence functions changed drastically between buffer sizes. The smallest buffer (400 m) showed the sharpest decline in car ownership probability as the number of bus stop increases and thus confirms that they are better suited to capture the effect on car ownership than larger buffers such as 1200 m or 1600 m (~ 1 -mile). While access to bus stops is a decent measure, the effect of bus accessibility on car ownership might be best captured in future research by including a level-of-service indicator at those bus stops. Overall, our results indicate that choosing the right scale (size of buffer or aggregation units) when computing accessibility variables for car ownership modelling is critical as it can lead to very different results. Furthermore, most accessibility variables exhibit non-linearity with car ownership probabilities, i.e., changes in probabilities show threshold effects where rapid changes are observed below or above a certain value followed by no or very slow changes. Thresholds effects are strongest when the variables are computed within small buffers. This indicates that caution is advised when including those buffer-based continuous variables in logistic regressions which usually assume homoscedasticity.

In terms of transport and planning policy implications, threshold values identified and summarized in Table 6 and Table 7 provide some empirical evidence on which values to aim for (e.g., number of opportunities, density value) and what distances to attain these values should be considered to support car-light and car-free living for a diversity of households.

A few limitations need to be mentioned. First, while income was controlled for in the models, its known heterogeneity to the influence of BE (Bhat & Guo, 2007) might not be adequately captured by the partial dependence plots method used. Second, measures of accessibility to work opportunities were not included and should be in future research. From a methodological viewpoint, PDP produced from GBM can only approximate the relationship between explanatory variables and the dependent variable and their accuracy can be low in the presence of complex

interactions between variables (Hastie et al., 2009). Another important limitation is the inability for the model to distinguish the “true” effect of BE on car ownership decisions from the potential effect of residential self-selection. High-density, mixed-use neighborhoods with high accessibility to mobility resources and local opportunities might attract households less inclined to car ownership, which could explain part of the observed relationship between the analyzed BE variables and household probabilities of being motorized.

Finally, future research should use alternative modelling methods with datasets from other cities to validate the threshold values obtained here - i.e., “how many” of each BE attributes – are necessary to influence household car ownership decisions and most importantly, validate what is the network distance required to reach those value.

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7.6.2 CRediT authorship contribution statement

Jérôme Laviolette: Conceptualization, Methodology, Software, Formal analysis, Writing – original draft. Catherine Morency: Conceptualization, Writing – review & editing, Supervision. E.O.D. Waygood: Conceptualization, Writing – review & editing, Supervision.

7.6.3 Acknowledgment

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CHAPTER 8 ARTICLE 4: CAR OWNERSHIP OR CARSHARING?

LATENT CLASS MODEL OF MOBILITY TOOL OWNERSHIP DECISIONS INCORPORATING CAR-RELATED ATTITUDES

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ABSTRACT

As cities are looking for ways to reduce car use and ownership, there is evidence that carsharing services can contribute to reach this goal by providing households with an alternative to ownership for access to a car. Because of obvious interdependence in the choice of how many cars to own and the decision to join a carsharing service, there is a need to model both decisions jointly. Previous research also suggests that important heterogeneity due to personal preferences might affect car ownership decisions and to a greater extent, carsharing membership decisions. This paper uses a survey of ~2000 respondents from Montréal, Canada to investigate how taste heterogeneity due to attitude toward the car and travel might influence the effect of built environment and household sociodemographic characteristics on the joint decision. This is done through a Latent-class Multinomial logistic model where attitudes are entered in the class-allocation model. Results indicate the presence of two psychological profiles (“car oriented” and “social-conscious”) in similar proportions (46 % and 54 %) that differ significantly in how they incorporate carsharing in their portfolio of car accessibility tools. “Car-oriented” households own systematically more cars and are less likely to subscribe to carsharing than “social-conscious” households while “social-conscious” are more sensitive to sociodemographic and built environment characteristics in their decision. For example, availability of carsharing vehicles within walking distance only affects this latter class in selecting carsharing over ownership. In terms of policy implications, this suggests that increasing access to carsharing services might not work for everyone and that other strategies are needed to encourage car-oriented households to reduce car ownership even in the most central neighbourhoods.

Keywords: Car ownership; Carsharing; Attitudes; Built environment; Latent-class choice model

8.1 Introduction

Facing the urgency of the climate crisis, cities around the world need to put in place a vast array of strategies to reduce reliance on the private automobile (IPCC, 2022). The high burden of excessive car ownership and car use on quality of life, public health, social inequalities, the environment, public and private finances has been well documented for decades (e.g., Gärling & Steg, 2007; Gössling et al., 2019; Parry et al., 2007; van Schalkwyk & Mindell, 2018).

In this context, shared mobilities have demonstrated their abilities to be transformative forces in urban settings (Maginn, Burton, & Legacy, 2018). Among shared mobilities, station-based (or “traditional”) carsharing services, which provide convenient short-term access to a vehicle through a membership have been shown to lead to an overall net reduction in car ownership (Giesel & Nobis, 2016; E. W. Martin et al., 2010) as well as in vehicle-kilometers travelled and green-house gas emissions (E. W. Martin & Shaheen, 2011). Based on user surveys, estimations ranges from 9 to 13 vehicles avoided for each carsharing vehicle in North America (through car shedding and postponing of vehicle purchase) (E. W. Martin et al., 2010).

In a city with a high quality and accessible carsharing service, a membership to such service can be a convenient alternative to car ownership for households looking to have an easy, regular, and low-cost access to a car. When 10 to 20 % of households in certain neighbourhoods have a carsharing subscription, its presence cannot be ignored when modelling car ownership. Neither can it be included as an exogenous explanatory variable in the model due to obvious interrelation between the choice of car ownership and carsharing membership (Becker et al., 2017) and vice-versa when modelling carsharing (Mishra et al., 2015). In this context, researchers have started to jointly model carsharing in a continuum of medium and long-term household decisions of mobility tool ownership that can also include other tools such as seasonal transit passes (Becker et al., 2017). Despite the potential offered by such modelling frameworks to investigate what factors affect household decisions to incorporate carsharing in their mobility tool portfolio, very few studies have been published using this approach outside of stated choice experiment.

An additional issue relates to taste heterogeneity within the population for car ownership and carsharing services. As carsharing services are expanding within cities, an increasing number of households can access a wider number of shared vehicles within walking distance, increasing convenience of the service. It is in the interest of the operator, but also of cities (as mentioned

above), to increase the share of households choosing carsharing as a substitute for vehicle ownership, including for a second or third vehicle. In an earlier study, Sioui et al. (2013) combined carsharing membership survey data with large-scale OD survey data from Montréal to compare carsharing members to typical households. They showed that for similar households in terms of sociodemographic characteristics and household locations, those with a carsharing membership had: 1) much lower vehicle ownership rates and, 2) never reached the level of car use that one or 2+ car households have. A more robust methodology using propensity-score matching on the California Household Travel Survey found similar results in San Francisco (Mishra et al., 2015). This indicates the presence of important heterogeneity in choosing carsharing over vehicle ownership that cannot be explained by observed characteristics such as household location, the built environment and sociodemographics. The above is in line with what is known from the literature on consumer behaviour (e.g., Keane & Wasi, 2013) and transportation research (e.g., Hess, 2014; S. H. Kim & Mokhtarian, 2018), that not everyone will be influenced similarly by external factors, *including* the availability of carsharing vehicles within one's neighbourhood.

One important source of heterogeneity are personal preferences arising from attitudes toward travel and various modes of transport. While there has been an increased interest in incorporating attitudes in travel behaviour research in general (Kroesen & Chorus, 2018), applications to car ownership modelling remains rare (Moody & Zhao, 2019) and even scarcer in mobility tool ownership modelling (Becker et al., 2017). Furthermore, there is evidence that preference for car ownership is not only associated with instrumental aspects of the car, but also from symbolic and affective values associated with its ownership and use (Gatersleben, 2011; Moody & Zhao, 2019; Steg, 2005). One important question that arises is how personal preferences, captured as attitudes toward the automobile and travel (including symbolic and affective aspects), might affect the relationship between availability of shared vehicles and the choice of carsharing as a viable way to access an automobile.

The objectives of the current research are two-fold: 1) Investigate how car-related and travel attitudes can explain some of the previously unobserved taste heterogeneity in the long-term household decision of car ownership and/or carsharing in the context of high availability of carsharing services; 2) Investigate how those attitudes might moderate the effect of built environment (BE) and household sociodemographic (SD) characteristics on the joint choice of car ownership/carsharing. The hypothesis is that households that are more car oriented will be less

affected in their car ownership/carsharing choices by various built environment characteristics (including availability of carsharing vehicles) than households that might be more public transit/active travel oriented. In other words, all else being equal, the latter will be more inclined to choose carsharing over car ownership.

To address the two objectives the current study uses a survey that was collected in Montréal in 2019 and the joint decision is modelled through a latent class discrete choice framework. While more advanced choice models have been recently proposed to handle the complex patterns of observed and unobserved taste heterogeneity (e.g., Keane & Wasi, 2013; Vij & Walker, 2014), the Latent-class Multinomial Logistic Models (LC-MNL) offer an intuitive way to easily interpret and understand how attitudes might affect taste heterogeneity in the choice process (Hess et al., 2011). This is done by incorporating attitudes in the class-allocation part of the model while keeping sociodemographic and built environmental characteristics in the utility function of the choice model. Furthermore, if more complex models might do a better job at estimating the choice process, well specified simpler models can make it easier to formulate clear, interpretable, policy recommendations that could be understood and applied by a wider audience.

The paper is structured as follows: section 2 reviews the literature on mobility tool ownership with a focus on latent-class discrete choice model and the integration of attitudes. Section 3 presents the data collection process, variable preparation and the carsharing ecosystem in the studied region (City of Montréal). It is followed by the modelling framework. Section 4 presents the results of the models with and without latent class and a deeper analysis of each class. The paper concludes (Section 5) on the implications for policies, for future research and the limitations of the current analysis.

8.2 Literature review

8.2.1 Car ownership modelling and the use of latent-class discrete choice framework

Car ownership is considered a medium-term decision by households and is widely recognized as a critical variable influencing various aspects of travel. It has received a lot of research attention in the last decades and has been analyzed with increasingly complex models (see review by

Anowar, Eluru, et al., 2014). In their review, the authors report that latent-class discrete choice models are an “elegant approach” to accommodate the heterogeneous ways in which explanatory variables might affect the choice process and recommend it for cross-sectional studies of vehicle count.

A number of authors have examined vehicle ownership using latent-class choice models. J. Zhang et al. (2009) used a latent-class discrete choice framework to model car types (small, medium, large) at the household level. In their model, each latent class represents a different household decision-making mechanism using different forms of utility functions to model interactions between household members. Beck, Rose & Hensher (2013) used a LC-MNL to model the choice of vehicle types in a stated choice experiment testing the effect of emission-based congestion charge. They included sociodemographics and seven measures of attitudes about climate change, vehicle externalities and environmental policy in the class allocation model. They concluded that the latent-class framework greatly improved the understanding of behavioural response to policy proposals such as an emissions-based congestion charge. Anowar, Yasmin, et al. (2014) compared the performance of LC-MNL and LC ordered logit (LC-OL) to their traditional versions (MNL and OL) using large-scale Origin-Destination survey data from Québec City. They concluded that the LC models with two segments were superior to traditional versions in terms of model fit and that among the two LC models, the MNL was better. To study potential moderation effects, they used a combination of sociodemographic and built environment variables both in the segmentation models and the choice models. However, except for transit accessibility, not much explanation is provided on why some variables were in one part of the model, while others were in the other. Other applications of the latent-class discrete choice framework in transportation include mode choice (e.g., Bhat, 1997; Shen, 2009; Vij, Carrel, & Walker, 2013), road type choice (Greene & Hensher, 2003), residential choice (e.g., Y. Lee, Circella, Mokhtarian, & Guhathakurta, 2019; J. L. Walker & Li, 2007).

The work by S. H. Kim and Mokhtarian (2018) is probably the most relevant application of the LC-MNL framework for the current research. They used a LC-MNL model to investigate how attitudes can moderate the effect of sociodemographic and built environment influences on household car ownership decisions. In other words, they tried to understand how attitudes induce systematic heterogeneity within the population related to the number of vehicles owned. They used three attitudinal factor scores obtained from a factor analysis of attitudinal statements in the class

allocation model and included sociodemographic and built environment variables only in the choice model. They showed that a two-class solution ("auto-oriented" and "urbanite") offered the best model fit and that the LC model was better than the simple MNL. The latent-class approach enhanced the behavioural understanding of the choice process by showing for example that the "auto-oriented" were quicker to add cars with increased income and household size while "urbanites" were more sensible to built environment features.

8.2.2 Car ownership modelling and joint modelling of mobility tool ownership

With the rapid expansion of carsharing services in cities across the world, ownership is no longer the single means of access to a car (excluding taxis or similar). In response to this trend, more holistic mobility tool ownership frameworks have been proposed to model the joint decisions of households or individuals to own or access several tools of mobility. The number and types of tools vary and might include car ownership, carsharing membership, various transit passes, bicycle ownership, two-wheel motor vehicles, having a driver's licence and more (e.g., Becker et al., 2017; Habib et al., 2018; Kowald et al., 2017; Yamamoto, 2009). We focus here on mobility tool ownership modelling that includes carsharing in the choice set.

Station-based carsharing services having been available in Switzerland since 1987 (Becker et al., 2017) alongside an extensive public transit system, it is not surprising that researchers there have been pioneering the work on mobility tool ownership (e.g., Beige & Axhausen, 2006; Kowald et al., 2017; Scott & Axhausen, 2006; Weis et al., 2010). However, the inclusion of carsharing in the models was only recently applied by Becker et al. (2017) who used a multivariate Probit model to jointly model a portfolio of mobility tools (car ownership, carsharing, local and national transit passes). The method controls for endogeneity in the choice of multiple tool ownership by allowing the error terms of the utility function of the choice sets to be correlated. The model also included two attitudinal latent variables about transport pricing and infrastructure investment. The modelling is done at the individual level due to availability of information on mobility tool ownership and attitudes only for one household member. Car ownership is thus modelled as individual access to the household cars. Their model shows strong correlation effects between the ownership of each mobility tool, indicating common unobserved factors affecting the choices that are not captured by the included attitudes. They also confirm the role of built environment and show the importance of attitudes on mobility tool ownership, concluding that it cannot be ignored in

future modelling. Other joint models that combine car ownership and carsharing membership have been done in Toronto (Petersen & Sweet, 2019) and Seattle (Petersen, Zhang, & Darwiche, 2017), confirming important substitution effects between both options. The later research confirmed the effect of proximity to carsharing vehicles on carsharing membership. Finally, Fatmi and Habib (2016) did not consider carsharing but used a Latent-Class MNL to model five mutually exclusive combination of travel tools ownership among the elderly population of the Greater Toronto Area. They considered transit passes, car ownership and driver's licence ownership as the travel tools. Their segmentation model was based on a single variable: trip frequency.

8.2.3 Carsharing, car ownership and the role of attitudes

As previously described, there is now extensive evidence using various methodologies (user surveys, analysis of large-scale travel surveys, joint modelling) in various contexts (Europe, North America) that station-based carsharing can reduce car ownership by either allowing households to get rid of an existing vehicle or postpone/forgo the acquisition of a new one (Becker et al., 2017; Cervero et al., 2007; Duteau, 2017; Giesel & Nobis, 2016; Klinevicius et al., 2014; E. W. Martin et al., 2010; Mishra et al., 2015) which leads to a reduction in vehicle-kilometers travelled (VKT) and emissions (e.g., E. W. Martin & Shaheen, 2011; Nijland & van Meerkerk, 2017). While the evidence suggests that the impacts are not as strong as for station-based carsharing, free-floating carsharing also seems to reduce car ownership through the same mechanism (Becker et al., 2018; E. Martin & Shaheen, 2016), the impact being less pronounced for the highest income users (Le Vine & Polak, 2019).

Earlier studies indicate that station-based carsharing members tend to be between 25 and 45 years old, be more educated and live within smaller (1 or 2 persons) urban household with medium or upper income levels (Le Vine, Zolfaghari, & Polak, 2014; E. W. Martin et al., 2010; Sioui et al., 2013). Another set of studies indicate that neighbourhood' built environment characteristics are more correlated with carsharing membership than sociodemographics (Celsor & Millard-Ball, 2007; Stillwater, Mokhtarian, & Shaheen, 2009). That research reports that carsharing is most successful in urban areas well served by public transit, with a high proportion of active travel and low car ownership. In such situations, carsharing serves as a complement to public transit and active travel. Note however that most of those studies were published roughly a decade or more

ago. With the growing trend of carsharing services around the world and the effect of the Covid-19 pandemic, user profiles might have evolved in recent years.

Despite the evidence of strong heterogeneity in the decision of how households choose to access cars (ownership, carsharing, both) that cannot be explained by observed sociodemographic and built environment attributes (Mishra et al., 2015; Sioui et al., 2013), the incorporation of attitudes in joint modelling of car ownership and carsharing is very limited. Attitudes are either integrated into the modelling of stated preference survey of mode choice (Ciari & Axhausen, 2012; J. Kim, Rasouli, & Timmermans, 2017; W. Li & Kamargianni, 2019) or on the intention of joining a carsharing program (e.g., Efthymiou & Antoniou, 2016; Paundra, Rook, van Dalen, & Ketter, 2017). These studies can nonetheless inform us on the role of various attitudes on the decision to choose carsharing.

In their choice experiment, Ciari and Axhausen (2012) report that the choice of carsharing for trips is mostly driven by cost and not inclined to any ideological considerations. On the contrary, in their latent-class discrete choice modelling of intention to replace an existing car or future car purchase by carsharing, Liao, Molin, Timmermans, and van Wee (2020) found that most carsharing system attributes (cost, availability, accessibility) had essentially no effect on the car-ownership oriented segment (~80 % of sample). This indicates the presence of strong unobserved factors affecting preference for the service. Using a hybrid choice and latent variable (HCM) model to analyze the propensity to join carsharing among 18-35 years old adults in Greece, Efthymiou and Antoniou (2016) observed that lower to medium income, environmental consciousness and dissatisfaction with current travel are positively associated with intention to join carsharing. J. Kim et al. (2017) found an opposite effect of environmental consciousness on choosing carsharing in their HCM model of stated preference mode choice to work. Relevant to the current study, another of their latent variables measured the symbolic value of the car, which was positively associated with choosing the private car and negatively associated with choosing a shared vehicle.

This review indicates important gaps in the literature: with the exception of the work by Becker et al. (2017) (1) joint modelling of *observed* carsharing and car ownership long-term decisions is limited (i.e., revealed rather than stated preference) and (2) analysis of the role of travel- and car-related attitudes on the joint decision has not been studied as far as the authors know.

8.3 Method

8.3.1 Data sources

8.3.1.1 Survey data and collection method

Two main data sources are used in the analysis: (1) The City of Montréal Mobility Survey (CMM-survey) 2019 and (2) the large-scale Montréal Origin-Destination survey (OD-survey) 2018.

City of Montréal Mobility Survey 2019

The City of Montréal Mobility Survey (CMM-survey) was designed on a web-based platform named Evolution developed by the Mobility Chair at Polytechnique Montréal. It was distributed and promoted by the City of Montréal for a period of one month (from May 8 to June 7, 2019) using the portal *Réalisons Montréal* (<https://www.realisonsmtl.ca/>) and shared using social media and other means. The survey area was limited to the City of Montréal and the 15 other municipalities located on the Island of Montréal. Its original goal was to explore the determinants of travel behaviour, including the incentives and deterrents to the use of various modes and the difficulties encountered in adopting sustainable travel behaviour and reducing car ownership. The survey asked questions about individuals, household composition, car ownership, usual places of work or school for a typical week for all adults of the households, other usual places visited by car and general attitudinal questions about mobility.

Due to the nature of the data collection process, the sample is non-probabilistic and cannot be used to make inference about the general population of the study area. Despite this, the sample can nonetheless be used to study participants' behaviours and the relationship between variables. A total of 2577 respondents completed the questionnaire representing households with a total of 5804 people. The distribution of the sample differs from the reference population as measured in the 2016 Canadian census in terms of household size, age of household members and spatial location of households (Morency et al., 2019). Fewer single-person households and more two-person households responded. A similar proportion for larger households responded (as compared to the census data). Those aged 25 to 44 years old are overrepresented while those aged 16 to 24 are slightly underrepresented and those aged 65 and above are highly underrepresented. There is also

a spatial misrepresentation with higher response rates in the central neighbourhoods than in the eastern and western suburban areas of the Montréal Island.

Large-scale Montréal OD Survey 2018

This is a conventional telephone-based and web-based (since 2018) survey conducted every five years since 1970 to record the trips of about 4-5 % of resident households over one fall weekday using a stratified sampling and weighting method based on the Canadian Census to be representative of the population of the Greater Montréal Area. The weighting process is done at the municipal sector, zones similar in size to transport analysis zones (TAZ). For the present paper, only data for the Island of Montréal subregion is used, which contains records for 33,202 households housing 71,914 individuals.

8.3.2 Built environment characteristics and accessibility at home location

Precise household coordinates were collected in the survey using an interactive map embedded on the web survey interface allowing respondents to pin their household location. They could also supply their address and postal code. To compute built environment characteristics around home locations, walking distance buffers of 1-km are built from household coordinates. This way of representing the neighbourhood, termed “network bands” by J. Y. Guo and Bhat (2007), is argued to be conceptually and methodologically superior to “fixed neighbourhood” definitions such as a census tract (Laviolette, Morency, & Waygood, 2022, under review-b). Using those walking distance buffers, measures of population density, design (four-ways intersection density), diversity (Shannon’s entropy for five land-use categories) as well as local accessibility to opportunities (grocery stores) were computed. Access to carsharing vehicles was computed by summing within each walking buffers the number of station-based carsharing vehicles. The dataset of carsharing stations was obtained from *Communauto*, the sole provider of carsharing services in the city at the time of the survey. Further details about the carsharing services available in Montréal are provided in section 8.3.4.

In addition to built environment measures at the neighbourhood level, a measure of transit accessibility to opportunities was prepared. Accessibility by transit was selected over accessibility to transit as it provides a more realistic indicator of the ease of access to destinations by alternatives to the automobile. As described next, the measure used considers walking time to and from the

public transport access points so access to transit is considered through this. Furthermore, research has shown that transit accessibility is a key complementary measure to carsharing services that is associated with higher rates of adoption (Becker et al., 2017; Stillwater et al., 2009). The platform *Transition*, developed by Polytechnique's Montréal Mobility Chair, was used to compute transit accessibility maps (Bourbonnais, 2014-2019; Bourbonnais et al., 2014-2019). The final variable represents the percentage of all the Montréal metropolitan area work destinations accessible within 45 minutes by transit during the morning peak period. More details about the calculation methodology are included in Appendix A.

Finally, Table 8.1 describes the sociodemographic, built environment, and transit accessibility characteristics for the final sample of households selected for modelling.

Table 8.1 Descriptive statistics of modelling sample

Variable	N	%	Mean	SD
Total	2184	100%	-	-
<i>Sociodemographics</i>				
Average age of HH adults (≥ 18 years old)			42.8	13.2
NB of adults in HH			1.85	0.69
1	625	29%		
2	1336	61%		
3+	224	10%		
HH with children (≤ 15 years old)	547	25%		
NB of workers			1.43	0.8
0	311	14%		
1	731	33%		
2	1063	49%		
3+	80	4%		
DA's Median HH after-tax income (k CA\$)			48 768	15004
<i>Built environment</i>				
Pop. Density WD-1 km [pers./ km ²]			9340	3018
Entropy (5 cat.) WD-1 km			0.59	0.13
Density of 4-ways intersection [int./km ²]			36.4	13.4
NB carsharing vehicles - WD-1 km			23.5	21.9
HH with at least 1 CS veh. within 15 min.	1933	88%		
Transit access: % of work dest. in 45 min.			34.6%	15.8%
<i>Car ownership and carsharing membership</i>				
NB of cars in HH				
0	756	35%		
1	1113	51%		
2+	316	14%		
HH with carsharing membership	694	32%		
Car ownership / Carsharing joint status				
No car, no carsharing	307	14%		
Carsharing only	449	21%		
Car ownership only	1184	54%		
Car ownership and carsharing	245	11%		

Note: CS = carsharing; DA = dissemination area; HH = households; NB = number; WD = walking distance

8.3.3 Attitudinal measures

The current analysis uses a set of 12 attitudinal statements about daily mobility. The survey questions were derived from previous research about attitudes toward the car and other modes, including instrumental, affective, and symbolic factors (e.g., Hunecke, Haustein, Böhler, &

Grischkat, 2010; Steg, 2005). As eight of the 12 statements relate specifically to the car, only respondents with a driver's licence were asked to answer these questions as having a driver's license is a legal prerequisite to drive a car or have a carsharing membership. The statements were preceded by the sentence "When thinking about your daily trips, please indicate how much you agree with the following statements" and was measured using a slider scale question on the web interface going from strongly disagree to strongly agree resulting in a score from 0 to 100. The sliders embedded in the web interface were designed in a way that respondents had to click on the slider to activate it and move it within the 0-100 range. This allowed for the detection of missing cases. Among the 2243 respondents with a driver's licence, 59.1 % answered all 12 statements, 15.8 % missed one and 22.5 % missed between 2 to 6 statements. A total of 58 (2.5 %) were discarded for having not answered 7 or more of the 12 attitudinal statements. This leaves 2185 cases on which was performed a two-step principal component analysis (PCA) to extract the underlying attitudinal constructs. The first step was multiple imputation for the missing values. For this, regularized PCA using the Expectation-Maximization (EM) algorithm method explained and tested by Van Ginkel, Kroonenberg, and Kiers (2014) and implemented in the R package *missMDA* was used. Then, the second step was to perform regular PCA on the dataset with imputed values. Two components had Eigenvalue above Kaiser's criterion of 1.0, explaining 53 % of variance. Because the scree plot was rather ambiguous, a careful analysis of 2, 3, 4 and 5 components solutions indicate that 2 or 4-components solutions with Oblique (oblimin) rotation are conceptually and theoretically relevant. The four-components solution was selected and the mean, standard deviations, and factor loadings for the 12 statements are presented in Table 8.2.

Table 8.2 Descriptive statistics and rotated factor loadings (PCA, oblimin) for the 12 attitudinal statements

Statements	Mean	Std. Dev	Rotated factor loadings (oblimin)			
			Car Appreciation	Car values	Social identity	Independence
I have fun driving a car	42.6	35.0	0.90			
I feel safe when I travel by car	48.6	33.3	0.82			
I find it more convenient to travel by car	45.9	37.0	0.54	0.34		
To be in a car is comfortable and relaxing	41.9	33.7	0.89			
It is important for me to minimize my trips environmental footprints	81.8	24.8		-0.88		
My transportation mode allows me to show who I am	34.1	36.4			0.72	
It is important to have my own space when I make trips	38.3	33.7				0.54
The car is the most suitable mode for someone like me	27.8	33.7	0.43	0.47		
Using a car is consistent with my values	22.7	28.1	0.37	0.54		
It is important for me to not depend on others for my trips	72.6	29.9				0.95
People that are important for me think it's normal to get around by car	33.5	33.1			0.77	
I always made my trips by car	21.8	29.4		0.42		

8.3.4 Carsharing services in Montréal

Traditional station-based carsharing has been available in Montréal since 1995, making it the oldest market in North America (Wielinski, 2018). Estimations specific to Montréal indicate that each station-based carsharing vehicle replaces approximately 10 private cars (Braham, 2011). In 2013, the Montréal based operator *Communauto* started a free-floating service in complement to its existing station-based service. Since then, both services have been greatly expanded. Details about membership to both services can be found on the operator's website (Communauto, 2022). As of September 2018 (eight months before the data collection period of the survey used in the current study), there were 964 station-based vehicles scattered across 368 stations located on the Montréal Island, with a few more located in the north and south suburbs. The *Communauto* free-floating service had 600 vehicles available in September 2018 scattered across an area of 109.5 sq km, or 22 % of the Island area. Another operator, Car2Go, was also offering a free-floating

carsharing service in Montréal from 2013 to February 2019 but was no longer available at the time of the data collection (May-June 2019).

A map of the free-floating area and the location of carsharing stations offered by *Communauo* are presented in Figure 8.1. While the free-floating zone and the stations are mainly located in the central part of the Island, accessibility to both services by the Montréal population is nonetheless very high. In total, 53 % of the Montréal Island households (2016 Census) are located within the free-floating zone and 72 % of the households have at least one carsharing vehicle within a 15-minute walk while 55 % have at least four.

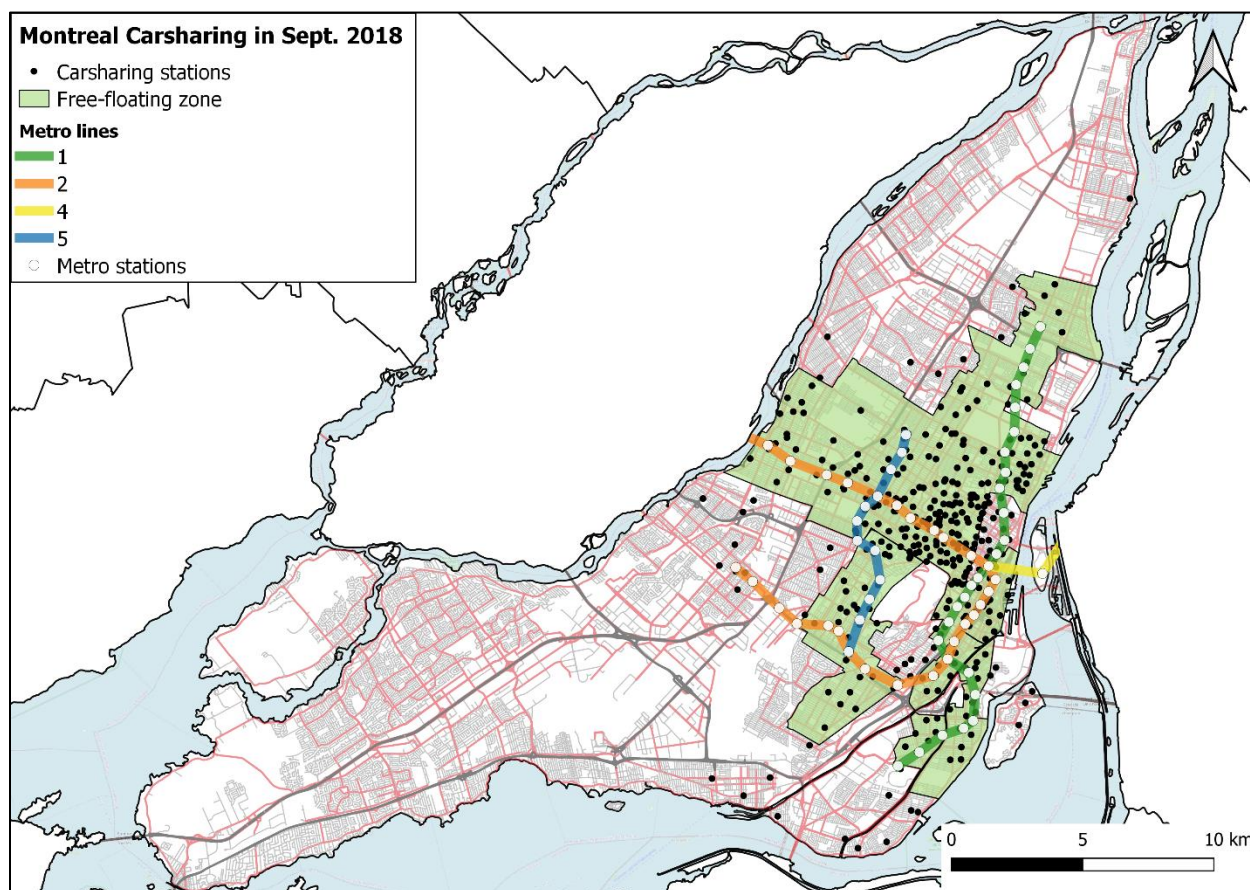


Figure 8.1 The Montréal carsharing ecosystem as of September 2018

8.4 Modelling framework

8.4.1 Modelling car ownership and carsharing membership as a joint household decision

The literature on car ownership modelling has, in most case, considered the decision to own cars as a household level decision (Anowar, Eluru, et al., 2014). To what extent that is true in practice can vary depending on household composition. For single adult households (with or without children below driving age), this, of course, holds true. For households with two or more adults, this assumption might vary based on the relationship between household members. For example, for couples in a long-term relationship who share finances (with or without children), the decisions on how many cars to own is likely the result of intra household debates between members and can thus be approximated as a household level decision. On the contrary, for adults sharing a house or apartment (i.e., housemates/flatmates/roommates), the decision to own a car is very likely a personal decision and the household level assumptions is therefore erroneous. Unfortunately, the level of information collected in most travel survey does not allow the identification of this latter household type with certainty. Other types of households where this assumption might not hold are multigenerational households (e.g., driving age children living with their parent and having “their own car”, senior parents living with their son/daughter and their son/daughter in-law). These atypical households remain nonetheless rare. Data analysis of the 2016 Canadian census for the Island of Montréal indicates that these “other types” of households represent only 6.8 % of all households (Ville de Montréal, 2020).

The same consideration about which types of households are likely to consider carsharing as a household level decision applies with even more caveats. That is, carsharing membership is an individual membership. However, in the region of the current study, Montréal’s carsharing provider, *Communauto*, offers Family memberships with substantial discounts for additional drivers living at the same address (Communauto, 2022). Furthermore, anyone with a *Communauto* membership can drive the carsharing vehicles, even if the reservation for the vehicle was made by someone else. These features make it convenient for a family to use carsharing as a substitute to car ownership altogether or as a supplement to car ownership.

One hypothesis is that accessibility to carsharing vehicles within one's neighbourhood allows households to consider a membership as an alternative or supplement to car ownership. A first option is for a household to neither own a car nor subscribe to a carsharing membership. This could be the result of a number of constraints (e.g., financial, strong parking limitations, functional limitations to driving) or simply by personal choice, i.e., the household sees a need to access a car on a regular basis or chooses to based on its personal values about the negative consequences of cars. For such households, the utility of not having a car access is superior to that of accessing a car through either option (sharing or owning). Other means of occasional car access are still available to such households which are not modelled here (e.g., traditional car rental, borrowing someone's car, taxi services, peer-to-peer car rental). The next logical step if a household has a higher need (real or perceived) for car access, is to consider either car ownership *or* carsharing. A fourth option, more likely to be considered by multi-adult households, is to have both a car and a carsharing membership. In such a situation, carsharing can serve as a second or even third car for the household. Individually, this can translate to each household member having a carsharing membership and access to the household car(s), or one household member being the dominant user of the household car while the other member(s) has a carsharing membership. In summary, if the number of household cars is not considered, the choice situation can be simplified to four mutually exclusive alternatives: (1) no car and no carsharing, (2) carsharing membership only, (3) car ownership only and (4) car ownership and carsharing. Discrete choice models can be used to estimate these choices.

An important issue of choosing the household as the modelling unit is that attitudes are individual characteristics, and, in the present case, are only measured for the survey respondent. This is a common problem when trying to integrate individual attitudes in mobility tool or car ownership models. One method is to circumvent the problem by modelling the mobility tool ownership at the *individual level* by considering car ownership as the level of access to the household car(s). This is the approach taken by Becker et al. (2017) who converted a three level access (*always*, *upon consultation* and *never*) to a two level access: available (*always*) and unavailable (*upon consultation* and *never*). This means however, that an individual in a 2-person household sharing one car will likely be considered as having no access to a car, which is erroneous and problematic. S. H. Kim and Mokhtarian (2018) modelled car ownership as a household decision and considered individual attitudes as *proxies* to household attitudes on the basis that attitudes are more likely to

be similar within households (homophily) than between households. Looking at within household differences in car and travel-related attitudes using latent class models, J. H. Lee and Goulias (2018) indicate that they did not find evidence of “strong” homophily. A deeper look at their results however reveals that “car lovers”/“neutral” and “transit lovers”/“neutral” cohabitation are common, but cohabitation between people with more opposite attitudes (“Car lovers” and “Transit lovers”) seems very rare. Based on those results, we opted here for the same approach as S. H. Kim and Mokhtarian (2018), adding that 29 % of our sample are one-adult households and 61 % are two-adults households, leaving only 10 % of households being more complex with 3-plus adults. Using individual attitudes as proxy for household attitudes thus seems reasonable.

8.4.2 The multinomial logistic model

The multinomial logistic model (MNL; McFadden, 1974) belongs to the random utility maximization (RUM) class of models and is one of the most used discrete choice models in the field of transportation. Furthermore, its unordered structure has been demonstrated to be superior to an ordered structure to model household car ownership decisions (Anowar, Yasmin, et al., 2014; Bhat & Pulugurta, 1998; Potoglou & Susilo, 2008). The popularity of the model comes from its ease of interpretation and estimation: it has a closed-form expression and estimation can be achieved by maximum likelihood (ML). MNL is widely available in many statistical software. However, this simplicity comes with two important drawbacks. First, because the errors are assumed to be identically and independently distributed, this leads to the Independence of Irrelevant Alternatives (IIA) property which can be quite restrictive. In practice this is an unrealistic assumption that is often violated (Croissant, 2020), particularly if important explanatory variables affecting the utility are missing (Train, 2009). Second, it lacks flexibility in accommodating preference variations across the population (Sarrias & Daziano, 2017). It can only capture systematic taste variations arising from observed individual characteristics of the decision makers.

While imperfect, the MNL is fairly robust to misspecification and can approximate random taste variation well (Train, 2009) and will serve as a first approximation of the choice process, from which subsequent models allowing for taste heterogeneity will be compared. For this first model, the hypothesis is that the utility of choosing one car accessibility option over the others is a function of alternative specific attributes and individual characteristics:

$$U_{nj} = V_{nj} + \varepsilon_{nj} \quad (8.1)$$

$$V_{nj} = \beta_{0j} + \beta_j SD_n + \beta_j BE_n \quad (8.2)$$

Having ε_{nj} independently and identically distributed (extreme value type I) for all alternatives representing the unobserved part of the utility function. SD is a vector of observed variables characterising the household (size, composition, income, etc.) and BE is a vector of built environment attributes (density, diversity, design, accessibility, etc.) defining the neighbourhood at the home location. Those attributes are specific to each respondent's household but are not alternative specific. Of course, the utility of each alternative to access a car is likely affected by alternative specific attributes such as, but not restricted to, cost, convenience, and comfort. However, like in most models of observed car ownership decisions, these characteristics are not measured and thus unobserved to the analyst. The contribution of these unobserved attributes to the overall utility of each alternative is captured in the alternative specific constant β_{0j} . Because only differences in utility matter, that constant along with the vector of coefficient β_j are fixed to zero for one of the alternatives (the reference alternative).

8.4.3 The latent-class multinomial logistic model

One way to account for taste heterogeneity is through the latent segmentation framework which relaxes the assumption of IIA (Greene & Hensher, 2003). In that framework, the population is assumed to be segmented into C unobserved, latent classes, each class having different tastes in relation to the choice process. This is accommodated by having different values of the vector of coefficients β (Hess, 2014). In other words, in a model with C classes, there will be C vectors of β coefficients determining how each attribute affects the choice process. A downside of using a latent class structure is the necessity to specify the number of classes, even though the classes are unobserved, and their number is *a priori* unknown to the analyst. The class allocation model is probabilistic, with an individual n having the probability p_{nc} to belonging to class c , having $0 \leq p_{nc} \leq 1$ and the probabilities for an individual to belong to each class summing to unity.

While not an absolute requirement, the class allocation often takes a logit form (Hess, 2014), where p_{nc} is given by:

$$p_{nc} = \frac{e^{\gamma'_c h_i}}{\sum_{c=1}^C e^{\gamma'_c h_i}}; c = 1, \dots, C \quad (8.3)$$

Having γ_c as a set of constants with γ_1 fixed to 0 and h_i a vector of individual covariates. By normalizing to zero the parameter of the first class, a model can be identified. In the most basic version of the latent class logit model, no variables are entered in the class allocation model, which leads to every individual having the same prior probability to belong to class c : $p_{nc} = p_c, \forall n$.

The probability of individual n selecting alternative i conditional to belonging to class c is:

$$P_n(i | c) = \frac{e^{V_{nic}}}{\sum_j e^{V_{njc}}} \quad (8.4)$$

Where V_{nic} takes the form of equation (8.2). And the unconditional probability of decision maker n choosing alternative i is:

$$P_{ni} = \sum_c^C p_{nc} \frac{e^{V_{nic}}}{\sum_{j=1}^J e^{V_{njc}}} \quad (8.5)$$

As for estimation, Greene and Hensher (2003, p. 683) explain that “this is a relatively difficult optimization problem, though not excessively so” and thus, maximum-likelihood can be used, however, the likelihoods are not globally concave (Sarrias & Daziano, 2017). This means that the starting values for the parameters to be estimated are important to avoid finding only local maxima instead of the global maxima.

The model is estimated with the *gmnl* package in R developed by Sarrias and Daziano (2017), which uses by default the BFGS optimization algorithm to maximize the log-likelihood function. The authors recommend trying alternative optimization algorithms, Newton-Raphson (NR) or Berndt-Hall-Hall-Hausman (BGGG), if convergence fails. This might happen because with an increasing number of classes comes a proliferation of parameters to be estimated while the number of observations and the variance of explanatory variables in each might not be able to produce a coherent estimation for all parameters.

Finally, one advantage of the LC-MNL over the more common mixed-logit model or even the more advanced Mixed-Mixed Logit Model is that it does not require making specific assumptions

about the distribution of parameters across decision-makers (Greene & Hensher, 2003). Additionally, both Greene and Hensher (2003) and Shen (2009) concluded that the LC-MNL offers superior model fit than the mixed-logit when tested on their datasets, while both being careful not to suggest that their results are evidence that this is always the case. And finally, the use of a latent class framework facilitates interpretation by making it a more intuitive way to understand the role of heterogeneity on the choice process and has been recommended for transportation applications by Hess et al. (2011).

8.4.4 Integrating attitudinal covariates in class allocation

A more realistic way to account for preferences (or taste) heterogeneity is by allowing some characteristics of the individual to enter the class allocation model. In previous research, sociodemographic characteristics have commonly been used for this purpose (e.g., Anowar, Yasmin, et al., 2014; Bhat, 1997; Vij et al., 2013).

Building on previous work (e.g., Daziano, Waygood, Patterson, & Braun Kohlová, 2017; S. H. Kim & Mokhtarian, 2018; Y. Lee et al., 2019), latent attitudes obtained from the PCA are entered into the class allocation model as *proxies* for the true values of attitudes. While the choice model and the segmentation model are estimated simultaneously, it remains a two-stage approach because the latent attitudes are estimated in the first stage (PCA) and the measurement error of the factor scores are not carried through to the segmentation model, which could lead to endogeneity bias and inconsistent estimators (Bhat & Dubey, 2014; J. L. Walker & Li, 2007). Guevara (2015) recognizes that this “proxy” method is not the optimal way to control for endogeneity bias in discrete choice model but can still correct in the right direction. It also remains the simplest way in terms of variable requirement and computational practicality. Furthermore, comparing results from a 2-stage method (latent attitude factor scores included as explanatory variable in MNL) to those obtained with a simultaneous estimation method using a hybrid choice model (HCM), Schmid, Schmutz, and Axhausen (2016, p. 19) concluded that coefficients estimates and standard errors were only marginally different between both models, thus leading to the same qualitative interpretation of modelling results.

Adding attitudes in the segmentation model allows for testing the hypothesis that taste heterogeneity in relation to the choice of car accessibility (ownership or sharing) might vary based on psychological characteristics of the individual. By keeping household sociodemographic and

built environment characteristics in the choice model, instead of integrating them in the class allocation model, this allows us to analyze the interactions between attitudes and SD and BE characteristics affecting the choice process. The framework is presented in Figure 8.2.

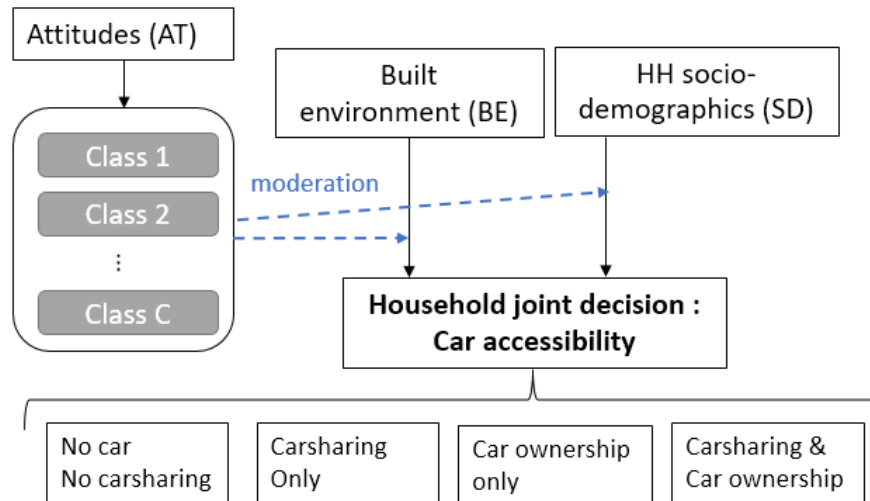


Figure 8.2 Proposed latent-class choice modelling framework

8.4.5 How many latent classes?

During the model building process, one must determine the number of latent classes. This number is *a priori* unknown, although in theory, previous research and knowledge of the process being studied can give indications on the number of classes to expect. As suggested by Masyn (2013), three information criteria that penalize the addition of new parameters are used: the Akaike's Information Criterion (AIC), the Bayesian Information Criterion (BIC) and the Consistent Akaike's Information Criterion (CAIC). Details about the calculation of each criterion are provided in Appendix B.

8.5 Results

As not all residents have access to a carsharing station in their vicinity, the sample for this study was limited to only individuals with access so that the choice would be possible from this perspective. The cut-off is set at one station-based carsharing vehicle within a 15-minute walk. This threshold might be conservative (allowing slightly more households) as recent research in the Montréal context has showed that carsharing availability really starts to have an effect on

household car ownership at four vehicles within a 10- to 15-minute walk (Laviolette et al., 2022, under review-b). However, one of the research objectives is to understand how access to carsharing vehicles influences household joint carsharing and car ownership decisions. Setting the threshold low allows us to test the hypothesis that increasing the number of vehicles available within a reasonable walking distance increases the likelihood of choosing carsharing to access a car. A total of 252 (11.5 %) households did not fit that minimum criterion and are removed, leaving 1933 observed households in the modelling sample. The dependent variable for all models is the joint car ownership/carsharing membership decision: 1) no car ownership and no carsharing; 2) carsharing only; 3) car ownership only; and 4) car ownership and carsharing. For all models, the reference category is (3) *car ownership only* as it is the most observed choice.

8.5.1 Base model: Multinomial logistic model

Like other studies using the LC-MNL (e.g., Anowar, Yasmin, et al., 2014; Daziano et al., 2017; Fatmi & Habib, 2016; S. H. Kim & Mokhtarian, 2018), the MNL model serves as a first approximation of the choice process of car ownership/carsharing decisions and a benchmark for subsequent models. In the final formulation, a total of eight individual explanatory variables are included: five household characteristics and three built environment attributes. Among the built environment variable tested, design (four-ways intersection density) and diversity (entropy) were discarded due to correlation with density and non-significance in the models. Results are presented in Table 8.3. In this model, only systematic (observed) heterogeneity arising from differences in SD and BE variables between households is accounted for.

Table 8.3 Base model - Multinomial Logistic model of joint car ownership / carsharing decision

Variable	Car Only (REF) 959 (49.6 %)	Car & CS Coeff. (SE) 238 (12.3 %)	CS Only Coeff. (SE) 444 (23 %)	No Car Coeff. (SE) 292 (15.1 %)
Intercept		-3.21 (0.679) ***	-1.721 (0.572) **	1.644 (0.64) *
<i>Household characteristics</i>				
Nb of adults		0.233 (0.132)	-0.366 (0.12) **	-0.605 (0.139) ***
Children (<15 years old) (dum)		0.566 (0.157) ***	-0.264 (0.148)	-0.775 (0.208) ***
Adults avg. age		-0.006 (0.007)	-0.018 (0.005) ***	-0.043 (0.006) ***
NB of workers		0.193 (0.134)	-0.116 (0.11)	-0.491 (0.125) ***
DA's median Income (kCAD)		-0.001 (0.005)	-0.002 (0.005)	-0.014 (0.007) *
<i>Built environment</i>				
Pop. density ('000s pers. / km ²)		-0.013 (0.044)	0.115 (0.037) **	0.045 (0.041)
NB of carsharing vehicles		0.01 (0.005)	0.014 (0.004) ***	0.009 (0.005)
Transit access to jobs		2.689 (0.84) **	2.869 (0.773) ***	2.059 (0.805) *
Model summary				
# of observations	1933			
# of parameters	27			
Log-Likelihood	-2169			
AIC	4392	BIC	4542	
McFadden Pseudo R ² (ρ^2)	0.087			

Note: CS = carsharing; Pop density is in 000's of pers./km²; NB of Carsharing vehicles within a 1-km walking distance; Transit access to jobs is the mean % of work destinations accessible in 45 min. by transit with a departure time between 7 and 8 AM

All household characteristics variables have a significant effect on the choice of at least one alternative. The presence of children in the household is positively associated with selecting carsharing *and* car ownership over car ownership only. However, the current model does not distinguish households with only one car from households with multiple cars. As household size increases, households are less likely not have a car or to have only a carsharing membership. Older households are more likely to own car than have only a carsharing membership or be carless. As for income, the variable included is a proxy: the median household income in the neighbourhood (using Statistics Canada smallest census division, the dissemination area). As tested by M. Adjemian and Williams (2009), using census aggregate when household level attributes are missing allows for adequate control of income in the model. Income is significant and negative only for no vehicle/no carsharing.

In terms of built environment characteristics, only the indicator of accessibility to work by transit is significant for all alternatives compared to car ownership only. As transit access increases, households are more likely to either combine carsharing with car ownership, select carsharing only or choose no car access. As population density and the number of carsharing vehicles accessible increases, households appear more likely to select a carsharing membership over owning a car as a mean of car access.

While this first MNL model is not perfect and does not account for possible heterogeneity in relation to the observed choice, the significance and direction of the independent variables are intuitive. Furthermore, it is likely that modelling this joint car ownership/carsharing choice with a MNL violates the IIA property. For the property to be valid, it would mean that the introduction of carsharing as a viable car accessibility option in the city would not affect the ratio of probabilities between the other alternatives: no car ownership, owning one car and owning multiple cars. In other words, this assumes proportionate shifting where the new option would drop the probabilities of all existing alternatives by the same proportion. Previous research has showed that complex substitution patterns between carsharing, car ownership and no car are very likely at play (Becker et al., 2017). Plausible substitution patterns are presented in Figure 8.3. The proportion of substitution is however unknown.

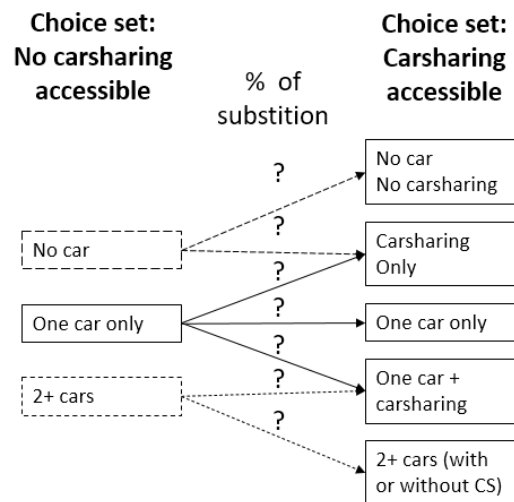


Figure 8.3 Possible substitution patterns with the addition of carsharing as an available alternative

The Hausman and McFadden (1984) test was used to examine whether the IIA property was violated. The results ($X^2 = 5.3662$, $df = 9$, $p\text{-value} = .80$) confirm that the property is rejected. Furthermore, some substitution patterns might be affected differently by taste heterogeneity in the population related to the choice of carsharing. This is one of the reasons why we turn toward the LC-MNL to handle this violation. Nonetheless, the model serves as a benchmark against which to compare results from the subsequent models.

8.5.2 Latent-class MNL without segmentation covariates

A first step was to estimate a model without including the attitudinal factor scores in the class-allocation model. Such a model is the most basic version of a LC-MNL where the heterogeneity between classes is only a function of unobserved factors. This allows us to verify the assumption that heterogeneity is indeed present in the joint choice of car ownership/carsharing. The constant in the class allocation model is significant ($p < .001$) confirming the presence of heterogeneity related to the choice of process. Without covariates, each observation has the same probability to belonging to Class 1 (81.4 %) and to Class 2 (18.6 %) and the expected values using prior probabilities are the same for all explanatory variables. For Class 2, all variables (except for the presence of a child under 15 years old in the household and population density) have significant coefficients for all alternatives indicating a greater sensitivity in general to SD and BE variables than Class 1. While not used in the model, it is nonetheless possible to compute expected values of the four attitudinal variables using posterior class probabilities. Results show that Class 2 has negative expected scores for *car appreciation* and *car values* and positive scores for *social identity* but has almost identical expected values to Class 1 for all SD and BE explanatory variables. This is a strong indicator that some of the “unexplained” heterogeneity is attributed to differences in attitudes and supports the idea of controlling for attitudes in the class allocation model to gain a better understanding of the heterogeneity in the long-term car ownership/carsharing decisions of households. Full model results are not reported here but can be supplied by the authors upon request.

8.5.3 Latent-class MNL with attitudes as covariates

The final model estimates the class allocation model with latent attitudinal variables and the choice model simultaneously. The first step is to decide on an optimal number of classes that strike a

balance between parsimony, model interpretation and model fit as described in section 8.4.5. The model with two classes is selected based on all the information criteria (see Appendix B for details). It is also the most parsimonious of the latent-class models and offers easy interpretation of the model results. Based on the same indices, it is possible to compare model fit between the simple MNL, the LC-MNL without any variables in the segmentation model and the LC-MNL with attitudes in the segmentation model (Table 8.4).

Table 8.4 Fit statistics for MNL and LC-MNL models

Model	# of Class	Param.	Df	LogLike	AIC	CAIC	BIC	ρ^2
MNL	1	27	1906	-2169	4392	4569	4542	0.087
LC-MNL no covariates	2	55	1878	-2097	4304	4665	4610	0.117
LC-MNL with attitudes	2	59	1874	-1968	4054	4442	4383	0.172

Note: McFadden Pseudo R^2 : $\rho^2 = 1 - \text{Loglike}(\text{Model}) / \text{Loglike}(\text{Null model})$

The index of fit (ρ^2) and three information criteria favor the LC-MNL with attitudes, despite its additional parameters. McFadden Pseudo R^2 (ρ^2) clearly indicates the strong improvement in incorporating attitudes in the class allocation model. While good, a $\rho^2 = .172$ remains below the threshold of .2 considered as “Excellent” by McFadden (1977). The results of the LC-MNL with attitudes are presented in Table 8.5.

Table 8.5 LC-MNL with attitudes latent variables in class allocation model

		Class 1 (REF)	Class 2	
Class share (prior probabilities)		45.7 %	54.3 %	
Class allocation model			Coeff. (SE)	
Constant			-0.113 (0.243)	
ATT1: Car appreciation			-1.538 (0.543) **	
ATT2: Car values			-1.331 (0.457) **	
ATT3: Social Identity			1.715 (0.666) **	
ATT4: Independence			-0.02 (0.166)	
Variable	Car Only (REF)	Car & CS Coeff. (SE)	CS Only Coeff. (SE)	No Car / No CS Coeff. (SE)
Overall share:	959 (49.6 %)	238 (12.3 %)	444 (23 %)	292 (15.1 %)
Class 1: Car-oriented^a	626 (70.9%)	122 (13.8 %)	84 (9.5 %)	51 (5.8 %)
Intercept		-3.379 (0.991) ***	-6.169 (3.263)	2.17 (2.236)
<i>Household characteristics</i>				
Nb of adults		0.301 (0.240)	-0.579 (0.689)	-0.105 (0.505)
Children (<15 yo) (dum.)		0.418 (0.250)	-1.303 (1.732)	-1.628 (1.377)
Adults avg. age		-0.023 (0.011) *	-0.031 (0.016)	-0.049 (0.026)
NB of workers		0.152 (0.242)	-0.448 (0.358)	-0.703 (0.452)
DA's median Income (kCAD)		0.005 (0.007)	-0.008 (0.020)	-0.025 (0.031)
<i>Built environment & accessibility</i>				
Pop. Density		0.057 (0.07)	0.162 (0.12)	-0.256 (0.201)
NB of CS vehicles		0.007 (0.008)	-0.014 (0.021)	0.035 (0.025)
Transit access to jobs		1.999 (1.214)	13.504 (6.053) *	1.598 (2.891)
Class 2: Social-conscious^a	333 (31.7 %)	116 (11.1 %)	360 (34.3%)	241 (23 %)
Intercept		-3.474 (1.43) *	-1.173 (0.96)	2.032 (1.051)
<i>Household characteristics</i>				
Nb of adults		0.187 (0.342)	-0.478 (0.204) *	-0.806 (0.234) ***
Children (<15yo) (dum.)		0.632 (0.314) *	-0.36 (0.236)	-0.85 (0.286) **
Adults avg. age		0.039 (0.017) *	0.019 (0.011)	-0.009 (0.012)
NB of workers		0.195 (0.354)	-0.189 (0.199)	-0.605 (0.203) **
DA's median Income (kCAD)		-0.015 (0.012)	-0.006 (0.009)	-0.019 (0.010)
<i>Built environment & accessibility</i>				
Pop. Density		-0.096 (0.096)	0.13 (0.063) *	0.096 (0.067)
NB of CS vehicles		0.018 (0.012)	0.021 (0.009) *	0.01 (0.009)
Transit access to jobs		3.405 (1.792)	1.334 (1.256)	1.242 (1.328)
# of observations	1933	# of param.	59	
Log-Likelihood	-1968	ρ^2	0.172	
AIC	4054	BIC	4383	

Note: CS = carsharing; Pop density is in 000's of pers. / km²; NB of CS vehicle within a 1-km walking distance; Transit access to jobs is the mean % of work destinations accessible in 45 min. by transit with departure time between 6 and 9 AM. ^aClass allocation based on prior probabilities.

Results of the class allocation models show three out of the four latent attitudes significantly affect the class allocation probabilities. The negative coefficient signs for *Car appreciation* and *Car*

values indicate that as both variable' scores increase for the survey respondent, the household is less likely to belong to Class 2. In other words, Class 1 groups together people who have more positive attitudes toward the automobile. We name this first class "car oriented", and the second class "social conscious" in relation to the effect of the third attitude factor, *Social Identity*, which is less intuitive. The factor is a composite score of two measured items: *People that are important for me think it's normal to get around by car* and *My transportation mode allows me to show who I am*. The first is a measure of descriptive norm regarding car use and the second a measure of symbolism, but not specific to the car. The hypothesis was that those who feel a higher pressure from peers to drive can also perceive the car as mean to show conformity with their peer's expectation. If that hypothesis was correct however, this factor would probably be aligned with the car value and car appreciation factors and would positively associate with the likelihood of belonging to the *car-oriented* class (Class 1). This is not the case. Looking at the modes of transport declared for commuting, those scoring highest on the *Social identity* factor and its two measurement items are the individuals declaring cycling only or declaring more than one non-driver modes (transit, walking, cycling). The other commuter categories, classified as car drivers only, multimodal with driving, transit users only and walkers only all scored statistically lower on that factor. A cautious explanation could be that those cyclists and multimodal non-drivers feel a pressure to drive from peers but are proud to show that not using the car is possible by relying on sustainable modes. Adding to this possible explanation, these two categories of commuters also score highest on the environmental item (*It is important for me to minimize my trips environmental footprints*) despite the item not contributing to the *Social identity* factor score. Finally, the *Independence* factor does not significantly affect class probabilities. In terms of market share, Class 1 ("car-oriented") represents 45.7 % of the surveyed household (based on the attitudes of the respondent) and Class 2 ("social-conscious") represents 54.3 %. Note that this cannot be extrapolated to the general population due to the non-representative nature of the survey (see section 8.3.1.1).

Turning to the choice model, most coefficients for Class 1 (car oriented; C1) are not significant, with two exceptions. For the household characteristics variables, only the average age of household adults is significant. Older households are less likely to combine carsharing and car ownership. For built environment characteristics, only the measure of transit accessibility to jobs is positively associated with an increased likelihood of choosing carsharing only over car ownership.

Interestingly, it has no impact on the probabilities of choosing to have no car instead of car ownership. These results indicate that for car-oriented households, not many factors seem to affect their choice of owning a car. In other words, once car attitudes are accounted for, these household will tend to own a car, no matter what, unless their transit access to jobs is very high.

For Class 2 (social conscious/non-car-oriented; C2), several household characteristics influences their choice of how they access a car. Unsurprisingly, a lower number of adults is associated with an increased probability to choose carsharing only or no access at all. This potentially indicates that for those households, the increased likelihood of choosing to combine carsharing and car ownership might indicate that carsharing is considered good enough to be a replacement for a second car. The effect of the average age of adults in the household is the opposite than the effect found for the car-oriented class (C1). Without using discrete groups for age, it is hard to clearly explain this effect. As the social-conscious class (C2) is on average 4-5 years younger than the car-oriented class (C1) (see section 8.5.4), but both classes have the same proportion of households with children, one tentative explanation is that, as for car-oriented class (C1): the older households in C1 are seniors with no children at home whom are less likely to combine carsharing and car ownership. Within the *social-conscious* class (C2), the older households are the families while the younger households are couples, or singles with or without children. With such distribution, it is intuitive that *social-conscious* households with children will choose to combine carsharing to car ownership to fulfill their needs of accessibility to an automobile while younger households might be satisfied with only one car. The distinction could be confirmed through a model which distinguish households with only one car (no carsharing) from households with 2+ cars (no carsharing).

The number of workers, the presence of children and the number of adults in the household are all significant and negatively associated with choosing no car/no carsharing. This is intuitive and suggests that single-person households without car-oriented attitudes can easily accommodate themselves without the need for owning a car or a carsharing membership. As for the effect of built environment characteristics on the choice process for this class, only population density and the number of carsharing vehicles accessible are significant and positively associated with the probability of choosing carsharing only as a means of car access. Interestingly, for households of that class, transit access to jobs has no discernable effect on their decision.

Unfortunately, is not possible to directly compare the magnitude of the β coefficients across classes because as explained by Train (2009, p. 44), the coefficients of each class are scaled by a parameter that depends on the variance of the unobserved part of the utility function. Even if in our LC-MNL, attitudes were included in the class allocation model, it is likely that the variance of the remaining unobserved part of the utility function might be different for each class. S. H. Kim and Mokhtarian (2018) used scenario analysis to overcome this limitation. In our case, because only one of the variables is significant in both classes (HH adults average age), we do not believe that it is necessary to include a deeper analysis to compare the magnitude of the coefficients between classes.

8.5.4 Class membership analysis

The next analysis is to investigate who belongs to each class. A first method to do this would be to impute to each observation its most likely class using the class with the highest probability (a process termed modal assignment (Masyn, 2013)). However, this method goes against the principle of probabilistic class assignment. A more adequate method, following Hess (2014), is by making use of these probabilistic class assignments and compute the most likely value for a variable of interest for an individual belonging to class c : $\bar{X}_c$. This expected value is a weighted mean of the variable where the weights are the class probabilities:

$$\bar{X}_c = \frac{\sum_n p_{nc} X_n}{\sum_n p_{nc}} \quad (8.6)$$

The class probabilities can be prior or posterior. The prior class probabilities are computed using Equation (4) and are only based on the variables used in the class allocation model. The posterior class probabilities consider the information provided by the selected alternative. In other words, it makes use of all components of the latent-class choice model to update class probabilities. Using Bayes theorem (Greene & Hensher, 2003; Hess, 2014), posterior class probabilities for an individual n is:

$$\hat{P}_n(c|i) = \frac{P_n(i|c) p_{nc}}{\sum_{c=1}^C P_n(i|c) p_{nc}} \quad (7.7)$$

where $P_n(i|c)$ is the probability of choosing alternative i , conditional to belonging to class c (Equation 4) and p_{nc} is the prior class probability to belonging to class c (Equation 3).

We first look at four attitudinal factors used in the class allocation model. Expected values using prior class probabilities are presented in Figure 8.4.

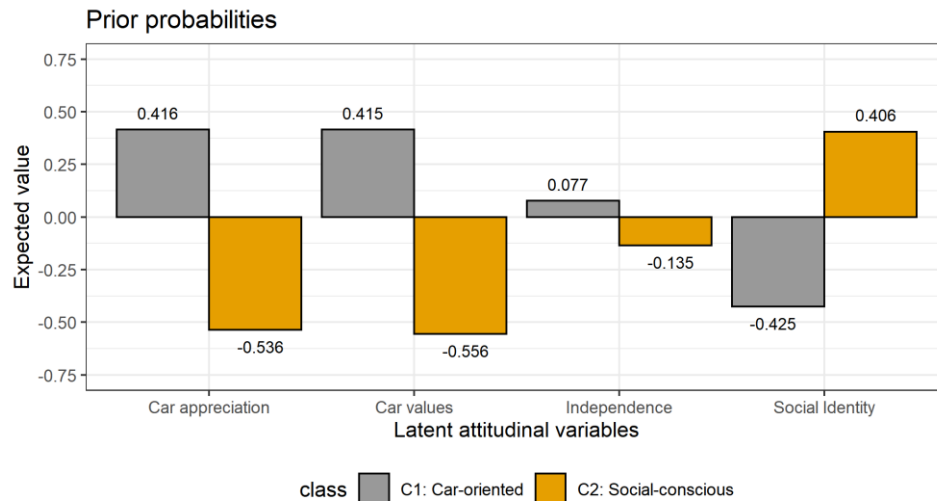


Figure 8.4 Expected values for the attitudinal factor scores using prior class probabilities

As expected, there are strong differences between the two classes except for the *Independence* score which has a non-significant coefficient in the class allocation model. We also computed expected values using posterior probabilities and found that they are the same up to the third digit of precision. This indicates that the additional information provided by the choice does not change the class allocation model much. The next important question is: how much do the classes differ on the household sociodemographic and built environment characteristics that were not used in the class allocation model? Table 8.6 presents the expected values using both prior and posterior class probabilities.

Table 8.6 Explanatory variables expected values by class

Variable	Class (share)	Prior probabilities		Posterior probabilities	
		C1 (45.7 %)	C2 (54.3 %)	C1 (47.7 %)	C2 (52.3 %)
		Car-oriented	Social-conscious	Car-oriented	Social-conscious
<i>Sociodemographics</i>					
NB of adults in HH		1.826	1.835	1.841	1.822
Children (<= 15 yo) (dum.)		0.252	0.250	0.256	0.246
Average age of HH adults		44.59	39.67	44.51	39.74
NB of workers		1.383	1.493	1.397	1.481
DA's Median HH Income (k CA\$)		48.09	46.36	48.23	46.24
Nb of cars in HH ^a		0.982	0.517	1.112	0.400
Carsharing membership in HH (dum)*		0.257	0.438	0.199	0.490
<i>Built environment</i>					
Pop. Density – 1-km walk radius [pers./ km ²]		9532	10 318	9508	10 339
Nb CS vehicles – 1-km walk		23.00	29.86	22.86	29.98
Tr access: % of work destinations (45 min.)		36.3 %	40.3 %	36.2 %	40.3 %
Nb of grocery/fruit stores – 1-km walk		11.27	13.72	11.22	13.77
Walk. Distance to metro [km] ^a		1.437	1.086	1.429	1.093
Distance to CBD [km] ^a		6.052	5.256	6.076	5.234

Note: ^a Indicates variables not used in the choice model but added here for context enhancement.

Looking at the difference between expected values based on prior versus posterior probabilities: the differences are minimal for all explanatory variables. The only exceptions are the number of cars per household and the presence of carsharing membership in the households which are the two components of modelled outcome of joint car ownership/carsharing decisions. It is thus not surprising that their expected values would change when the information on the observed choice is integrated in the class probabilities.

Turning to between classes differences for sociodemographic characteristics of the household, no notable differences are observed on the number of adults in households and the presence of children. *Social-conscious* households tend to be 4-5 years younger, which could also explain why they have on average more workers per household. As for income, *car-oriented* households tend to live in areas with slightly higher median income than the *social-conscious* class, but the difference remains very small. As for the number of cars per household, it was to be expected that *car-oriented* households would own on average more cars than the *social-conscious* class while

the latter would be more likely to have a carsharing membership. Households with carsharing membership remain high even among *car-oriented* households (25 % using prior probabilities).

The analysis of the differences in built environment characteristics indicates that *social-conscious* households tend to live in slightly denser neighbourhood, more central and closer to metro stations which follows a self-selection theory (e.g., Xinyu Cao et al., 2009; van Wee & Cao, 2022). They have better access to local grocery and fruit stores, to station-based carsharing vehicles and have a higher transit accessibility to jobs. This difference, however, is not very large and *car-oriented* households do not live in areas only accessible by car due to the studied area selected and the spatial non-representativity of the survey within that area.

8.5.5 Simulate the effect of an increased in carsharing availability

The final analysis is to model the effect of an increase in carsharing vehicle availability on the joint household decisions of car ownership/carsharing. Unlike other built environment variables (e.g., density, diversity, design, etc.) increasing carsharing vehicle availability could be achieved easily and very quickly without the need for massive investment in infrastructures. While carsharing is provided by a private operator, public policy can foster faster growth of the service in many ways, for example by providing free exclusive on-street or off-street parking spaces to carsharing vehicles or by subsidizing or providing low interest loans to carsharing operators to increase their fleet size.

Both discrete choice models (MNL and the LC-MNL) are used to simulate an increase of 25 % in the variable “number of carsharing vehicles within 1-km walking distance” for all households in the survey with a minimum increased of one vehicle for households with currently 0 to 3 within walking distance. In practice, this can be achieved in two ways: 1) increasing the number of stations within or outside the area presently served by station-based carsharing, thus increasing the number of households living in the proximity of a station and 2) increasing the number of vehicles in existing stations, thus increasing vehicle availability. Both methods having potentially different effects on the choice process. However, the fine details of the operational deployment of additional carsharing vehicle are beyond the scope of the current paper. For this simulation, all other variables are held constant, and the model is used to predict the market shares. Results are presented in Table 8.7. For the LC-MNL, overall changes in market share as well as changes by class are presented. In the perspective of using the model to make out-of-sample predictions (where we do not have

knowledge for the observed choice), using posterior probabilities would be inadequate. Thus, prior class probabilities are used for the scenarios.

For this analysis, the full survey sample ($n = 2184$) is used, instead of only the subsample with current minimum access to carsharing ($n = 1933$) that was used to train the models. Applied to the full sample, MNL achieves a unit-weight¹⁶ sample accuracy of 55 % and the LC-MNL, using prior probabilities, achieves 60.8 %.

¹⁶ See S. H. Kim and Mokhtarian (2018) for a discussion on probability versus unit weight using prior versus posterior probabilities.

Table 8.7 Scenario analysis for an increased in carsharing availability for the full sample (n=2184)

Market share	No car	CS only	Car only	Car and CS
Observed	14.06%	20.56%	54.17%	11.22%
Base scenario				
MNL prediction	14.01%	20.88%	53.45%	11.67%
LC-MNL overall predicted shares	13.80%	20.77%	53.77%	11.66%
C1: Car-oriented shares	3.30%	5.86%	76.24%	14.60%
C2: Social-conscious shares	23.70%	35.01%	30.59%	10.70%
S1: +1 to those with 0-3 cs vehicle and + 25 % in NB of CS vehicles otherwise (1-km walk)				
MNL prediction	14.11%	22.08%	51.89%	11.92%
LC-MNL overall predicted shares	13.82%	21.56%	52.64%	11.98%
C1: Car-oriented shares	4.32%	5.18%	75.41%	15.09%
C2: Social-conscious shares	23.11%	36.80%	29.17%	10.92%
Difference with baseline scenario				
MNL prediction	0.10%	1.20%	-1.56%	0.26%
LC-MNL overall predicted shares	0.02%	0.79%	-1.13%	0.32%
C1: Car-oriented shares	1.02%	-0.68%	-0.83%	0.49%
C2: Social-conscious shares	-0.59%	1.79%	-1.42%	0.22%

As expected, considerable differences in market shares are observed between both classes. Turning to the scenario with a 25 % increase in carsharing vehicle availability, the MNL gives slightly larger changes than the LC-MNL. That is, there is a more important increase in “CS only” and more important decrease in “Car only”. However, based on the results of the current research (Table 8.4) and from previous research (S. H. Kim & Mokhtarian, 2018) the inclusion of taste heterogeneity through latent attitudes in the segmentation model makes the LC-MNL a better fit to the data than the MNL. The scenario results indicate that without the inclusion of attitudes, a simple MNL model seems to overestimate the effect of the carsharing accessibility variable on the car ownership/carsharing joint decision. Another consideration is that by increasing carsharing vehicle availability, there is a reduction in the share of “no car” households for the **social-conscious** class, indicating that the increase in the share of “CS only” comes from a reduction in “car only” and a reduction in “no car” households. Whether that is considered a positive or negative outcome is up for debate.

8.6 Discussion and conclusion

This paper tried to fill an important gap in the literature by analyzing how car and travel-related attitudes can moderate the effect of sociodemographics and built environment characteristics on households' mobility tool ownership decisions (private car and carsharing). Using a 2019 Mobility survey from Montréal, Canada, the joint choice is modelled through four mutually exclusive categories: 1) no car and no carsharing, 2) carsharing only, 3) car only and 4) car and carsharing using a Latent-class multinomial-logistic model (LC-MNL) where attitudinal latent variables are entered into the class allocation models.

While imperfect, the MNL results indicate that all included sociodemographic and built environment variables are significant for at least one alternative. The sign and magnitude of coefficients are intuitive and consistent with previous research. In the final model, latent attitudes obtained from the principal component analysis are entered into the class allocation models, information criteria indicates that the 2-class models should be preferred. Three of the four included latent variables have significant impacts on the class-allocation models, with the independence factor being not significant. Class 1, named *car-oriented* is characterised by positive values for car appreciation and car values and negative scores for the social identity variable. Class 2, named *social-conscious* display the opposite patterns of scores. The *social identity* variable represents the pressure to use the car along with a desire to show one's identity through other transport modes (cycling and multimodality notably). Both classes are similar to the “auto-oriented” and “urbanites” of S. H. Kim and Mokhtarian (2018) obtained from slightly different attitudinal variables. However, the shares for each class are different. The *car-oriented* class represents 46 % of our sample and 65 % of theirs. This difference is likely due to non-representativity of both surveys and the difference in the surveyed regions (the entire state of North Carolina versus the City of Montréal).

Further class membership analysis reveals that both classes have almost an identical number of adults and presence of children. However, *car-oriented* households are 4-5 years older and have less workers than the *social-conscious* which confirms some evidence that younger generations (Millennials, Z) tend to be less auto oriented than older ones (late Gen X, Boomers) (Chatterjee et al., 2018; Ortar, Vincent-Geslin, & Boudreau, 2018) and more inclined to adopt carsharing (Le Vine, Zolfaghari, et al., 2014). *Social-conscious* households tend to live in slightly denser

neighbourhoods, more mixed-used, more central and closer to mass transit and to carsharing vehicles. This difference, if noticeable, is not very large and *car-oriented* household in this survey sample do not live in deep suburban areas with no alternatives to driving. On the contrary, in many contexts, the expected values of these built environment characteristics for the *car-oriented* class would usually be considered dense, mixed use urban areas with good access to transit service. Nonetheless, these differences suggest that residential self-selection might be playing a role: *social-conscious* households, which favor sustainable ways of travel, tend to locate themselves in denser, better served transit areas, closer to the city-center. Data reported here suggests that access to carsharing services could be another motivator for sustainable-travel oriented households to locate themselves where many carsharing vehicles are within walking distance, thus allowing them to reduce their reliance on private cars. Alternatively, another hypothesis is "environmental determinism" (Ewing et al., 2015), also called "residential determination" (Lin et al., 2017), where the built environment influences people's attitude toward travel (Kroesen, 2019). In the current case, people with more favorable attitudes toward sustainable mobility (and less favorable toward the car), the *social-conscious* class, might have developed such attitudes by living in dense urban settings with good non-automobile accessibility. These areas also tend to be less efficient for car use and ownership due to higher congestion and parking constraints, likely leading to lower car appreciation. Realistically, those studies suggest that both effects might be playing a role, but the cross-sectional data and modelling framework of the current analysis do not allow to investigate which effect has more influence.

Results from the choice models confirm the hypothesis that *car-oriented* are much less sensitive to both sociodemographic and built environment characteristics affecting their choice of car ownership/carsharing. This suggests that these households will tend to own cars, no matter what. Something confirmed by the share of car only households among *car-oriented* being more than double (71 %) the share for the *social conscious* (32 %). While "car and carsharing" has similar proportions for both segments, the *social conscious* are significantly more likely to choose carsharing only (34 % vs 9.5 %) or no car access at all (23 % vs 6 %) than the *car-oriented* households, the latter possibly being a difference between choice and constraint (financial or otherwise). Density and the number of carsharing vehicles accessible within a 1-km walking buffer positively impact the choice of carsharing only for the *social conscious*, while accessibility to jobs by transit has no influence on them but does influence some *car-oriented* to choose carsharing

only. These built environment effect on choosing carsharing are the opposite of what was found by Becker et al. (2017) in Switzerland where transit access has a positive and significant effect on carsharing membership while access to carsharing vehicles was not significant. However, their variable only considered the *distance* to the nearest carsharing station and not the *intensity* of vehicles available as is considered here. In both cases, correlations between the two variables might confound the results ($\rho = .40$ for them, $\rho = .57$ for us).

Using the MNL and LC-MNL to test a scenario of increased access to carsharing vehicles, results indicate that the simple MNL, without attitudes, seems to overestimate the effect of the carsharing accessibility variable on car ownership reduction. The LC-MNL scenario results show two things: 1) that increasing access to carsharing vehicles for *social-conscious* households leads to an increased in “carsharing only” and “car ownership and carsharing” which comes from a decreased in “car only” but also a decrease in “no car/no cs”. This confirms previous research on carsharing based on members surveys (e.g., E. W. Martin et al., 2010). For *car-oriented* households, improving access to carsharing vehicles leads to a reduction in “car only” but also a reduction in “carsharing only” and an increased in “car ownership and carsharing”, thus not necessarily reducing overall car ownership rates for this class.

In terms of policy implications, this suggests that increasing the number of carsharing vehicles accessible might only affect the decisions in the expected direction for *one segment* of the population. This is in line with stated-choice experiments where car ownership oriented people appear unaffected by carsharing system attributes when choosing between carsharing and ownership (Liao et al., 2020). This suggests that in addition to an increase in vehicle availability, other sets of more targeted measures to increase awareness and knowledge of carsharing might be needed to increase uptake of the service by households that are *not* car oriented. About 25-30 % of those *social-conscious* households in areas most well-served by carsharing still own a car without carsharing membership. Providing incentives to replace that car by carsharing should be tested, as they might be more open to it.

The results obtained here also raise other transport policy questions: while there is considerable research focus on how to change the built environment to favor sustainable travel, what is the potential for car ownership (and use) reduction among those that *already* live in environments that facilitates car-free or car-light lifestyles? Is there excessive and unnecessary car ownership in such

areas that could be avoided, for example, through an uptake in carsharing? Who is structurally constrained to own and use automobile for their daily travel and who is in a situation of choice but prefer the car over alternatives, nonetheless? The questions are of high relevance for cities with old central neighbourhoods where on-street parking represents a high percentage of all available parking. When free or subsidized on-street parking is considered a “right” by many car owners, there is strong opposition by residents to any pedestrianization, protected bike lane projects, priority bus lanes or any other street space reallocation projects (Adrian Field, Wild, Woodward, Macmillan, & Mackie, 2018; Gössling, 2020). These oppositions represent important barriers to further increase the uptake of walking, cycling and transit use. In such cases, other means than changes to the built environment such as soft-behavioural change measures like those applied to encourage public transit use (e.g., Zarabi et al., 2021) could be tested to facilitate car ownership and use reduction through carsharing adoption and, in turn, reduce opposition to street space reallocations.

Several **limitations** are worth mentioning. First, the survey sample, while being large (~2000) is not fully representative of the general population and is spatially concentrated in the central part of the Island of Montréal. A larger variety of environments where carsharing is available with a representative sample of the population should be used for future research. Second, income was not collected despite its notable impact on car ownership and carsharing decisions. Third, using attitudes measured for a single household member when modelling household level decisions is problematic. This could be corrected through modelling intra-household decision mechanism (e.g., J. Zhang et al., 2009), by collecting attitudes from more than one household member (e.g., J. H. Lee & Goulias, 2018) or both. In terms of choice, only station-based carsharing was considered despite evidence that complex adoption dynamics can occur when free-floating and station-based carsharing are integrated within a common ecosystem (Wielinski, 2018).

Finally, while the use of attitudes in discrete choice model based on cross-sectional data can enhance behavioural understanding of the choice process being examined, the model cannot be used to predict the effect of changes in attitudes (Chorus & Kroesen, 2014). Optimally, longitudinal survey data with attitudes measured at different points in time should be employed to examine the evolving role of carsharing on long-term households’ decisions.

Overall, this paper expands the literature on car ownership and carsharing by revealing how sociodemographics, built environment and attitudes are influencing the complex substitution patterns between both ways of accessing an automobile.

8.7 Acknowledgments

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8.9 Appendix A. Computing Destination accessibility by transit

Accessibility by transit was computed using the platform *Transition*, developed by Polytechnique's Montréal Mobility Chair, (Bourbonnais, 2014-2019; Bourbonnais et al., 2014-2019).

The online tool takes as input the design of the transit network and the transit schedule in the form of General Transit Feed Specification (GTFS). GTFS of all the transit agencies operating in the area in 2018 were imported into the software, which encompasses bus, metro, and suburban train services. Each surveyed household's coordinates were then entered as origin from which the transit access maps would be calculated. The following parameters were selected: a 15-minute walk maximum access time at origin or destination (walking speed of 5 km/h or roughly 1.4 m/s), a 10-minutes maximum transfer wait time, and a total travel time of 45 minutes, which is slightly more than the mean transit home-work travel time in Montréal (41 min.) according to the 2016 Canadian Census (Statistique Canada, 2017b).

As transit frequency can be highly variable throughout the day, it was important to select a realistic departure time to assess transit accessibility to common destinations. For this, the 2018 Montréal Large-scale OD Survey was used. Information (destination location and time of departure) were extracted from the survey for work trips by adults. The dominant hour of departure is between 7 and 8 AM, during which 28 % of all trips to a work destination depart. Transit accessibility maps were then created using *Transition* with departure times at every 15 minutes between 7 and 8 AM on a weekday. The final map (or polygon), for each household, is the average surface area accessible by transit in less than 45 minutes within this hour of departure. The final step of the procedure is to sum the number of work trip destinations extracted from the 2018 OD survey with departures within that dominant hour (7 to 8 AM) that are within each household's transit access polygon. Finally, to normalize the variable, that sum is divided by the total number of work destinations (for the entire metropolitan region) extracted from the OD survey with departure times between 7 and 8 AM. The final variable is thus the percentage of all the Montréal metropolitan area work destinations accessible within 45 minutes by transit during the morning peak period. The same procedure was repeated for shopping and leisure trips. The respective departure times determined from the OD survey were 10 to 11 AM (shopping) and 6 to 7 PM (leisure).

8.10 Appendix B. Determining the number of classes

Masyn (2013) explains in her chapter on finite mixture modelling, there is not one ultimate single method for comparing models with different number of classes and decide which is best. It requires looking at several fit indices, while also considering theoretical aspects and ease of interpretation of the latent class model. In terms of tools of relative model fits, Masyn (2013) suggests using information-heuristic tools (e.g., BIC, AIC) over inferential methods such as likelihood ratio tests because the former allows comparison of multiple model that are not necessarily nested. As additional parameters tend to increase the fit of a model, these information criteria usually penalize the addition of new parameters, thus considering parsimony in the equation. A common one is the Akaike's Information Criterion (AIC), as suggested by Shen (2009) for example. Masyn (2013) recommends using the Bayesian Information Criterion (BIC) and the Consistent Akaike's Information Criterion (CAIC). Having LL the maximum value of the log likelihood function, n the number of observations and k the number of parameters to be estimated, the four information criteria can be computed as follow:

$$AIC = -2LL + 2k \quad (B.1)$$

$$BIC = -2LL + k\log(n) \quad (B.2)$$

$$CAIC = -2LL + k[\log(n) + 1] \quad (B.3)$$

To get a sense of “how much” better one model is relative to the other based on its information criteria, some decision rules can be applied. When using AIC, Páez and Boisjoly (2022, in press) suggest using the relative likelihood defined as:

$$RL = \exp \left(\frac{AIC_{min} - AIC_q}{2} \right) \quad (B.4)$$

Where the interpretation of the RL being that model q is as likely as the model with the lowest AIC to minimize information loss. Masyn (2013) recommends the approximate Bayes Factor (BF), which is the same as the relative likelihood, but using the BIC.

Table 8.8 presents the fit statistics for models with 1 to 5 classes. The model with one class is the simple MNL. No statistics are reported for the 5-class model because of convergence issue. Different strategies suggested by Sarrias and Daziano (2017), including rescaling the variables, changing the optimization algorithm and changing the starting values were tried but convergence of the maximum-likelihood estimation procedure still failed for the 5-class model.

Table 8.8 Fit indices and information criteria for the LC-MNL with attitudes covariates, $C = 1$ to 5

# of class	Parameters	Df	LogLike	AIC	CAIC	BIC	RL ^a
1	27	1906	-2169	4392	4569	4542	0.000
2	59	1874	-1968	4054	4442	4383	1.000
3	91	1842	-1948	4079	4676	4585	0.000
4	123	1810	-1909	4064	4872	4749	0.009
5	155	1778	-	-		-	

Note: ^a RL = Relative Likelihood

CHAPTER 9 ARTICLE 5: CAR OWNERSHIP, NEIGHBOURHOOD TYPES AND TRAVEL ATTITUDES

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ABSTRACT

The availability of carsharing in cities around the world has allowed more households to take advantage of the service as an alternative or a complement to private car ownership. While most research has looked at the effect of carsharing on car ownership decisions using carsharing users' surveys, very few have modelled the choice of car ownership and carsharing jointly using independent surveys. This paper investigates the complex relationship between this joint decision, the built environment, and travel-related attitudes. Using data from two surveys in Montréal, latent-cluster analysis is used to identify a typology of residential neighbourhoods and a segmentation of attitude profiles. Cross-analyzing the two segmentations suggests that those with more positive attitudes toward the car are more likely to own cars and less likely to join carsharing across all neighbourhood types compared to less car-oriented profiles. However, people from all attitude profiles own fewer cars in more central neighbourhoods than in more suburban locations. Finally, a MNL model where sociodemographics and residential parking are controlled for confirms that both the built environment and attitudes independently influence the joint decision. Results also suggest that attitudes are associated with residential location choice, hinting at the presence of residential self-selection.

9.1 Introduction

Over the last 20 years, there has been a sustained focus in transportation research on the role of attitudes on travel behaviour. Notably, how attitudes confound the relationship between the built environment and observed travel behaviour by simultaneously affecting several levels of travel-related decisions: long-term residential and employment locations, medium-term car ownership decisions, and more broadly, mobility tools ownership decisions and short-term decisions regarding daily travel (mode choice, trip frequency, distance travelled). This leads to endogeneity

biases where not controlling for attitude-induced residential self-selection when modelling medium and short-term decisions might misestimate the true effect of the built environment on those decisions (e.g., van Wee & Cao, 2022). This issue likely applies to the joint decision of car ownership and carsharing, but this has not yet been properly investigated.

In Chapter 8, it was illustrated using a latent-class discrete choice framework that attitudes are moderators of the effect of the built environment and sociodemographic characteristics on the joint car ownership/carsharing decisions. The present chapter is a direct extension of that work. The objective is to explicitly analyze how the built environment and attitude interact to influence the joint choice of car ownership and carsharing. Specifically, it aims to provide answers to the following questions: **Are car ownership/carsharing decisions still associated with the built environment when attitudes are controlled for?** For example, do people with favourable attitudes toward the car who live in denser, more central, and more accessible neighbourhoods own as many cars as car-oriented households living in more suburban environments? Do people with a preference for sustainable mobility and car-light lifestyles but living in suburban settings, own more vehicles than their urban peers? Are their car ownership levels lower than similar profiles in the suburbs?

This main research question implies two other sub-questions: First, **is there evidence of the attitude-induced residential self-selection hypothesis?** And second, **are there mismatches between the type of built environment at the home location and individual travel attitudes?** Do we find car-oriented people in the most central areas and vice-versa? What differences in car ownership/carsharing can we observe between matched and mismatched people?

To provide answers to those questions, two segmentations are built using latent-cluster analysis. The first uses a set of built environment variables at the home location to identify a latent categorization of neighbourhood types. The second uses measured attitudinal indicators toward the car and travel in a latent psychographic segmentation. The two segmentations are then cross-analyzed with respect to the variable of interest, the joint choice of car ownership and carsharing. To control for the effect of sociodemographics, that choice is then modelled using a multinomial logistic model (MNL) where neighbourhood types and attitudes profiles are entered as explanatory variables.

The sections are organized as follows: section 9.2 presents a short overview of attitude-based segmentation and neighbourhood typology and their interactions with car ownership. Section 9.3 details the methodology used to identify the neighbourhood types and latent-attitude profiles. The neighbourhood typology is presented in section 9.3, the attitude profiles in section 9.5. The results of the cross-analyses in and the MNL model in section 9.6.3. This is followed by a discussion and implications for travel behaviour research and transport policies in section 9.7 and a conclusion in section 9.8.

9.2 Literature review

The first section describes some relevant attitude-based segmentation research found in the literature and how the segmentation relates to car ownership. The second section reviews some studies classifying neighbourhoods.

9.2.1 Attitude-based segmentation

In a landmark work in travel-based attitude segmentation, Anable (2005) identified six groups with distinctive mobility intentions and behaviours in a sample of 666 respondents from visitors to tourist sites in the UK served by public transport (and thus not an overview of the general population). The segments were identified using the *k-means* clustering algorithm. The segmentation was based on their scores on 17 latent psychological and attitudinal variables obtained from principal component analysis of 105 measured statements. Of these six groups, four were composed of car owners while the other two groups were non-vehicle owners and marginal. Furthermore, for all four groups of car owners, there was no significant relationship with sociodemographic characteristics, except for graduation rates. The attitude segments showed similar values of vehicles per drivers, ranging from 0.77 to 0.88. However, segments were not analyzed with respect to their built environment context. That study was the basis for a much larger European segmentation project (SEGMENT project) which aimed to identify latent attitude profiles based on a range of mobility related-attitudes and use those segments to design mobility management campaigns (Anable & Wright, 2013; J. Walker, Schwartz, Rehorova, & Vicek, 2021). The segments are identified using the *k-means* algorithm, where 18 "golden questions" measuring attitudes toward the car (for drivers only), public transit, walking and cycling. Five driver profiles are identified (*Devoted drivers*, *Image improvers*, *Malcontented Motorists*, *Active Aspirers* and

Practical Travellers) and three non-drivers (*Car contemplators*, *Public transit dependents* and *Car-Free choosers*). The proportion of each segment varies based on where the surveys were conducted. An adaption of the method in North American yielded slightly different results (Lester, Winters, & Pham, 2019; Winters, Lester, & Pham, 2018).

More recently, von Behren, Bönisch, Vallée, and Vortisch (2021) used surveys conducted in Berlin and Munich to identify psychographic profiles of car owners. They used Latent Class analysis (LCA) with ten indicators derived from the Theory of planned behaviour and further mobility-related attitudes based on three dimensions (privacy, autonomy, and car excitement) as input. They identified six latent profiles: *Car Independents* (20.5 %), *Car captives* (7.5 %), *Car lovers* (21.2 %), *Convinced car users* (19.1 %), *My Car is my Home* (15.5 %) and *Privacy-aware car owners* (16.2 %). The profiles are then compared based on various aspects of travel behaviour, household sociodemographics, a single characteristic of the built environment (population density) and other psychological factors not used in the segmentation. Household car ownership varied from 1.12 vehicle per household (*Car independents*) to 1.39 (*Convinced car users*). The population density was significantly different for three of the six classes, indicating a probable relationship between residential location and car-related attitudes.

In North America, McBride and Goulias (2021) used a COVID-19 survey conducted in May 2020 in Los Angeles to identify latent attitudinal profiles. They used Latent profile analysis (LPA) of attitudes (6 measured items about independence in travel, driving, carpooling and transit). They identified six profiles: *Car Haters* (6.4 %), *Indifferent Respondents* (9.9 %), *Freedom Lovers* (12.9 %), *Car users* (25.25 %) and *Car Lovers* (45.7 %). They then compare those latent profiles with latent mobility behaviour classes for commuting. They concluded that both classifications are correlated. They did not investigate differences in built environment context between the attitudinal profiles.

J. H. Lee and Goulias (2018) used ten waves (1989 to 2002) of the Puget Sound Transportation Panel (PSTP) to investigate the relationship between attitudes, car ownership, residential location, and travel behaviour. Perceptions of specific transport modes (mostly instrumental and affective aspects) and satisfaction with transportation services were used as input into multilevel latent class clustering analysis. Attitudes were collected for more than one household member, allowing for investigation of within-household variation of attitudes. They identified three clusters of persons

and three clusters of households. On the person level, the three classes were: *Car lovers*, *neutral persons* and *carpool and transit lovers*. As for household-level, the three classes were *Car oriented HH* (25.5 %), *neutral HH* (44 %) and *carpool and transit-oriented* (18.8 %). Each is composed of a majority of individuals from the classes with the same name. They observed that opposite views (i.e., *car lovers* and *carpool and transit lovers*) do not cohabit together unless there is also a neutral person in the household. Unlike Anable (2005), they found that attitude classes were very different in terms of sociodemographics. Then, using a subset of 230 households who participated in all ten waves, they did a longitudinal investigation of built environment characteristics, travel behaviour and car ownership. They also showed a strong correlation between built environment characteristics and attitude classes, notably for the *carpool and transit-oriented* who lived in distinctively higher density, mixed-use areas. *Car-oriented* and *neutral* households showed consistently higher car ownership levels over time, with the mean value staying relatively stable. The *carpool and transit-oriented* households had lower car ownership levels and it tended to diminish between 1989 and 2002.

Many other mobility-related attitudinal segmentations have been conducted (Haustein & Hunecke, 2013; Hunecke et al., 2010; Jensen, 1999; Kandt, Rode, Hoffmann, Graff, & Smith, 2015; Olde Kalter et al., 2020; Prillwitz & Barr, 2011), but none of those research contrasted their segmentation with a precise characterization of the built environment like it was done by J. H. Lee and Goulias (2018).

9.2.2 Neighbourhood typologies

This section presents some examples of neighbourhood typologies developed using North American data. Many more neighbourhood typologies, conducted at the household or zonal level, can be found in the literature, but it is beyond the scope of this short review to summarise them all.

Miranda-Moreno, Bettex, Zahabi, Kreider, and Barla (2011) identified a typology of neighbourhoods in Québec City using *k-means* clustering at the household level. The input variables were population density, land use diversity (entropy index) and accessibility to public transit (index considering average daily headway and distance to bus stops). They identified five neighbourhood types (with % of observed households): Downtown (3.6 %), New Suburbs (27.7 %), High accessibility (9.1 %), Periphery (53.8 %), and Old Suburbs (5.9 %). The typology

was then used to bundle residential location and car ownership within a joint choice. The joint choice is then considered an endogenous variable within a simultaneous equation system to predict the daily distance travelled. They conclude that dummies for neighbourhood types have much higher elasticity values than the three individual urban form variables when tested independently. They suggest that this is because the neighbourhood typology captures other neighbourhood aspects that are not captured by the individual built environment variables.

Other studies analyzed the neighbourhood level. For example, Shay and Khattak (2007) used a set of 34 built environment (BE) measures computed at the level of the block group of the American Census to identify seven neighbourhood types in the metropolitan area of Charlotte, North Carolina. The 34 BE measures were first reduced to five underlying factors using exploratory factor analysis to be used as input for the cluster analysis. The five factors, the seven neighbourhood types, and four direct BE measurements are then compared in regressions of car ownership and the number of trips. In the model with only neighbourhood types, none were significant in explaining car ownership. This might be contextual to the surveyed area.

Expanding the work by Shay and Khattak (2007), Voulgaris et al. (2017) developed a comprehensive typology of all US neighbourhoods at the census tract level (over 73,000 tracts). They used data from the 2010 Census and other sources to compute 20 variables describing the built environment: job and housing densities, the number of jobs and retail opportunities within tracts, accessibility to jobs by car, and design of the street, pedestrian and transit networks. They also considered variables describing the types and home tenure. As a first step, they factor analyzed those 20 variables to reduce them to five factors which are then used as input in a hierarchical clustering analysis. They identified seven neighbourhood types across the US (with % of population living in each between parentheses). Three are urban: Mixed use (5 %), Old urban (4 %) and Urban residential (14 %); three are suburban: Established suburb (13 %), Patchwork (18 %), New development (27 %); one is Rural (19 %). The typology is then used to analyze individuals' travel behaviour using the 2009 US National Household Travel Survey. However, they did not specifically investigate how car ownership varies by neighbourhood type.

Another approach is to use model-based segmentation instead of machine-learning clustering methods. For example, Jahanshahi and Jin (2016) developed a latent-class analysis structural equation modelling (LCA-SEM) of travel behaviour which considered car ownership as a mediating variable. The model identifies a latent classification of UK neighbourhoods based on

five built environment and accessibility variables while controlling for sociodemographic covariates.

In summary, many independent segmentations of both attitudes and neighbourhoods can be found in the literature. Some were conducted using unsupervised machine-learning methods like the well-known *k-means* algorithm while others used model-based clustering (e.g., LCA, LPA). However, no study seems to have cross-analyzed a neighbourhood segmentation with an attitude-based segmentation to investigate car ownership or the joint car ownership/carsharing decisions.

9.3 Methodology

9.3.1 Data sets

To conduct this analysis, two primary datasets are used. The first is the one-time City of Montréal Mobility Survey 2019 (CMM19), and the second is the 2018 edition of the large-scale Montréal Origin-Destination survey (OD18) conducted every five years. The former covers only the Island of Montréal and is not representative of the Montréal population. The latter covers the entire metropolitan area and uses a stratified sampling method with expansion factors based on the 2016 Canadian census. Further details about those two surveys are presented in the thesis's methodology section (4.3.1). For the OD survey, only the subset of households located on the Island of Montréal is used to match the surveyed area of the CMM19 survey. The CMM19 survey is necessary to analyze attitudes because the OD survey does not collect any measures of attitudes.

Furthermore, using precise household coordinates, both datasets were enriched with several built environment characteristics computed within walking-distance buffers (“network bands”), following the methods described in section 4.5.

9.3.2 Latent-cluster modelling

Latent-cluster analysis (or latent-class analysis) is a type of finite mixture model. It takes as input a set of *indicator* variables to identify two or more homogenous subgroups of observations, called *latent classes* (Masyn, 2013). The model's outcome is thus a categorical variable with k unordered categories. When applied to individuals, it assumes heterogeneity in the population with respect to behaviours, characteristics, attitudes, values, etc. The terminology of the method varies by discipline, but Masyn (2013) reports that the term “latent-class analysis” (LCA) refers to models

where the indicators are categorical. When the indicators are continuous, the term “latent-profile analysis” (LPA) is used. Nowadays, latent-cluster models can take as input a mix of continuous, categorical, ordinal or count indicators (Haughton, Legrand, & Woolford, 2009). For the following paragraphs, the term “latent-cluster analysis” or “latent-cluster model” encompassing both models is used. The term “cluster” will refer to the latent categories/classes/segments/profiles when discussed in general. For the specific analysis of this chapter, the neighbourhood clusters will be referred to as *types*, while the attitude clusters will be called *profiles*. Unlike traditional supervised data-mining clustering methods such as k-means or hierarchical clustering, latent-cluster analysis is a probabilistic model-based method. The model estimates, for each observation, a probability to belong to one of the latent classes based on its indicators’ values.

To conduct the present analysis, latent-profile analysis (continuous indicators) is performed using two sets of indicators. The first is used to classify surveyed households of both samples in latent *neighbourhood types* based on indicators describing the built environment around each home location. The second is used to classify the respondent of each household in *latent psychological profiles* using attitude indicators. In terms of assumptions regarding the continuous indicators to be used, Masyn (2013, p. 585) explains that the model assumes a multivariate normal distribution of indicators *within each identified class/segment*, but no assumption is made for the distribution in the overall sample population.

As to which package should be used to perform the modelling, Haughton et al. (2009) compared *Latent GOLD*® to two R packages: *mclust* and *poLCA*. They concluded that *mclust* outperformed the two other packages in terms of the efficacy of the cluster analysis based on within-cluster homogeneity and between-cluster heterogeneity. Furthermore, among the R packages, they specifically recommend *mclust* if the input indicators are continuous, as is the case for the two models estimated. The *mclust* R package developed by Scrucca, Fop, Murphy, and Raftery (2016) is thus used.

9.3.2.1 How many latent clusters should be used?

An essential aspect of latent-cluster analysis is determining the *number* of latent clusters. Unless the approach is confirmatory, that number is *a priori* unknown to the analyst. However, in theory, previous research and knowledge of the process being studied can give indications on the number of clusters to expect. Unfortunately, as Masyn (2013) explains in her chapter on finite mixture

modelling, there is not one ultimate single method for comparing models with different numbers of classes to decide which is best. It requires looking at several fit indices while considering theoretical aspects and ease of interpretation of the latent cluster models. In terms of tools of relative model fits, Masyn (2013) suggests using information-heuristic tools (e.g., BIC, AIC) over inferential methods such as likelihood ratio tests because the former allows comparison of multiple models that are not necessarily nested. As additional parameters tend to increase the fit of a model, these information criteria usually penalize the addition of new parameters, thus considering parsimony in the equation. Finally, the authors of the *mclust* R package recommend three indices: the Bayesian Information Criteria (BIC), the Integrated complete-data likelihood (ICL) and the Bootstrapped Likelihood Ratio Test Statistic (BLRTS) (Scrucca et al., 2016). As these are readily integrated within the package, these indices are used for the present analysis. As a final validation step of the selected solution, Masyn (2013) recommend using the relative entropy as an indicator of classification diagnostic. It evaluates the precision of classification across all latent classes for the whole sample. Unfortunately, the *mclust* package does not provide built-in calculation of the relative entropy. Following Masyn's nomenclature, the indicator is computed using equation 9.1.

$$E_k = \frac{\sum_{i=1}^n \sum_{k=1}^K [-\widehat{p}_{ik} \ln(\widehat{p}_{ik})]}{n \log(K)} \quad (9.1)$$

Where E_k is the posterior classification uncertainty for a K -class model. It takes a value between 0 and 1 (inclusively) where 0 means the model is not better than random guessing and 1 there is perfect posterior classification for all observations. p_{ik} is the posterior probability for individual i to belong to class k . The relative entropy should not be used for selecting the number of classes. Rather, it serves as a diagnostic tool to identify overextraction of latent classes and to evaluate the utility of a latent class analysis using a particular set of indicators. A value above 0.80 is considered acceptable (Weller, Bowen, & Faubert, 2020).

9.4 Building the neighbourhood typology

The typology is created using a set of seven built environment variables. As previously explained, the City of Montréal Mobility Survey 2019 (CMM19) containing attitudes is not geographically representative of the studied region. For this reason, the neighbourhood typology is created using the large-scale 2018 Montréal Origin-Destination (OD18) survey. This approach ensures that all

the possible residential built environment contexts on the Island of Montréal are represented. In short, it produces a “calibrated” neighbourhood typology. The process is illustrated in Figure 9.1.

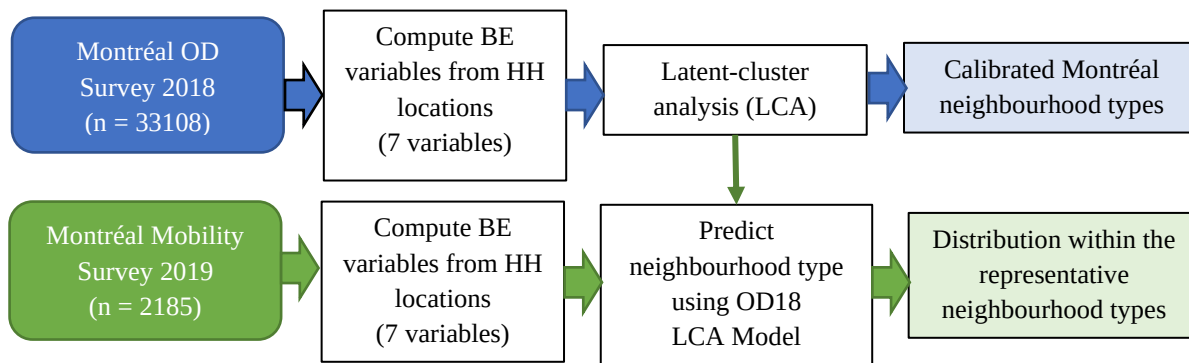


Figure 9.1 Neighbourhood typology building process

At first, ten built environment variables were considered for this analysis based on the literature review of section 3.4. After numerous tests and analyses, three variables were dropped from the latent-cluster model-building process for various reasons. For regional accessibility, the variable measuring the *distance to Montréal’s CBD* was initially included but was found to be too highly correlated with the variable “walking distance to metro station” (Pearson’s correlation = .92 for the OD18 dataset, .80 for the CMM19 dataset). Because the metro network is located mainly in the central part of the Island of Montréal, the variable measuring the distance to the nearest Metro station can be seen as a general proxy for regional accessibility. Including both variables risks putting too much weight on regional accessibility and the relative location of households within the city compared to the other measures. The *number of bikesharing stations* (BIXI) within a 1-km buffer was also considered to measure access to mobility services. However, the variable was too highly correlated with the number of carsharing vehicles ($\rho = .88$) as both services are offered in the same neighbourhoods while completely absent from others. The variable was also highly correlated with the density of retail establishments ($\rho = .82$). Access to carsharing vehicles was kept because of its higher theoretical and empirical relationship with car ownership and lower correlation with retail establishments’ density. The *number of grocery stores* (a variable used in all three published/submitted contributions) was also considered for local accessibility to commercial opportunities. It was dropped in favour of the density of retail establishments, which was more normally distributed and appeared to cause less distortion within the identified

neighbourhood types. The variable also relates to a variety of needs beyond food acquisition. The descriptive statistics for the seven final input variables are presented in Table 9.1.

Table 9.1 Descriptive statistics of the seven selected built environment variables for both survey samples

Variables	OD18 Survey n = 33103				CMM19 Survey n = 2815			
	Min	Max	Mean	SD	Min	Max	Mean	SD
Pop. density [pers. / km ²] ^a	18	41652	7703	3241	180	14620	9341	3018
Entropy [0-1] 5 categories ^a	0	0.97	0.58	0.15	0	0.952	0.59	0.13
Density of 4-ways intersections ^a	0	77	28.9	13.9	0	75.0	36.4	13.4
Density of retail opportunities ^a	0	863	76.6	94.2	0	758	107	96
NB of carsharing vehicles ^a	0	93	10.8	15.8	0	92.0	21.0	20.6
Walk dist. to metro station [km]	0.3	30.1	4.0	5.4	0.1	23.563	2.1	3.2
Bus LOS ^b	0	1992	323	237	0.0	1523.0	334	209

Note: ^a Computed within a 1-km walking distance buffer. ^b Computed within a 400 m (~5 minutes) walking distance buffer.

Using those seven built environment indicators, the next step is to determine the number of clusters that best fit the data while allowing an investigation of the relationship between attitudes, built environment and car ownership/carsharing decisions. To help with the decision, the indices introduced in section 9.3.2.1 are presented in Table 9.2.

The *mclust* package provides 14 Gaussian models with different parameterizations of the covariance matrix. When using the package's built-in calculation of the fit indices (BIC, ICL, etc.), all 14 parameterizations are tested along with the range of number of clusters, allowing the identification of the model and the number of clusters that best fit the data. See Scrucca et al. (2016) for details. The top eight best-performing models for all indices had the same parametrization (VEV: Ellipsoidal distribution, variable volume, equal shape, variable orientation).

Table 9.2 Fit indices for the neighbourhood typology latent-cluster model

K	BIC	ICL	LRTS	BLRT p-value	Entropy
1	-2080823	-2080823	67362	0.004	-
2	-2013773	-1959844	98594	0.004	0.985
3	-1916659	-1919678	31645	0.004	0.998
4	-1900467	-1907269	25183	0.004	0.948
5	-1893456	-1901338	11077	0.004	0.972
6	-1850008	-1879716	7325	0.004	0.889
7	-1836131	-1853039	6371	0.004	0.931
8	-1835006	-1838570	9114	0.004	0.899

Note: BIC = Bayesian Information Criterion; ICL = Integrated Complete-data Likelihood; LRTS = Likelihood ratio test statistics; BLRT = Bootstraps (250) likelihood ratio test statistic.

The indices point toward an 8-cluster solution. Due to the large sample size ($n = 33,108$), the Likelihood ratio test statistics and the bootstrapped p -value indicate that each K -cluster model should be rejected in favour of a $K+1$ clusters model. However, as Masyn (2013) pointed out, the “best” model for the specific analysis conducted is the one with the lowest number of clusters, the highest conceptual clarity, conceptual simplicity and ease of interpretation. Having eight classes is likely to increase the complexity of the subsequent analysis greatly. Furthermore, when looking at the curve for BIC and ICL as the number of clusters increases, there is diminishing returns with each additional cluster in model fit improvement after the third cluster. Careful analysis of the mean and variance of each of the seven indicators led to the selection of **a four-cluster solution**.

Following standard *post hoc* classification (Masyn, 2013), each observed household of the OD survey is then assigned the cluster (“neighbourhood type”) with the highest probability. This calibrated latent-cluster model of neighbourhood types is then used to *predict* the most likely type for the 2185 observed households of the Montréal Mobility Survey 2019 using the same seven built environment variables. Classification within the four neighbourhood types for both datasets, along with the within-type mean score and standard deviations for the seven indicators, are presented in Table 9.3.

Table 9.3 Summary statistics and classification within the four neighbourhood types

Survey	Suburban		Mid-Suburban		Central		Ultra-central	
	n	%	n	%	n	%	n	%
OD 2018 survey (n = 33103)	9123	27.6%	5121	15.5%	14974	45.2%	3885	11.7%
CMM 2019 survey (n = 2185)	260	12.0%	171	7.8%	1282	58.6%	472	21.6%
OD 2018 values	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Pop. density [pers. / km ²]	4251	1899	7458	2502	9028	2338	11021	2427
Entropy [0-1] 5 categories	0.49	0.15	0.56	0.13	0.6	0.11	0.7	0.15
Density of 4-ways intersections	14.6	7.9	25.56	10.5	34.1	9.0	46.5	10.99
Density of retail opportunities	18	18	38	24	70	38	288	117
NB of carsharing vehicles	0	0	1.4	1.1	12.9	10.1	40.7	20.6
Walk dist. to metro station [km]	9.9	6.6	4.4	3.0	1.1	0.63	0.62	0.32
Bus LOS	179	158	311	225	378	232	470	255
MTL Mobility Survey 2019 values	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Pop. density [pers. / km ²]	4430	1554	6936	1917	9788	2292	11704	1932
Entropy [0-1] 5 categories	0.49	0.17	0.57	0.14	0.59	0.11	0.64	0.13
Density of 4-ways intersections	16.3	7.9	26.0	11.4	37.4	8.7	48.6	11.4
Density of retail opportunities	19	19	34	22	79	39	256	88
NB of carsharing vehicles	0	0	1.6	1.1	17.2	11.5	49.7	19.2
Walk dist. to metro station [km]	8.0	5.2	4.7	3.5	1.1	0.6	0.7	0.3
Bus LOS ^a	181	158	241	210	346	192	420	220

Note: ^aAll variables are computed within a 1-km walking distance buffer except for Bus LOS which is computed within a 400 m walking distance buffer.

Thus, the names are kept simple to facilitate interpretation and are based primarily on their relative location within the city. Indeed, by inspecting the geographical distribution of the neighbourhood types on the map (Figure 9.2), it seems that the centrality of the neighbourhood types correlates well the seven BE indicators. The higher the values for all variables (except for distant to the metro network), the more “central” the neighbourhood and the lower the values, the more “suburban”. However, this means that the 4-cluster latent model could not detect neighbourhood types where, for example, density could be high, but diversity and retail opportunities very low. A higher number of clusters could have allowed such patterns of disparity between the built environment indicators to emerge. However, this would have significantly complicated the subsequent analyses, which require a certain level of parsimony in the number of clusters.

As for the difference between the two samples, the distribution of households within the four types shows an apparent disparity. This confirms that the CMM19 survey is not geographically representative of the studied region. Specifically, the shares of households in *Suburban* and *Mid-*

suburban neighbourhoods are about half of what is found in the OD Survey. In contrast, the shares in *Central* and *Ultra-central* neighbourhoods are much higher. However, within each neighbourhood type, the mean values of the seven variables are very similar between the two samples. This suggests that the within-neighbourhood type distribution of households of the CMM19 survey is, at least, more representative than the entire sample.

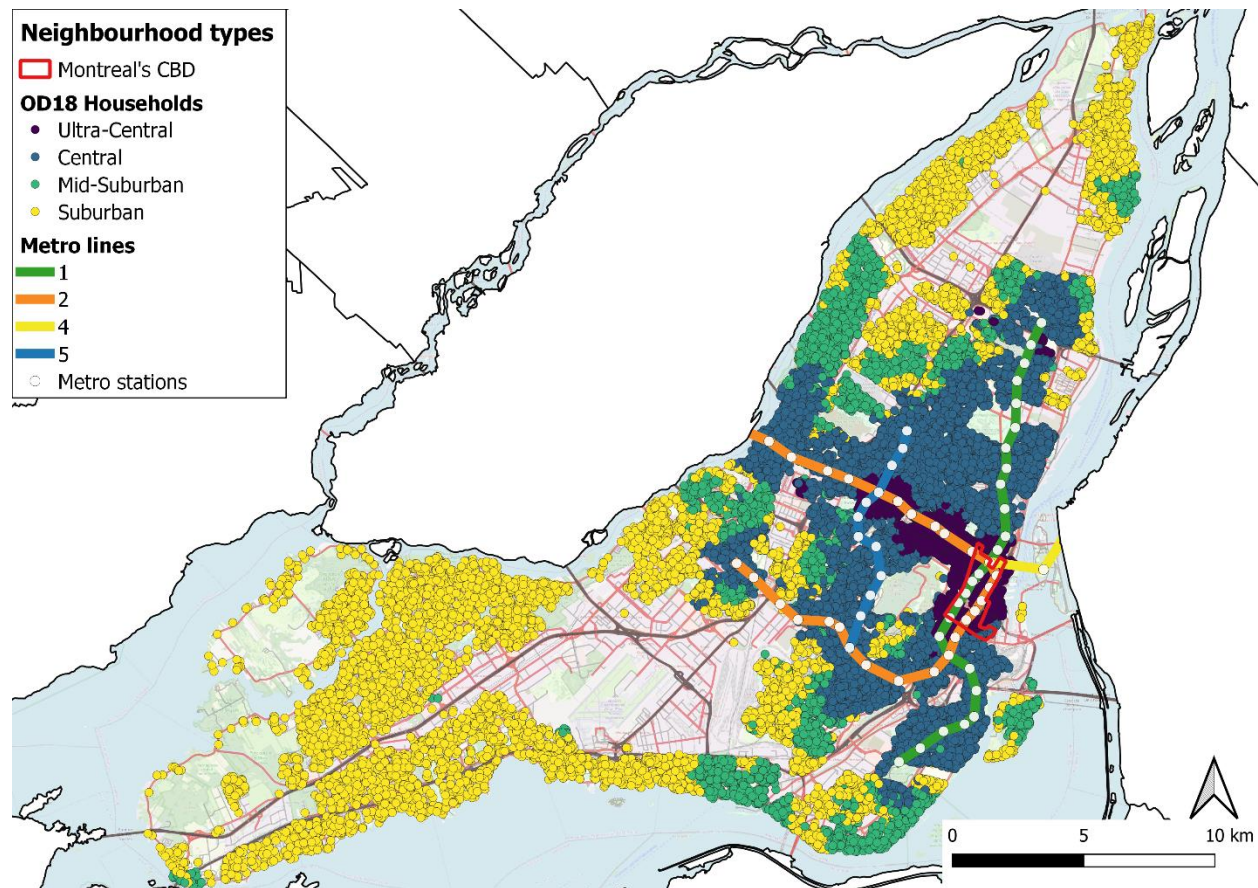


Figure 9.2 Spatial distribution of the four neighbourhood types for OD18 households

Visual inspection of the spatial distribution of each neighbourhood type indicates that very few households seem to be outliers. Two small pockets of *Ultra-central* households are located much further away from the CBD. In both cases, those households are located near two major commercial centers (Marché Central and Galleries d'Anjou), which means they have very high values or retail density within walking distance. This skewed their inclusion in the *Ultra-central* category despite the values for their six other variables more aligned with the *Central* type. Similarly, a pocket of *Suburban* households is located slightly west and very close to Montréal's

CBD. This neighbourhood is Westmount, a very wealthy low-density independent City with large single-family mansions built on the hillside of the Mont-Royal. Finally, the influence of the metro on the identified neighbourhood type is apparent with the households in the near or medium vicinity of the metro network classified as *Central* or *Ultra-central*. This is adequate since the Montréal Metro network, as the backbone of the entire transit system, has a tremendous structural impact on the travel behaviour of Montréalers.

9.4.1.1 Sociodemographic characteristics within each neighbourhood type

The next step is to analyze if there are differences in key sociodemographic characteristics between the four types of neighbourhoods for both samples. Table 9.4 and

Table 9.5 presents the mean value of the six household characteristics. The Kruskal-Wallis test is used as a non-parametric and robust alternative to ANOVA when the variables are not normally distributed (as is the case of the count variables in the table). The *post-hoc* analysis is done with the Pairwise Wilcoxon's test between neighbourhood types.

Table 9.4 Key sociodemographic characteristics by neighbourhood type – OD18

	Mean value					KW		Pairwise Wilcoxon's Test: Significance					
	All	Sub.	M Sub.	Central	Ult-C.	Chi-Square	Stat. Sign.	Sub. M-Sub.	Sub. Central	Sub. Ultr-C.	M-Sub. Central	M-Sub. Ultra-C.	Central Ultra-C.
OD18, n =	33108	9123	5121	14974	3885								
1-adult HH (1 = yes)	0.38	0.27	0.36	0.42	0.49	752	***	***	***	***	***	***	***
NB of adults	1.8	1.99	1.84	1.71	1.6	1006	***	***	***	***	***	***	***
NB of children (<=17 yo)	0.37	0.42	0.41	0.36	0.25	140	***	NS	***	***	***	***	***
Avg. age of HH adults	53.47	55.7	55.7	52.0	51.0	444	***	NS	***	***	***	***	**
Age amplitude of adults ^a	11.77	13.4	13.3	10.6	9.0	805	***	***	***	***	***	***	***
NB of full-time workers	0.86	0.93	0.81	0.84	0.81	66	***	***	***	***	***	NS	NS
Median HH Inc. in DA	53661	67593	52543	48004	44218	5310	***	***	***	***	***	***	***
Nb of licensed drivers	1.44	1.73	1.44	1.32	1.22	1337	***	***	***	***	***	***	***
Nb of cars	1.03	1.47	1.14	0.84	0.60	4291	***	***	***	***	***	***	***
Cars per driver	0.62	0.81	0.70	0.54	0.40	3004	***	***	***	***	***	***	***
CS in HH (1 = yes)	0.09	0.02	0.03	0.12	0.19	1357	***	***	***	***	***	***	***

Note: HH = Household; KW = Kruskal-Willis Test; CS = Carsharing.

^aThe age amplitude of adults is calculated only for multiple adults HH. It is the maximum age of adult household members (>= 18 years-old) minus the minimum age of adults.

Table 9.5 Key sociodemographic characteristics by neighbourhood type – CTP2019

	Mean value					KW		Pairwise Wilcoxon's Test: Significance					
	All	Sub-urban	Mid-Sub.	Central	Ultra-Central	Chi-Square Stat.	Sign.	Sub. M.Sub	Sub. Central	Sub. Ultra-C.	M-Sub. Central	M-Sub. Ultra-C.	Central Ultra-C.
CMM2019, n =	2185	260	171	1282	472								
1-adult HH (1 = yes)	0.29	0.24	0.36	0.28	0.30	7	NS	NS	NS	NS	NS	NS	NS
NB of adults	1.85	1.98	1.78	1.84	1.83	12	**	*	*	*	NS	NS	NS
NB of children (<=17 yo)	0.46	0.47	0.41	0.49	0.37	9	*	NS	NS	NS	NS	NS	NS
Avg. age of HH adults	42.82	49.5	47.0	41.1	42.2	99	***	NS	***	***	***	***	NS
Age amplitude of adults ^a	7.42	11.0	8.3	7.0	6.2	14	**	**	***	**	NS	NS	NS
NB of full-time workers	1.25	1.15	1.12	1.29	1.24	10	**	NS	NS	NS	NS	NS	NS
Median HH inc. in DA	48768	61909	51135	46774	46087	194	***	***	***	***	***	*	*
Nb of licensed drivers	1.7	1.85	1.65	1.68	1.68	18	***	**	***	**	NS	NS	NS
Nb of cars	0.82	1.42	1.13	0.75	0.55	277	***	***	***	***	***	***	***
Cars per driver	0.49	0.78	0.7	0.45	0.34	242	***	*	***	***	***	***	***
CS in HH (1 = yes)	0.32	0.04	0.11	0.35	0.45	172	***	**	***	***	***	***	***

Note: HH = Household; KW = Kruskal-Willis Test; CS = Carsharing.

^aThe age amplitude of adults is calculated only for multiple adults HH. It is the maximum age of adult household members (>= 18 years-old) minus the minimum age of adults.

The Chi-Squared values of the Kruskal-Willis test are significant for all variables for both datasets, indicating statistical differences for the six household sociodemographics between the four neighbourhood types. For the OD18 dataset, likely due to its vast sample size, Wilcoxon's pairwise *post-hoc* tests indicate that there are only a few non-significant pairwise differences. Those results are indicative of residential self-selection based on household characteristics. Specifically, larger households (more adults and children) are more likely to locate themselves in more suburban areas. The difference in the number of full-time workers is not as significant. Younger households are more likely to locate in more central locations. And finally, median neighbourhood income is higher in suburban neighbourhoods. Unfortunately, while household level income as available in the OD18 dataset, it was not collected in the CMM19 Survey. This is why neighbourhood level-income is used as proxy following M. Adjemian and Williams (2009)'s recommendation.

9.5 Identifying the latent attitudinal profiles

To identify latent attitudinal profiles, 12 attitudinal statements about daily mobility collected in the CMM19 survey are used. The survey questions were derived from previous research about attitudes toward the car and other modes, including instrumental, affective, and symbolic factors (e.g., Hunecke et al., 2010; Steg, 2005). As 8 of the 12 statements relate specifically to the car, only respondents with a driver's licence were asked to answer these questions, as having a driver's license is necessary to drive the household car and to have a carsharing membership. The 12 statements were preceded by the sentence "When thinking about your daily trips, please indicate how much you agree with the following statements" and was measured using a slider scale question on the web interface going from strongly disagree to strongly agree, resulting in a score from 0 to 100. The sliders embedded in the web interface were designed so that respondents had to click on the slider to activate it and move it within the 0-100 range. This allowed for the detection of missing cases (i.e., people who skipped the question). Among the 2243 respondents with a driver's licence, 59.1 % answered all 12 statements, 15.8 % missed one, and 22.5 % missed between 2 to 6 statements. 58 observations (2.5 %) were discarded for not answering seven or more of the 12 attitudinal statements. This leaves 2185 cases to perform multiple imputations for the missing values. For this, regularized PCA was used using the Expectation-Maximization (EM)

algorithm method explained and tested by Van Ginkel et al. (2014) and implemented in the R package *missMDA*. Descriptive statistics for the 12 statements are presented in Table 9.6.

Table 9.6 Descriptive statistics for the 12 attitudinal statements

	Variable name	Statements	Mean	Std. dev
1	personalspace	It is important to have my own space when I make trips	38.3	33.7
2	showoff	My transportation mode allows me to show who I am	34.1	36.4
3	nodependancy	It is important for me to not depend on others for my trips	72.6	29.9
4	environement	It is important for me to minimize my trips environmental footprints	81.8	24.8
5	alwaysusedcar	I always made my trips by car	21.8	29.4
6	practical	I find it more convenient to travel by car	45.9	37.0
7	feelsafe	I feel safe when I travel by car	48.6	33.3
8	comfort	To be in a car is comfortable and relaxing	41.9	33.7
9	likedriving	I have fun driving a car	42.6	35.0
10	mostappropriate	The car is the most suitable mode for someone like me	27.8	33.7
11	accordancewithvalue	Using a car is consistent with my values	22.7	28.1
12	socialpressure	People that are important for me think it's normal to get around by car	33.5	33.1

Note: The first four indicators relate to general attitudes toward travel, and the last eight are specific to the car.

The same process used for the neighbourhood's segmentation is conducted to help identify an optimal number of clusters. Unlike the identification of the neighbourhood types, here, the three indices point toward a different number of clusters. Table 9.7 presents the indices with the covariance matrix parameterizations that offers the best model fit for all values of K (VEV: Ellipsoidal distribution, variable volume, equal shape, variable orientation). It is the same parameterization as for the neighbourhood types.

Table 9.7 Fit indices for the latent-profile analysis model of attitudes. VEV covariance parameterization.

K	BIC	ICL	LRTS	BLRT.pvalue	Entropy
1	-246897	-246897	3839	0.004	-
2	-243672	-243868	1893	0.004	0.972
3	-243116	-242688	389	0.004	0.953
4	-242050	-241989	982	0.004	0.964
5	-241402	-242208	2250	0.004	0.958
6	-241091	-241093	684	0.004	0.892
7	-240510	-241165	539	0.004	0.807
8	-240402	-241228	936	0.004	0.900

Note: BIC = Bayesian Information Criterion; ICL = Integrated Complete-data Likelihood; LRTS = Likelihood ratio test statistics; BLRT = Bootstraps (250) likelihood ratio test statistic.

The ICL suggests a solution with four, six, seven or eight clusters. The BIC keeps diminishing as the number of clusters increases, something confirmed by the bootstrapped *p*-value of the Likelihood ratio test. After inspection of the means and standard deviations for the 12 indicators for the 4, 6 and 7- clusters models, **the 4-cluster solution is selected for parsimony and ease of interpretation of each cluster.** Then, as for household classification within the four neighbourhood types, modal assignment is conducted where each observed individual of the CMM19 survey is assigned the cluster (*travel attitude profile*) with the highest probability.

The mean values by latent profile for the 12 attitude indicators are presented in Figure 9.3. The first four indicators relate to general travel, while the last eight are car specific. The attitude profiles were named based on the mean values of those statements and are described below. The first two profiles are dominant, with 37 % and 45 % of the sample, respectively, while the last two are much less common, with about 9 % each.

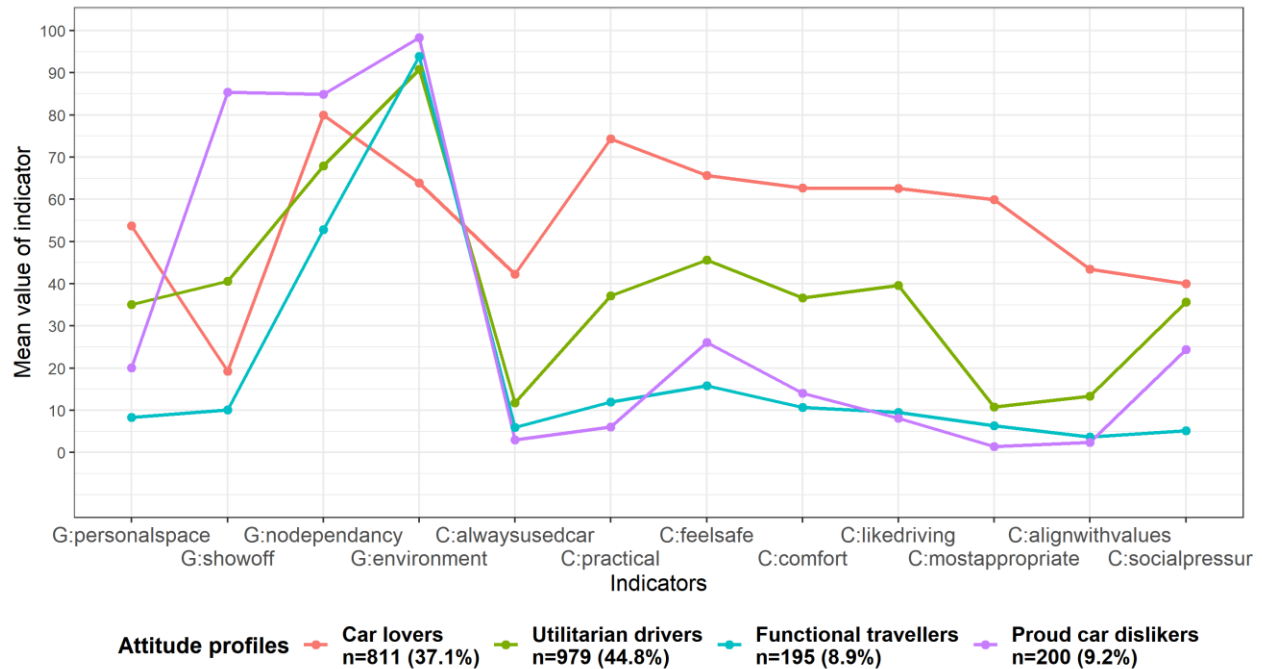


Figure 9.3 Mean values of the 12 input attitudinal indicators (G: general, C: car-related), 4 attitude profiles. CMM19 Survey, n = 2185

Profile 1: Car lovers (n = 811, 37.1%)

Individuals of this profile score the highest on the eight car-related indicators. Notably, they are the only segment scoring high on the statements *mostappropriate* (“the car is the most appropriate for someone like me”) and *alignwithvalue* (“Using a car is consistent with my values”). Together with the statement *likedriving* (“I have fun driving a car”), this suggests that these individuals who have always used the car (*alwaysusedcar*) derive affective function from its use in addition to its practical benefits. However, their low score on the indicator *showoff* (“My transportation mode allows me to show who I am”) might indicate that they are unlikely to admit their attachment to the car explicitly. This is not surprising considering the difficulty observed by Steg (2005) long ago to explicitly measure the symbolic value of the car. They also seem to feel slightly more social pressure to use the car than the other profiles but the difference with the **Utilitarian drivers** is barely significant (Pairwise Wilcoxon Test, $p = .04$). People from this profile are also apart from the three others on the environmental aspect of travel as it seems less important for them.

Profile 2: Utilitarian drivers (n = 979, 44.8%)

The largest of all groups, this profile groups together individuals who find some clear utilitarian benefits to the car (second highest mean value for *feelsafe*, *practical*, *comfort* and *personal space*, *although those scores are on average below 50*), despite indicating that it is important for them to minimize their environmental footprint during their daily trips. This suggests that they might live in a more car-dependent environment than the following two profiles, thus not allowing them to align their daily travels with their environmental values. Unlike **Car lovers**, they do not associate themselves strongly with the car (*mostappropriate* and *accordancewithvalue*) but seem nonetheless to find some pleasure in driving (*likedriving*).

Profile 3: Functional travellers (n = 195, 8.9 %)

This profile is characterized by its lower mean score on the *nodependancy* indicator (“It is important for me to not depend on others for my trips”). They also score lowest on the general travel indicator *personalspace* (“It is important to have my own space when I make trips”). This suggests that independence from others and having their bubble is less important for them in their daily mobility needs. The other indicators are aligned with the last profile except for the *showoff* indicator discussed below.

Profile 4: Proud car-dislikers (n = 200, 9.2%)

Like the Functional travellers, people from this last profile show very low mean scores for all the eight car-related indicators, suggesting they do not see many utilitarian, affective or symbolic benefits to its use for their daily travels, except maybe in its protective aspect (*feelsafe*). Furthermore, they show a mean score substantially above the three other profiles for *showoff* (“My transportation mode allows me to show who I am”). This suggests they strongly identify themselves with another mode than the car. Further investigation into the other variables collected in the survey might be needed to determine which mode of transportation allows them to express their identity (cycling? public transit? walking?).

9.5.1.1 Sociodemographic characteristics of each travel-attitude profile

Some previous studies on travel-attitude segmentation found that the psychographic profiles they identified were not related to most sociodemographic characteristics except education (e.g., Anable, 2005) while other showed statistical differences between profiles (J. H. Lee & Goulias,

2018). Due to this inconsistency in previous research, sociodemographic of the four attitudinal profile are investigated here. Because the attitudes are individual measures, a slightly different set of sociodemographic characteristics than those used to analyze the neighbourhood types are compared between groups. As most variables are not normally distributed, the Kruskal-Wallis non-parametric and robust alternative to ANOVA is used. The post-hoc analysis is done with the Pairwise Wilcoxon's test between groups. Statistics are presented in Table 9.8.

Table 9.8 Individual and household sociodemographics for each travel-attitude profile

CMM19		Mean value					KW (Chi-Square)		Pairwise Wilcoxon's Test: Significance Level					
		All	Car lovers	Util. Driv.	Fun. Trav.	Car dis.								
		n	2185	811	979	195	200	Sign. Stat.	Level	CL UD	CL FT	CL CD	UD FT	UD CD
Individual	Gender (1 = woman)	0.58	0.53	0.61	0.55	0.62	14	**	**	NS	*	NS	NS	NS
	Age	43.43	46.8	40.51	48.52	39.09	137	***	***	NS	***	***	NS	***
	Is a worker	0.76	0.72	0.8	0.75	0.78	18	***	***	NS	NS	NS	NS	NS
	CS membership	0.28	0.15	0.34	0.35	0.5	136	***	***	***	***	NS	0	**
	Commute dist. [km] ^a	6.71	8.07	6.11	5.6	5.77	49	***	***	***	***	NS	*	NS
Household	1-adult HH (1 = yes)	0.29	0.32	0.27	0.23	0.28	11	*	NS	*	NS	NS	NS	NS
	Size	2.31	2.26	2.34	2.41	2.27	6	NS	NS	NS	NS	NS	NS	NS
	NB of children	0.46	0.41	0.49	0.49	0.45	4	NS	NS	NS	NS	NS	NS	NS
	HH Income (proxy) ^b	48.8	51.8	46.8	48.7	46.4	43	***	***	*	***	NS	NS	NS
	Nb of cars	0.82	1.16	0.66	0.69	0.3	353	***	***	***	***	NS	***	***
	Cars per driver	0.49	0.72	0.38	0.38	0.17	425	***	***	***	***	NS	***	***
	Residential parking (1 = yes)	0.45	0.58	0.4	0.42	0.26	97	***	***	***	***	NS	***	**

Note: Significance level: * < .05, ** < .01, *** < .001; CS = Carsharing; ^a Commute distance was only computed for those declaring a usual place of work or school outside the home (n = 1534 / 2185). ^b Median household income in the dissemination area (in 000's of Canadian dollars).

The Kruskal-Willis test indicates significant differences between the group on all variables except household size and the number of children. If the household size is not different, a smaller proportion of **Functional travellers** live in single-adult households, but the difference is only significant with **Car lovers**. The pairwise Wilcoxon's test results indicate that some pairs are statistically different for most variables. **Car lovers** and **Functional travellers** are older, a higher proportion of them are men, and live in slightly wealthier neighbourhoods than the other two profiles.

The profiles exhibit very different patterns of mobility tool ownership (number of cars in the household, cars per driver in the household and individual carsharing subscription, off-street parking at home). A higher proportion of **Car lovers** have access to residential off-street parking at home, which is the opposite for **Car dislikers**. **Car lovers** who are workers or students also have a slightly longer mean commute distance. However, a much larger proportion of them lives in the two suburban neighbourhood types, as illustrated below, which could explain some of those differences.

9.6 Results

9.6.1 Car ownership/carsharing by neighbourhood types

Turning to our variable of interest, a bar plot is used to show the distribution of **household car ownership and carsharing decisions by neighbourhood type** in Figure 9.4. For all the analyses, carsharing (CS) was considered at the household level: if a household member, either the respondent or another driver, has a carsharing membership, then the household is deemed to have access to carsharing.

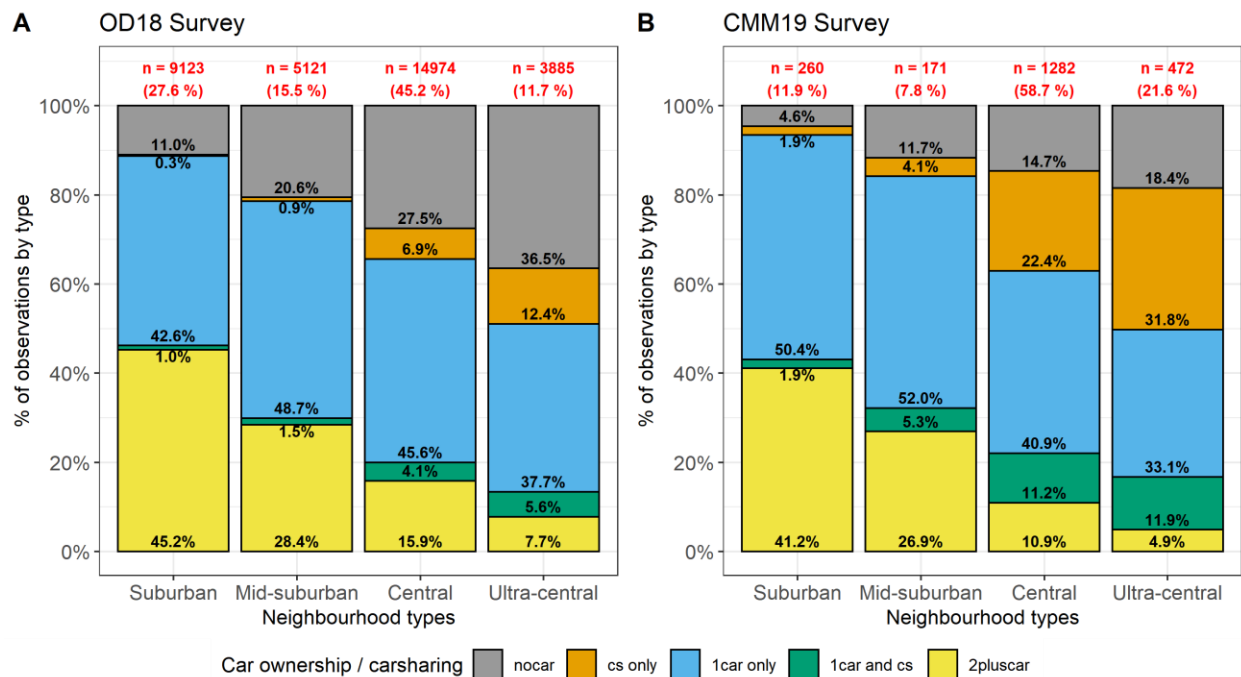


Figure 9.4 Household car ownership distribution by neighbourhood type for OD18 (A) and CMM19 (B)

As expected, the difference between neighbourhood types and vehicle ownership is striking and highly significant (OD18, $\chi^2 = 5062$, Df = 12, p-value < .001; CMM19, $\chi^2 = 351$, Df = 12, p-value < .001) for both samples. There are slight **differences between the two surveys**. A lower proportion of households in the CMM19 survey have no cars compared to the more representative OD18 Survey. In *Central* and *Ultra central* neighbourhoods, this seems to be explained by a higher carsharing adoption. In all neighbourhood types, more CMM19 households have only one car, and fewer have two or more cars compared to the OD survey, again, compensated by a higher proportion having one car plus carsharing. As for **differences between neighbourhood types**, both surveys show similar patterns: the proportion of one-car households is the most constant. What changes drastically is the proportion of zero-car households, carsharing only, a car and carsharing and households with two or three or more cars. This indicates that owning one car is likely a necessity for many households across neighbourhood types. Although *the composition* of those one-car households might be different: in more central neighbourhoods, larger households might accommodate themselves with a single car, while in more suburban settings, one-person households are likely to need a car.

9.6.2 Car ownership/carsharing by attitude profiles

As most of the measured attitudes relate to some aspects of the car, a strong association between car ownership/carsharing and the four latent profiles is expected. One caveat is that those attitudes were measured only for the respondent who might not be the only person responsible for decisions regarding car ownership within the households. As mentioned earlier, carsharing was considered here at the household level. If anyone in the household had a carsharing membership, then the household was considered to have a membership. With this important caveat in mind, the next cross-analysis (Figure 9.5) looks at the car ownership levels and carsharing decisions for the four profiles.

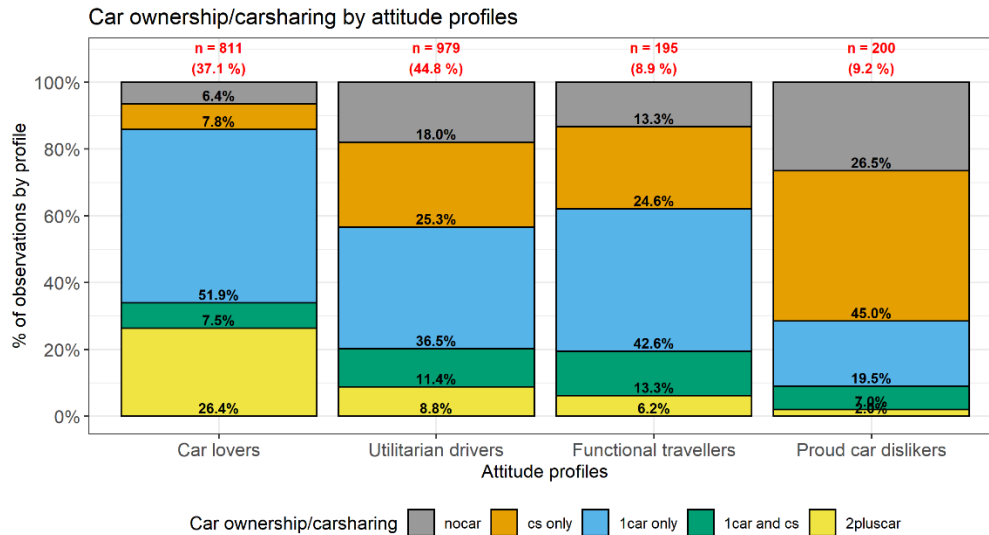


Figure 9.5 Household car ownership/carsharing status by attitude profile

The Chi-Squared test of independence indicates a significant correlational relationship between the attitudinal profiles and car ownership levels ($\chi^2 = 396$, Df = 12, p-value < .001). A substantially higher proportion of **Car lovers** own two or more cars than the other profiles. On the other end of the spectrum, far more **Proud car-dislikers**, without much surprise, live car-free. **Functional travellers** and **Utilitarian drivers** have similar car ownership/carsharing distributions. However, more **Functional travellers** have one versus no car compared to **Utilitarian drivers**, but fewer have two or more cars. The figure reveals that for *all four attitudinal profiles*, more than half of households without a car have a carsharing membership. That proportion is highest for **Functional travellers** (65 %) and lowest for **Car lovers** (55%). This suggests that for households owning no cars, carsharing is considered an option across the spectrum of car-related attitudes.

Because attitudes are measured at the individual level, and car ownership is considered a household-level decision, the relationship between attitude profiles of the respondent and the number of cars in households with multiple adults might not be strong unless there is strong homophily (similar attitudes within households) or if the respondent has a higher responsibility in car-related household decisions than non-respondent members. However, previous research has shown that individuals with very opposite attitudes about travel modes rarely live together (J. H. Lee & Goulias, 2018). In the survey sample, households with one, two and three or more adults represent 28.6 %, 61.4 % and 10.25 % of households. The last two categories are grouped as

“2+adultsHH” for this analysis. The proportion by household types (*1adultHH* and *2+adultsHH*) are presented in Figure 9.6.

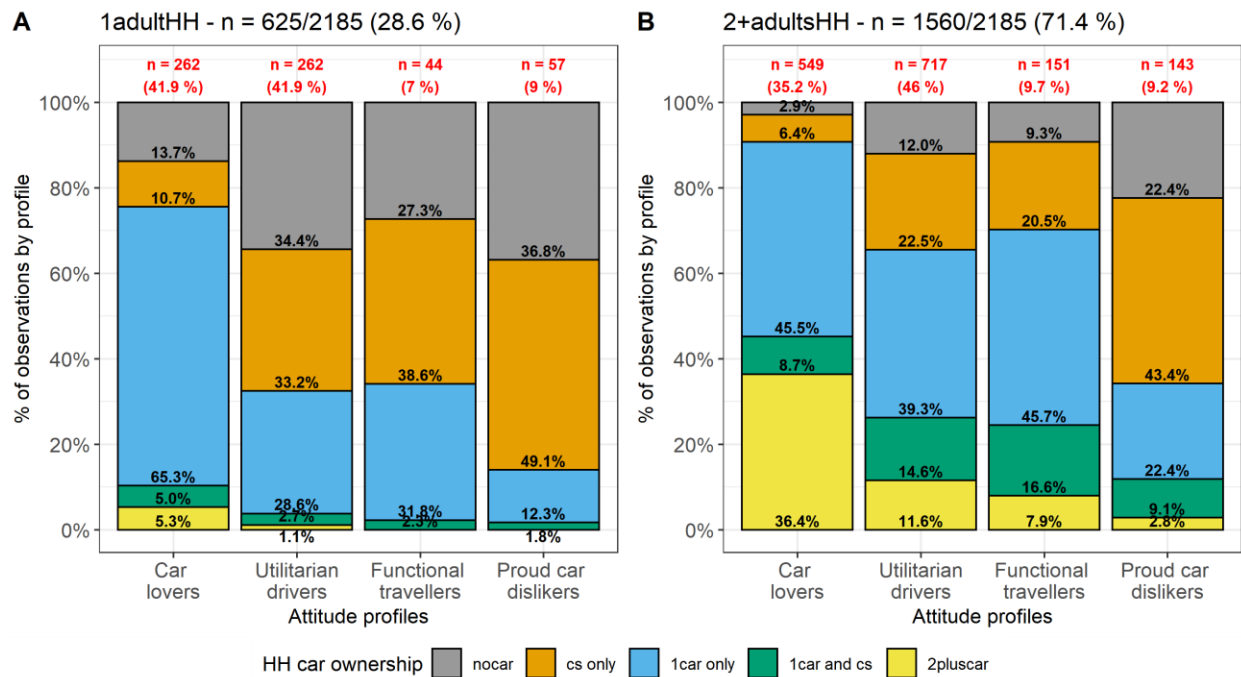


Figure 9.6 Household car ownership distribution by attitude profile of the respondent by household type (*1adultHH* and *2+adultsHH*).

The Chi-square test of independence is significant for both household types, indicating a relationship between the variables (*1adultHH*: $\chi^2 = 140$, Df = 12, p -value < .001; *2+adultsHH*: $\chi^2 = 318$, Df = 12, p -value < .001). First, looking at single adult households, the proportion owning two or more cars or owning a car and having a carsharing membership is marginal for all profiles except for **Car lovers** for which these choices represent small, but non-negligible proportions. Similar proportions of **Utilitarian Drivers**, **Functional travellers** and **Car Dislikers** have no car or carsharing membership, while considerably less **Car lovers** are in that situation. However, a larger proportion of **Car Dislikers** prefer to rely only on a carsharing membership instead of owning a car compared to **Utilitarian Drivers** and **Functional travellers**. This means that half as many **Car Dislikers** own a car compare to the large groupe of **Utilitarian Drivers**.

Among two or more adults' households, **Car lovers**, again, stand apart from the other profiles with a substantial proportion of them owning two or more cars, a marginal proportion having no car and a small proportion choosing a carsharing membership only. Unlike for single-adult

households, here **Car dislikers** stand apart from the two more moderate attitude profiles with twice as many opting for no car/no carsharing or carsharing only. It is among **Utilitarian Drivers** and **Functional travellers** that we find the highest proportion of households using carsharing as a second car (“1 car and carsharing”).

9.6.3 Cross Analysis of neighbourhood types and attitudes

9.6.3.1 Attitudes distribution within Neighbourhood types

According to the residential self-selection hypothesis, more car-oriented households should be found in suburban settings, while a higher proportion of those preferring to travel by sustainable transportation modes would be more likely to reside in more central areas. That question is investigated by showing the distribution of the four **travel-attitudes profiles** within the four *Neighbourhood types*. Figure 9.7 shows the results. Pearson’s Chi-Squared Test confirms that the two variables are correlated ($\chi^2 = 208$, Df = 9, p-value < .001).

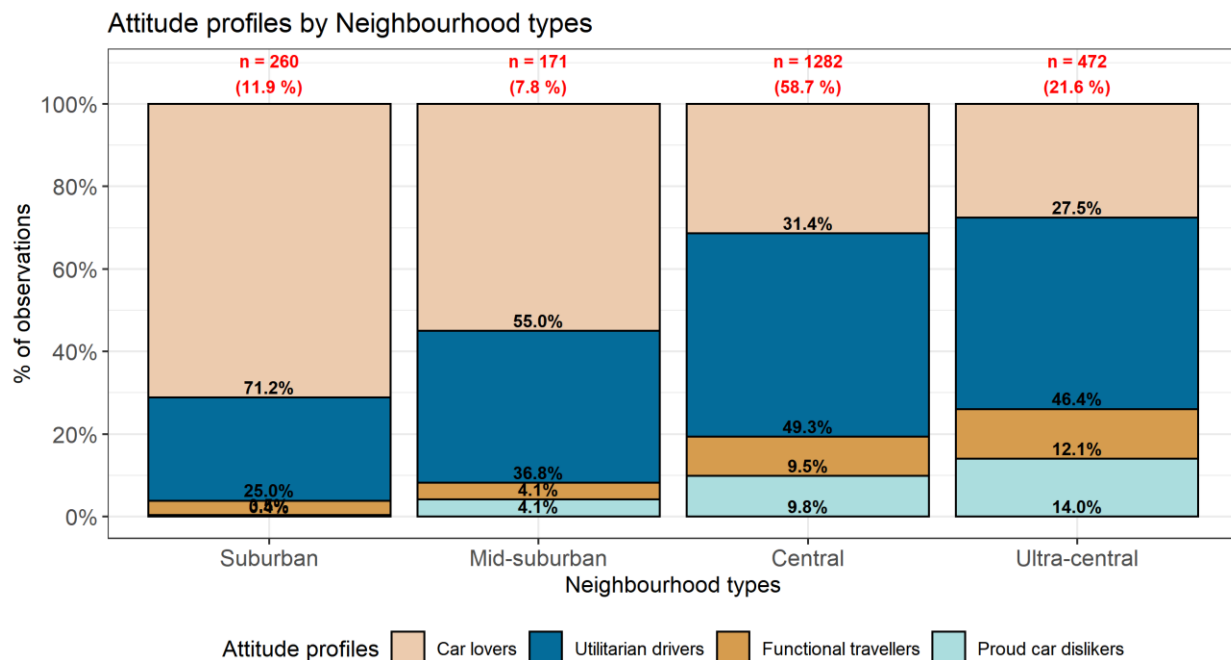


Figure 9.7 Distribution of attitudes profiles within the four Neighbourhood types

Specifically, the proportion of **Car lovers** gets lower when moving toward more central neighbourhoods. However, their presence in *Central* (31.4 % of households) and *Ultra-central* neighbourhoods (27.5 % of households) is far from marginal. **Utilitarian drivers** are dominant in

the *Central* neighbourhood type with a higher proportion than in the overall sample. They remain the dominant group in the *Ultra-central* neighbourhood as well. This indicates that even in areas of the city that are the most conducive to active travel and public transit, many people perceive practical benefits in using the car for daily trips. Without a deeper investigation of their travel activity sphere (i.e., work location and other constrained activities), it remains hard to infer why they remain dominant in those areas. Finally, the **Functional travellers** and **Car-dislikers** are marginal in the suburban neighbourhoods, represent their average total sample proportion in the *Central* neighbourhoods and are overrepresented in the *Ultra-Central* neighbourhoods. **Car-dislikers** are virtually absent from the *Suburban* type (one observed household), and only seven are in the *Mid-surburban* type. Insights from those results are discussed further below in the discussion section.

9.6.4 Cross-analysis: car ownership/carsharing by neighbourhood types and attitude profiles

The final analysis of this section is to investigate how *car ownership* and *car ownership/carsharing* relate to both characteristics of the built environment (*Neighbourhood types*) and travel-related attitudes (**Attitude profiles**). One question is: do **Car-lovers** systematically own more cars and are less likely to have a carsharing membership than the others in all neighbourhood types? And conversely, does the built environment affect their car ownership decisions? The *Suburban* and *Mid-suburban* neighbourhood types are grouped for this final cross-classification. This is necessary because of the low sample sizes in those types due to the non-spatial representativity of the CMM19 Survey. The distribution of household car ownership by neighbourhood types for each attitude profile is presented in Figure 9.8.

The figure shows that in a *suburban/mid-suburban* context, the differences between **Car lovers**, **Utilitarian drivers** and **Functional travellers** are less striking than what was observed in Figure 9.5 where neighbourhood types were not considered. Second, attitudes seem to matter even in contexts where the car is favoured and likely essential for many trips. **Utilitarian drivers** are more likely to be car-free (with or without carsharing) and less likely to have two or more vehicles than **Car Lovers**. The Chi-Square test indicates that the difference is significant. Overall, in *suburban neighbourhoods*, having a carsharing membership remains marginal. Note that the category “2+ cars” also includes a few households with a carsharing membership. Last, very few **Functional**

travellers (n=16) and **Proud car-dislikers** (n=8) live in the *Suburban/Mid-suburban* neighbourhood types, so drawing conclusions would not be wise.

In the *Central* neighbourhood type (the most common), the differences between the four attitude types are highly apparent and display similar patterns as in the Suburban context: **Car lovers** have more cars, followed by **Functional travellers** and **Utilitarian travellers**, then **Car-dislikers**, 75 % of whom live without owning a car. This neighbourhood type is ideal for studying the role of attitudes in a built environment context where people are not constrained to the automobile and where driving is not heavily restricted either. Table 9.3 shows that in *Central* neighbourhoods of Montréal, people have alternatives to the car: the mean distance to a metro station is 1.1 km, bus service is frequent, many local destinations are accessible by foot (high retail density) and carsharing is highly available and thus becomes a real alternative to car ownership altogether or to a second car. The results of Figure 9.8 suggest that car-related attitudes have a strong association with car ownership/carsharing decisions in a context where multiple mobility styles are possible. Again, the difference between the two largest attitude profiles, **Car lovers** and **Utilitarian drivers**, reveals the non-utilitarian (affective, symbolic, associated values) aspects of car ownership for **Car lovers**. However, while carsharing is far less popular among **Car lovers** than the three other profiles, almost 20 % of them nonetheless select it as part of their portfolio of car accessibly tools. A similar proportion of **Utilitarian drivers** and **Functional travellers** chose to access a car only through carsharing (25 %) or add carsharing as a substitute for the second car (13-15%). It also appears very clear when looking at the group of **Car dislikers** that carsharing might be the tool that allows 75 % of them to live without the necessity to own a car.

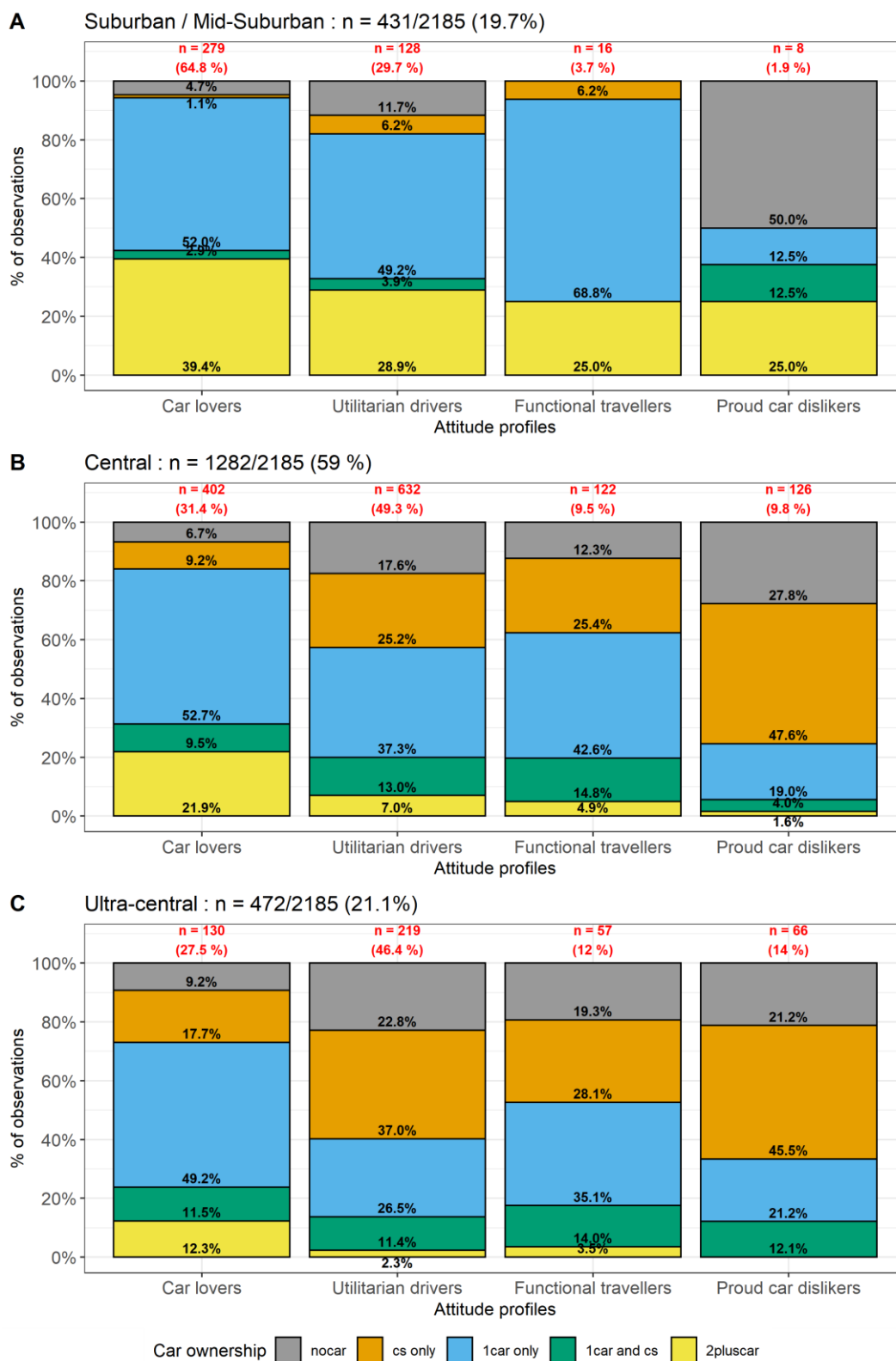


Figure 9.8 Car ownership/carsharing by attitude profile within each neighbourhood type

In the *Ultra-central* neighbourhoods, the four profiles display similar patterns as in *Central* neighbourhoods but with a more significant proportion of them being able to live without a car or with carsharing only, as would be expected (except for **Car dislikers**). In this dense, very mixed-use environment with plenty of alternatives for daily trips, **Utilitarian drivers** and **Functional travellers** show more similarities in their car ownership decisions with **Car-dislikers** than with **Car-lovers**. The opposite situation is observed in the *Suburban/Mid-suburban* neighbourhoods, where they aligned more with **Car lovers**. In fact, in this type of environment, **Car lovers** stand apart (once more!) from the rest, with a substantial majority of them still owning cars (73%) despite the built environment being conducive of car-free living and wide availability of carsharing vehicles.

Among **Utilitarian drivers**, **Functional travellers** and **Car-dislikers** the proportion of those without easy access to a car (“no car, no carsharing”) hovers around 20 % for the three less car-oriented attitude profiles. Only the **Car-lovers** stand out, with half as many choosing this alternative (9 %). It is worth mentioning that the mean number of carsharing vehicles available within a 1 km walking distance (~50) is almost three times as high as in the *Central* type (~17). Despite this substantial difference in accessibility, the uptake of carsharing is only slightly higher in the *Ultra-Central* than in the *Central* area for those with the least favourable attitudes toward the car, the **Functional travellers** and **Car dislikers**. Among **Utilitarian Drivers**, the proportion choosing carsharing only in *Ultra central* is about 1.5 times higher than in the *Central* type and among **Car-lovers**, this ratio is close to 2.

For all four attitude profiles, the more central people live, the less likely they are to own one car and, to a greater extent, two cars and the more likely they are to replace the first or second car with carsharing. The second key takeaway is that even the most dedicated car enthusiasts (**Car-lovers**) own fewer cars in more central locations. In the *Ultra-central* type, they remain the only attitude profile with a non-negligible proportion owning two or more cars (12.3 %). Still, 27 % do not own cars despite their strong appreciation of their value.

9.6.4.1 Multinomial Logistic Model of car ownership / carsharing

One would be quick to raise that sociodemographics are not accounted for in the cross-analysis of the previous section. As demonstrated in Table 9.8, some key demographics affecting car ownership are not statistically different between the four attitudinal profiles (household size,

number of children). Other differences that could confound the higher car ownership levels between **Car lovers** and the three other types are usually associated with *lower* car ownership levels (higher proportion of single-adult households and lower proportion of workers). Only higher income might confound the attitudinal effect, as the mean values for the neighbourhood income proxy suggest. There might be a more substantial household-level difference in income, but the information was not collected.

Nonetheless, as one final step to ensure the validity of those results with proper control of sociodemographics, two MNL model formulations are presented. One with car ownership (0, 1, 2+ cars) as the outcome and the other one with the joint car ownership/carsharing set of alternatives (no car and no carsharing; carsharing only; car(s) only; car and carsharing). Included explanatory variables are the same for both models. Results are presented in Table 9.9 and Table 9.10. Furthermore, unlike the models presented in Chapter 8, here we introduce a measure of residential off-street parking. Yes, the variable might suffer from endogeneity issues with car ownership, but because we control for both neighbourhood type and travel attitude preferences, this endogeneity issue is reduced. The idea is to test if all three types of variables (Neighbourhood types, Attitude profiles and parking) retained significance in the presence of the other two.

Table 9.9 MNL model of car ownership (0, 1, 2+ cars) with neighbourhood types and attitude profiles

Variable	0 veh.	1 vehicle			2+ vehicles		
	REF	<i>Coeff.</i>		<i>OR</i>	<i>Coeff.</i>		<i>OR</i>
Constant		-0.49	NS	0.61	-4.664	***	0.01
<i>Sociodemographics</i>							
Resp. gender (1 = women)		-0.058	NS	0.94	-0.151	NS	0.86
Resp. age		-0.005	NS	1.00	0.061	NS	1.06
Resp. age squared ^a		0.000	NS	1.00	-0.001	NS	1.00
Resp. is worker		0.419	**	1.52	0.951	***	2.59
1-adult HH (1 = yes)		-1.034	***	0.36	-2.989	***	0.05
HH has children (1 = yes)		0.510	***	1.67	0.050	NS	1.05
HH income in DA (in '000 \$) ^b		-0.002	NS	1.00	0.007	NS	1.01
NB of HH parking spots (0, 1, 2+)		1.220	***	3.39	1.955	***	7.06
<i>Neighbourhood types</i>							
Central (REF)			REF			REF	
Suburban/Mid-suburban		0.706	***	2.03	1.303	***	3.68
Ultra-central		-0.394	**	0.67	-1.005	***	0.37
<i>Attitude profiles</i>							
Utilitarian Drivers			REF			REF	
Car lovers		1.424	***	4.15	2.260	***	9.59
Functional travellers		0.214	NS	1.24	-0.320	NS	0.73
Car dislikers		-1.059	***	0.35	-1.862	***	0.16
N observations	756	1113			316		
% observations	35%	51%			14%		
Total Obs.	2185	# param.	28				
LR Test with const. only model	chisq = 1105.2 (p.value = < 2.22e-16)						
Fit statistic for full model:	LL	-1612	AIC	3279	Pseudo R ²	0.255	
Fit stat. reduced model (no parking)	LL	-1716	AIC	3485	Pseudo R ²	0.207	
Fit stat. reduced model (no att. profiles)	LL	-1742	AIC	3528	Pseudo R ²	0.195	

Note: Resp. = Respondent; ^a Age squared was included to control for the non-linearity of the influence of age on car ownership. This method was used by others before, for example by Macfarlane et al. (2015) and Weinberger and Goetzke (2010). ^b Median income in dissemination area;

The car ownership model suggests that results are consistent with what was observed from the proportion plots. Both *neighbourhood types* and **attitude profiles** are significant and have the expected sign, even when sociodemographics and the number of off-street residential parking are included. For attitudes, differences between **Utilitarian drivers** and **Functional travellers** are not significant for car ownership decisions, as was expected. Gender, age, and age squared are not statistically significant for this model. Neighbourhood income (as an imperfect proxy for

household income) has no statistical significance. In an alternate model without the parking variable (not reported for concision), neighbourhood income is negatively associated with the propensity to have two or more cars. This indicates a correlation between the two variables. This is expected since wealthier, more suburban neighbourhoods tend to have more single-family homes with off-street parking. Fit statistics for the model, either without parking or without attitudes, indicate that both variables substantially improve model fit.

Table 9.10 MNL model of car ownership/carsharing with neighbourhood types and attitude profiles

REF: 1 Car only	No car, no CS		Carsharing only		1 car and CS		2+ cars	
Variables	Coeff.	OR	Coeff.	OR	Coeff.	OR	Coeff.	OR
Constant	1.79 *	5.99	-1.911 *	0.15	-3.774 **	0.02	-4.184 ***	0.02
Sociodemographics								
Resp. gender (1 = women)	0.151 NS	1.16	-0.111 NS	0.89	-0.353 *	0.70	-0.152 NS	0.86
Resp. age	-0.075 NS	0.93	0.101 *	1.11	0.140 *	1.15	0.081 NS	1.08
Resp. age squared	0.001 NS	1.00	-0.001 *	1.00	-0.002 *	1.00	-0.001 NS	1.00
Resp. is worker	-0.537 **	0.58	-0.287 NS	0.75	0.162 NS	1.18	0.547 *	1.73
1-adult HH (1 = yes)	1.291 ***	3.64	0.602 ***	1.83	-0.977 ***	0.38	-2.051 ***	0.13
HH has children (1 = yes)	-0.591 *	0.55	-0.368 *	0.69	0.277 NS	1.32	-0.387 *	0.68
Neighb. income ^a	-0.002 NS	1.00	0.003 NS	1.00	-0.003 NS	1.00	0.009 *	1.01
NB of HH parking spots ^b	-1.488 ***	0.23	-1.092 ***	0.34	-0.060 NS	0.94	0.724 ***	2.06
Neighbourhood types								
Central	REF		REF		REF		REF	
Suburban/Mid-suburban	-0.116 NS	0.89	-1.615 ***	0.20	-1.113 ***	0.33	0.443 *	1.56
Ultra-central	0.396 *	1.49	0.507 ***	1.66	0.315 NS	1.37	-0.534 *	0.59
Attitude profiles								
Utilitarian Drivers	REF		REF		REF		REF	
Car lovers	-1.475 ***	0.23	-1.524 ***	0.22	-0.454 *	0.64	0.751 ***	2.12
Dependent travelers	-0.266 NS	0.77	-0.219 NS	0.80	-0.032 NS	0.97	-0.541 NS	0.58
Car dislikers	1.015 ***	2.76	1.112 ***	3.04	0.051 NS	1.05	-0.790 NS	0.45
N observations: REF=900	307		449		213		316	
% observations: 41.2%	14.0%		20.6%		9.8%		14.5%	
Total Obs.	2185	# parameters						
LR Test const. only model	chisq = 1298.1 (p.value = < 2.22e-16)							
Fit stat. Full Model:	LL -2569	AIC 5250	Pseudo R ² 0.202					
Fit stat. M2: no parking	LL -2676	AIC 5456	Pseudo R ² 0.168					
Fit stat. M3: no att. Prof	LL -2704	AIC 5495	Pseudo R ² 0.160					

Note: ^a Neighbourhood income take as the median income within the dissemination area; ^b Parling spots: 0, 1, 2+

The car ownership/carsharing model in Table 9.10 suggests that results are consistent with what was observed from the proportion plots in Figure 9.8. Both *neighbourhood types* and **attitude profiles** are significant and have the expected sign for most alternatives, even when sociodemographics and the number of off-street residential parking are included.

Most sociodemographic characteristics have the expected effect on the joint decision. Age and Age² indicate that being in mid-life is associated with higher probabilities of choosing carsharing only or one car and carsharing versus owning a car only, while being a senior reduces the odds of choosing carsharing. The number of residential parking spots is negatively associated with the no car alternative (with and without carsharing) and positively associated with having two or more cars. The proxy for income (neighbourhood-level income) is only significant for owning two plus cars. The true household-level income would likely lead to different results. The effect of *neighbourhood types* is generally as expected. Living in the *Ultra-central* type increases the odds of choosing no car/no cs or carsharing only and reduces the odds of having two or more cars. Surprisingly, living in *Suburban/Mid-Suburban* neighbourhoods has no statistical association with choosing no car/no cs compared to the reference (one car, no cs) when attitudes are controlled for, but this might be due to very few observed households with no cars in this neighbourhood type.

For the **attitude profiles**, differences between **Utilitarian drivers** and **Functional travellers** are not significant for any alternative. As expected, **Car lovers** are less likely to have no car, choose carsharing only or even combine one car and carsharing, but they are more likely to own two or more cars compare to **Utilitarian drivers**. **Car dislikers** are less likely to own a car and more likely to have no car, either with or without carsharing.

9.7 Discussion

The results presented in the previous sections revealed interesting insights into how attitudes and built environment characteristics interact to influence car ownership and carsharing decisions. Coming back to the research questions, some answers can be provided.

Are car ownership/carsharing decisions still associated with the built environment when attitudes and residential selection are controlled?

Results from both the cross-analysis and the MNL model suggests that the answer is yes, built environment matters. For each of the four attitude types, the more suburban the area, the more cars

the households living their own. The more central, the higher the proportion of those living car-free for all attitude profiles, including **Car-lovers**. Alternatively, results show that attitudes *also* matter when the built environment context is controlled for. **Car lovers** notably own systematically more cars than the three other profiles across all types of neighbourhoods, even when the built environment is highly conducive of alternative means of travel (*Central* and *Ultra-central neighbourhoods*). On the other end of the spectrum, **Car-dislikers** are significantly more likely to be car-free than others. As for carsharing, it seems clear that the very scarce availability of vehicles in the *Suburban* and *Mid-suburban* neighbourhoods makes it so that very few people, across attitude profiles, choose to subscribe to the service as an alternative to car ownership.

The availability of station-based carsharing vehicle is almost three times higher in the *Ultra-central* than in the *Central* neighbourhood types. However, the differences observed in the inclusion of the service in the portfolio of car accessibility tools between the four attitude profiles suggests that the more car-oriented people are, the higher is the threshold of carsharing vehicle availability necessary to convince them to become member of the service.

The MNL model confirms that all categories of variables (sociodemographics, neighbourhood types, attitude profiles and parking) have a significant association with the modelled choices in the presence of the other variables. This is not always the case. Previous research on car ownership modelling found that most built environment variables become insignificant when attitudes are directly included in car ownership models (e.g., Xinyu Cao et al., 2007a). Finally, fit statistics for reduced models either without parking or without attitudes, indicate that both models have substantially less explanatory power than the full model which includes both. This suggests an independent influence of both parking and attitudes on household car ownership/carsharing decisions.

Is there evidence of residential-self selection (RSS) effects?

There is an association between some sociodemographic characteristics and home location. There is also a strong association between attitudes profiles and the type of neighbourhoods. The more suburban the area, the higher the proportion of **Car-lovers**. More neutral households, the **Utilitarian Drivers**, are more dominant in *Central* neighbourhoods that offer a higher balance between the various mobility options (car, transit, active travel). **Functional travellers** and **Car-dislikers** are marginal in the *Suburban/Mid-Suburban* context and more heavily present in *Central*

and *Ultra-Central* neighbourhoods. However, the method cannot test the direction of influence. This means that an alternative explanation for the relationship between attitudes and the built environment at the residential location is "environmental determinism" (Ewing et al., 2015), where the built environment influences people's attitudes toward travel (Kroesen, 2019). In the current case, people with more favourable attitudes toward sustainable mobility (and less favourable toward the car), the **Car-dislikers** and **Functional travellers**, might have developed such attitudes by living in dense urban settings with good non-automobile accessibility. These areas also tend to be less efficient for car use and ownership due to higher congestion and parking constraints, likely leading to declaring lower car appreciation in the survey. Realistically, those studies suggest that both RSS and environmental determinism might be playing a role, but the cross-sectional data and framework of the current analysis do not allow testing which effect has more influence.

Is there a mismatch between the type of built environment at the home location and people's travel attitudes?

Yes, there seems to be a mismatch, but that mismatch appears to be one-way: **Car-Dislikers** are virtually absent from *Suburban/Mid-Suburban* locations, while **Functional travellers** are marginals. However, **Car-lovers** still have a significant presence in *Central* (31.4 %) and *Ultra-central neighbourhoods* (27.5%). Other considerations than travel and car-related attitudes might have played a more decisive role in their residential location choice. One could have a strong preference for cars and, at the same time, appreciate the amenities, cultural lifestyle, and proximity to a network of friends and families of living in the city center. While people are free to choose to live wherever they prefer, the presence of people with a strong preference for cars and high car-ownership levels in central neighbourhoods that are highly conducive to active and public transportation can lead to some issues. This asks the question of excessive car ownership in tightly-knit urban environments and its consequences. One example is the substantial space required for storing private cars on the public domain. Off-street parking being less common in *Ultra-Central* neighbourhoods, **Car-loving** households are likely using a disproportionate share (relative to their demographic weight) of limited public space to store their private vehicles. The strong attachment to their cars could also lead them to strongly oppose any infrastructure project aiming to convert some of that on-street parking to other use (segregated bike lanes, public squares, vegetation, sidewalk widening, etc.). Car ownership levels of lesser car-oriented households (the three other profiles) in those central areas show that living in those neighbourhoods with fewer cars (either

with only one or car-free) is possible. The **Utilitarian drivers**, the largest and more “neutral” group in terms of car-related attitudes, exhibit apparent differences in their car ownership and carsharing membership level between the three neighbourhood types. The survey did not ask if those living in *suburban neighbourhoods* would like more alternatives to the automobile, allowing them to reduce their dependence on it. But looking at their like-minded peers in more central areas, where alternatives are more abundant and convenient, suggests that they could be willing to reduce their car ownership if they had the opportunity to do so. Helping this group of people to reduce their reliance on the car by providing better alternatives to the car in all types of neighbourhoods could yield the most substantial results in terms of behaviour changes.

Comparison with attitude profiles in Chapter 8

In the paper presented in Chapter 8, the fit indices of the latent-class discrete choice models favoured a solution with two classes. These were named “Car-oriented” (45.7 %) and “Social-conscious” (non-car-oriented, 54.3 %). However, the indicator used in the segmentation model were the factor scores resulting from a principal component analysis of the 12 measured attitudes indicators. This induced some loss of information, thus not allowing the segmentation model to identify subtleties in attitudes that were captured in the present chapter when using the 12 measured attitudes directly. The reason for using factor scores as indicators in Chapter 8 was due to the convergence issue of the LC-MNL model, which was impossible to achieve with 12 segmentation indicators. Overall, the approach taken here provided richer insights into the interactions of attitudes and the built environment and their association with car ownership and carsharing decisions.

9.8 Conclusion

This chapter presented one last analysis to investigate the role of car-related attitudes on residential selection, the effect of built environment and attitudes on household car ownership and carsharing decisions and the interactions between all three (BE, ATT, CO). The analysis was conducted by building two segmentations using latent-cluster analysis. The first segmentation of built environment characteristics used seven objective measures around the home location to identify four distinct neighbourhood types in Montréal. The segmentation was conducted using the region's representative 2018 large-scale Origin-Destination survey and then applied to predict the same

neighbourhood types for a smaller (non-representative) survey with attitudes: the City of Montréal Mobility Survey 2019. The second segmentation of car and travel attitudes was conducted using 12 measures of attitudes collected in that second survey. Four attitude profiles of respondents were identified.

The analysis conducted by crossing the *neighbourhood types* with the *travel-attitude profiles* confirmed a statistical association between the two segmentations. Because the direction of influence cannot be ascertained, this can be evidence of residential self-selection, environmental determinism or, more likely, a bit of both. Comparing the joint car ownership/carsharing decisions of households using a cross-classification of neighbourhood types and attitude profiles indicates that, yes, the built environment is still associated with car ownership after controlling for attitudes and their effect on residential selection. Results from the MNL model confirm that this association holds when sociodemographic and residential parking are controlled for. The results also confirm important attitudinal effects within the same built environment context, suggesting their important role in car ownership and carsharing decisions. Overall, this chapter contributes to refining our understanding of how household decide to include carsharing as a viable alternative to car ownership in urban settings.

9.8.1 Limitations

The analysis has several limitations. The first and most important is the non-representativeness of the City of Montréal Mobility Survey 2019 (CMM19). The data collection was conducted by the City using various methods but not using a stratified sampling approach. The survey differs from the general population in terms of sociodemographics and residential location (skewed toward the city's center). It might also not be representative in terms of attitudes, but this is impossible to validate. This does not mean the analyzed relationships between the variables are invalid, but that the sample *distribution* within the four attitudinal profiles cannot be extrapolated to the studied area's population. As mentioned in the discussion, only a small set of 12 attitudinal variables were measured. While the selection of the 12 items was heavily influenced by previous research, the attitudes were not measured using reliable and validated multi-item scales. Something that *should* be considered in any future study.

The cross-analysis conducted do not explicitly control for sociodemographic characteristics. Two MNL models were then run to validate the outcome obtained from those cross-analyses and ensure

they do not change once sociodemographics are controlled (however, household-level income couldn't not be controlled for). Furthermore, households might have other fixed constraints that explain their car ownership decisions, such as the work locations of household members and the transit/car accessibility ratio to those locations. These were not controlled for. The method cannot confirm the causal effects of both built environment and attitudes on car ownership/carsharing decisions.

9.8.2 Future research

More robust modelling methods are needed to reinforce the findings obtained here. One avenue is using a latent variables and integrated choice modelling framework, also known as Hybrid Choice models. Such a model could simultaneously estimate the latent neighbourhood types from a set of built environment indicators and the latent attitude profiles from a set of measured attitude indicators. It can associate both with sociodemographic covariates (as both neighbourhood types and attitude profiles show statistical association with sociodemographics) and integrate all of these in a discrete choice model of car ownership/carsharing decisions.

CHAPTER 10 GENERAL DISCUSSION

In this chapter, the first section (10.1) contributes to the general objective of the thesis by providing an overview of what influences household motorization. The second section (10.2) proposes a general discussion of the findings from the four main contributions (Chapter 6, Chapter 7, Chapter 8 and Chapter 9). The key findings are summarized and their meaning for both car ownership modelling research and transportation policies is discussed. The **last section** (10.3) presents a discussion of the main limitations of the general approach taken here and suggests avenues for future research.

10.1 General framework of factors influencing car ownership

As the final contribution of this thesis, a conceptual framework of factors influencing mobility tools ownership decisions within the broader context of long-term residential and work location decisions and short-term travel behaviour is proposed in Figure 10.1. The model draws from the extensive literature review presented in Chapter 3. It shows most variables that were included and tested in models reviewed in section 3.4. It also indicates the (usually assumed) main direction of influence between those five categories of variables using arrows. Lines without arrows are simply connections between concepts/variables. Round-corner rectangles indicate choices and straight-corner rectangles indicate variables directly measured. Full-line circles in the psychological construct section indicate that those variables cannot be directly measured. They are latent variables derived from measured indicators. Dotted circles represent more complex concepts that have been investigated but are not explicitly measured. Finally, variables in *grey tone* have been identified as understudied (one or no study found).

The proposed framework does not, however, include reverse causation hypotheses where attitudes (ATT) are influenced by context (BE; built environment) ($BE \rightarrow ATT$), ownership/membership of mobility tools ($CO/CS \rightarrow ATT$) or travel behaviour ($TB \rightarrow ATT$) and leading to feedback loops between the three levels of decisions. Not enough evidence has been produced yet to support them. This is however quickly changing as new research is being conducted with more sophisticated methods to validate the endogeneity of those relationships and test the dominant direction of influence (e.g., Kroesen, 2019; Moody & Zhao, 2019; Olde Kalter et al., 2020).

In a second version of the framework presented in Figure 10.2, the relationships that were explicitly studied within the chapters of this dissertation are indicated in blue.

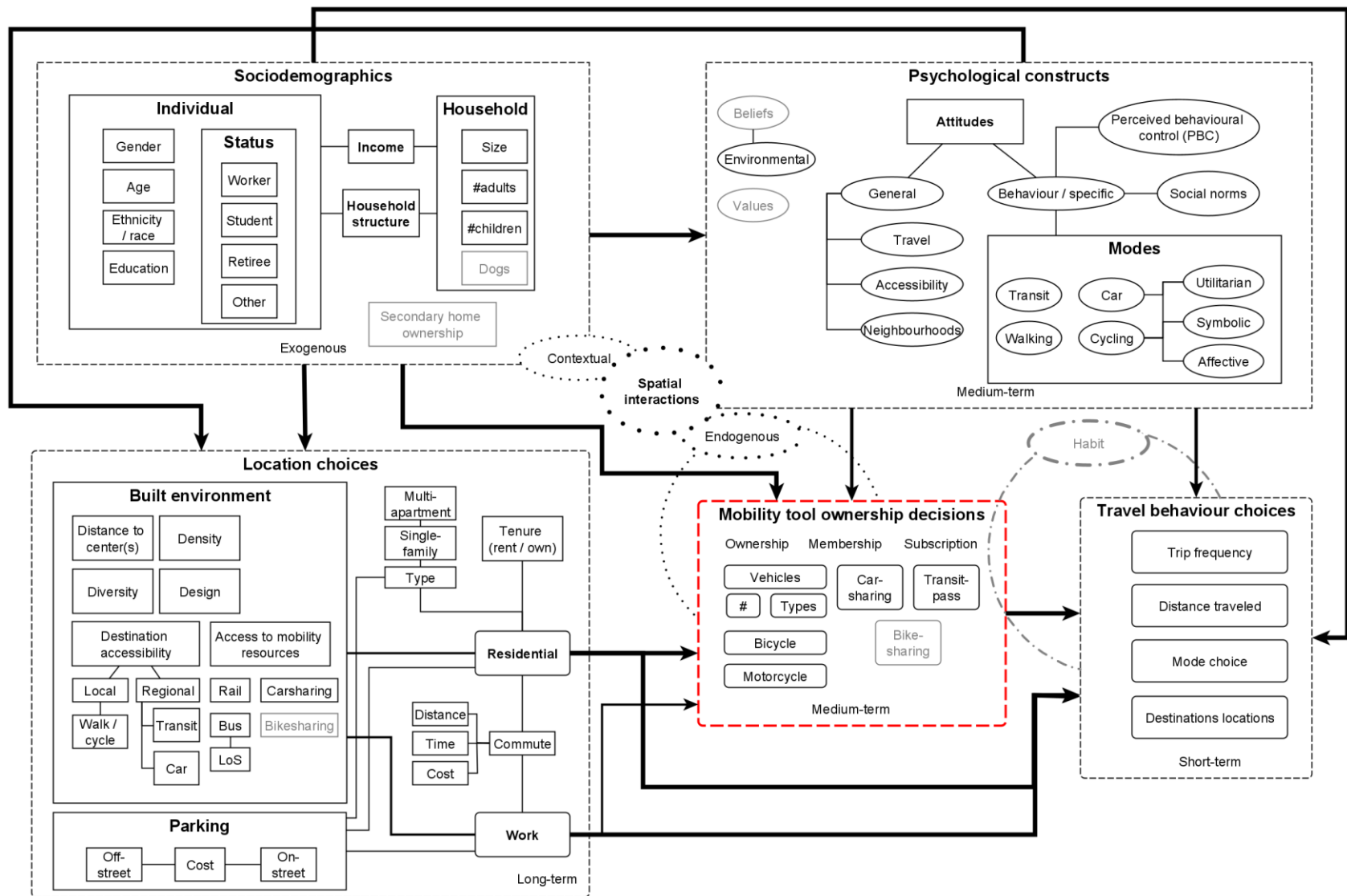


Figure 10.1 Conceptual framework of factors influencing mobility tool ownership decisions

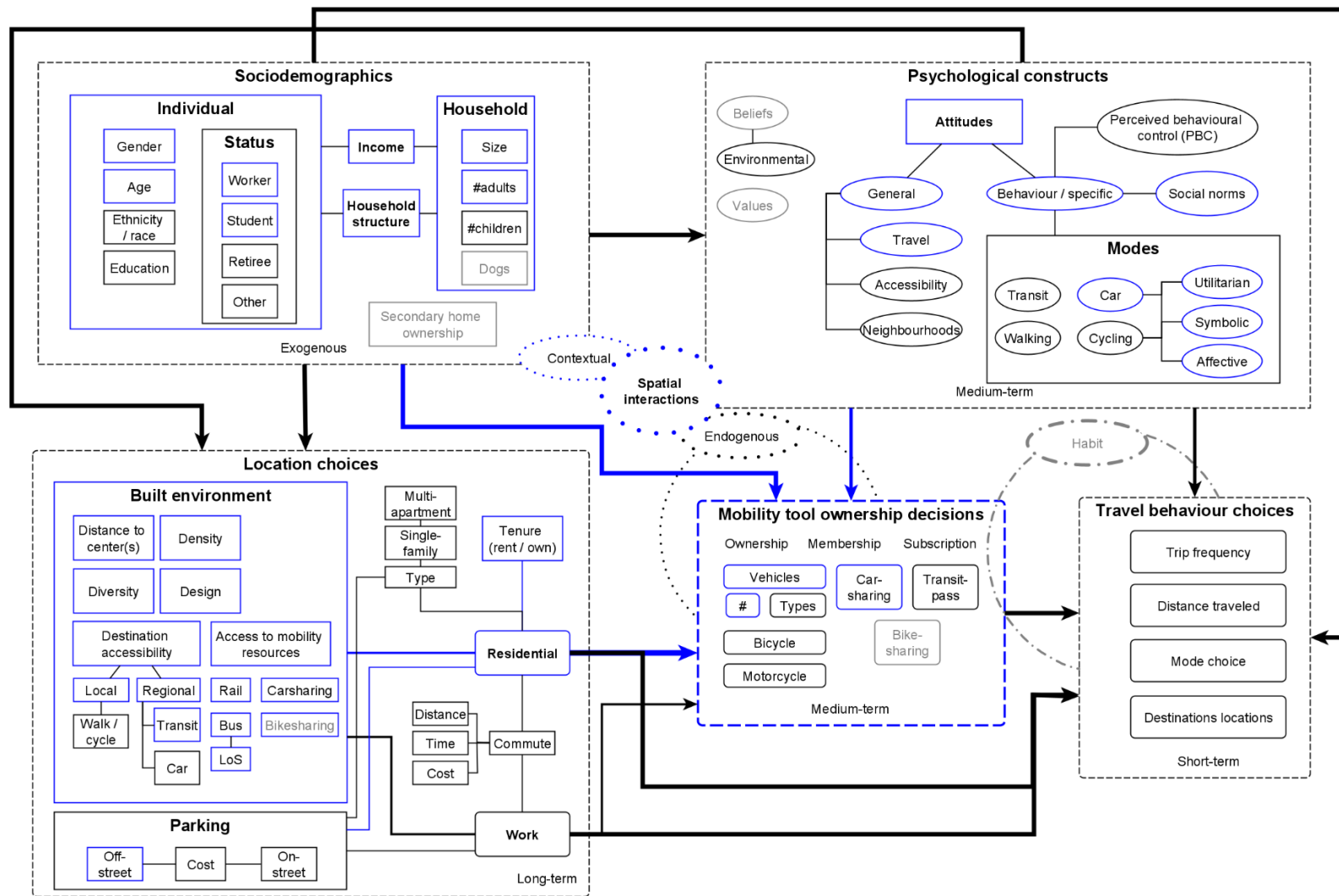


Figure 10.2 Conceptual framework of factors influencing mobility tools ownership decisions. Factors explored in the contributions of this thesis in blue.

10.2 Discussions of results

Spatial dependence

The first contribution presented in Chapter 6 confirmed the presence of strong spatial dependence effects on car ownership rates between small neighbouring areal units using advanced spatial models. Spatial dependence (or spatial autocorrelation) means that adjacent areas exhibit similar values of an investigated variable, here, car ownership rates. This is in line with previous research from aggregate (3.3.1.1) and disaggregate car ownership models (0). Going one step further, the approach tested if the observed spatial autocorrelation could be entirely explained by *observed contextual effects* (characteristics of nearby zones). For contextual effects, sociodemographic and built environment characteristics within neighbouring areal units were considered (for BE, the hypothesis was that because dissemination areas are small units, the range of influence of the built environment is larger than most units). The answer was *no*: there was still residual spatial dependence that could not be explained. This means that unobserved effects are playing a role in influencing neighbourhood car ownership rates. Three possible explanations are proposed: 1) missing variables whose effects are not captured by the included variables (e.g., very localized variation in on-street parking crowdedness), 2) evidence of the residential self-selection hypothesis where people with similar unobserved attitudes and preferences regarding mobility and car ownership cluster together in the same neighbourhoods conducive of their travel preferences and 3) the presence of endogenous social interactions effects. In the studied case, this would mean that the car ownership decisions of households living in one unit could be influenced by the car ownership decisions of households in neighbouring units. This third possibility is a concept vastly studied in geography and spatial econometric domains (e.g., Manski, 2000) and tested explicitly for car ownership decisions by Goetzke and Weinberger (2012). This explanation was, however, judged unlikely to be happening at the specific scale of the modelling presented in Chapter 6. But it cannot be ruled out to be happening at a smaller resolution than was tested here, for example, between direct neighbours such as households on the same street.

For future research, those results, along with the few disaggregate car ownership models in the published literature controlling for spatial dependence, suggest that, yes, spatial dependence should always be tested and, if significant, controlled for. The magnitude of coefficients, as illustrated in Chapter 6 and previous research (e.g., Paleti et al., 2013), can be seriously affected. This could

affect policy recommendations regarding the impact of built environment characteristics. There is no further need for cross-sectional aggregate models of car ownership to investigate spatial dependence. However, more readily available methods that do not require highly complex computations should be developed to facilitate the integration of spatial interaction effects in discrete choice car ownership models. These models should be used to try to disentangle possible causes of that unexplained spatial correlation of household car ownership decisions. One possible avenue to test the spatial aggregation of similitude of attitudes without requiring extensive surveys could be to use finely aggregated electoral results (e.g., from municipal elections as transport policies are more often discussed at that level of government or, even better, from transportation-related referendums). If people with similar travel behaviour preferences aggregate themselves in the same neighbourhood and vote the same way, using the proportion of votes could serve as a proxy for aggregate attitudes within neighbourhoods.

Buffer size and threshold (“non-linear”) effects

The second contribution presented in Chapter 7 investigated if the way built environment variables are measured matters when modelling car ownership. This was done using two interpretation tools of a machine learning method called gradient boosting decision trees (GBDT): partial dependence plots and the relative influence of explanatory variables. **First**, as explained in the literature review of Chapter 7, “sliding” neighbourhoods in the form of buffers around surveyed households should always be used to compute built environment variables over “fixed” zones such as census tracts or transport analysis zone. Unfortunately, recent studies still use fixed zones (see Table 7.1). When buffers are used, pedestrian network distance buffers should be preferred over circular buffers as they can best approximate how people perceive their neighbourhoods by accounting for street network connectivity.

Second, when choosing the *size* of those buffers: one-size-fits-all might not work. Results reported in Chapter 7 suggest that for the three typical “D”s of the built environment: density, design and diversity, sizes between 800 m and 1600 m of walking distance tend to produce consistent results. However, this was not necessarily the case for smaller buffer sizes. For accessibility to mobility resources (number of bus stops, number of carsharing vehicles, number of bikesharing stations) and local opportunities (number of local grocery stores), buffer size seems to matter a lot. The partial dependence plots suggest different effects as the buffer size increases from 400 m to 1600

m. The takeaway is that for **bus stops** and **grocery stores**, very local accessibility should be considered (400-600 m). For **bikesharing** and **carsharing**, larger buffer sizes (1600 m) seem better suited to capture the influence for single-adult households while medium buffers (800-1000 m) appear better for households of two or more adults. Those differentiated impacts for different household structures require further investigation. For **carsharing**, sensitivity analysis of the buffer size should also be conducted on the joint choice of car ownership/carsharing.

Third, almost all variables computed within buffers exhibit *non-linear effects*. Distance-based variables (distance to downtown and distance to the nearest metro stations) also exhibit threshold effects. The partial dependence plots reveal that above or below specific values, the variables do not seem to have further effects on car ownership. An example is the network distance to the nearest metro station. Car ownership probability increases almost linearly between 0.5 km to about 4.5 km. Past that distance, the impact becomes null or marginal. Accessibility to metro stations measured this way also performed substantially better within the model than a dummy variable indicating whether there is a station or not within walking distance. It also indicates that the metro network in Montréal has an area of influence on car ownership decisions that exceeds the typical walking distance of 800 m to 1200 m. Results also confirm that assuming linear-in-parameter relationships within discrete choice models is invalid and could cause biases with coefficient estimates. This is especially problematic when discrete choice models are used to obtain aggregate elasticities or evaluate the impacts of changes in the built environment (e.g., + 10 % of population density) on the total number of vehicles within a region using scenarios. Both methods are common in car ownership studies.

Observed threshold effects suggest that having 4 to 8 grocery stores within 400-800 m is associated with much lower car ownership probabilities. For carsharing, the aim should also be between 4 and 8, but this can be considered up to 1600 m. While these values might be unique to Montréal and need validation in different contexts, they are a good starting point for urban and accessibility planning looking to curb car ownership and use.

However, *the method* proposed in Chapter 6 to assess those threshold values is easily accessible (GBDT was applied using open-source and easy-to-use packages in R). It could be used *before* including the variables as continuous within discrete choice models to identify where to apply the cut-off points when splitting the variables into dummy variables.

Common findings about the impacts of built environment characteristics on car ownership

The three main contributions (Chapter 6, Chapter 7 and Chapter 8) used similar sets of sociodemographic and built environment variables to assess their influence on car ownership. Furthermore, as described in the methodological section (4.5), the built environment variables were computed in similar ways for all three papers. The three contributions employed different modelling methods (respectively, aggregate spatial models, Gradient Boosting decision trees (GBDT) and latent-class multinomial logistic model (LC-MNL)). They used different representations of car ownership as the outcome variable (aggregate rate within the neighbourhood, categorial representation of car ownership status (no car access: no vehicle; partial access: less than one vehicle per adult, and full access: one or more vehicle per adult in household) and unordered representation of the joint choice of car ownership / carsharing) and controlled for or investigated different aspects likely influencing the sensitivity of the results (spatial dependence, buffer-size and thresholds effects and heterogeneity due to attitudes). *Despite those differences* and the limitations of each method, all results point toward the same direction of influence on car ownership for the tested built environment characteristics. This suggests that the results reported in this thesis represent robust empirical confirmation of the association of those factors with car ownership. However, the magnitude of the coefficients obtained (or their relative influence within the model in the case of GBDT) for the same variable between the three approaches cannot be directly compared. Scenarios simulating the effect of changes in built environment variables on aggregate car ownership level would have to be used. Table 10.1 summarizes the sign of the obtained coefficient (or observed direction on partial dependence plots for Chapter 7) and if the variables were significant. Those results confirm many previous findings about the role of some specific built environment characteristics on car ownership. Population density, diversity, design, access to transit and accessibility *by* transit are associated with car ownership, with higher values of those variables (or shorter distances for access to transit) associated with lower car ownership rates or levels.

The results also expand the sphere of knowledge about two specific factors rarely or never used in car ownership modelling: **accessibility to carsharing vehicles** and **accessibility to grocery stores**. Their inclusion and statistical significance within the models thus constitutes a novel empirical contribution of this thesis.

First, from a theoretical and intuitive perspective, having access to several **local grocery stores** within a short walking distance from home can contribute to car-free living or living with fewer cars. Of course, the variable can be a proxy for accessibility to a host of other local commercial opportunities that collectively make it easier to live with fewer cars. But this suggests that its role in the large scheme of things influencing car ownership decisions should be further investigated. This can have important implications for planning policies to reduce car ownership and use. Future research should investigate in what context is walking accessibility to grocery stores influencing car ownership. Can it only affect car ownership in neighbourhoods already conducive of walking? Would the variable still be significant if attitude-based residential self-selection was controlled for? Is accessibility to grocery stores, as one component of local neighbourhood accessibility to opportunities, only sought by active travel and transit-oriented people? From a policy standpoint, municipalities can directly influence the availability of this type of store by changing zoning laws to allow their presence in areas where they are currently prohibited. A study in Toronto and Vancouver reported that 20 % (Toronto) and 25 % (Vancouver) of those living in a suburban area declared strong, and presently unmet, preferences for better walking access to a variety of food stores (Frank, Kershaw, Chapman, Campbell, & Swinkels, 2014). Could this be one of the tools to retrofit suburbia to make it less car dependent?

As for **carsharing**, accessibility to carsharing vehicles was only considered in two previous car ownership models (Klinkevicius et al., 2014; Mishra et al., 2015) and one mobility tools ownership model (Becker et al., 2017) reviewed in the section 3.6. Chapter 6 and Chapter 7 showed a negative correlation with car ownership. In Chapter 6, the influence of carsharing was only assessed using a dummy variable for the presence of at least one station within the dissemination area. In Chapter 7, the variable was refined by computing the number of carsharing vehicles within buffers. The method revealed that the effect varied depending on the buffer size and a non-linear relationship with car ownership (the first 4 to 8 vehicles have a much stronger influence with diminishing influence for additional ones). Finally, in Chapter 8, the number of carsharing vehicles within a 1 km buffer was only significant for one of the two attitudinal latent segments: the non-car-oriented households. Within that segment, access to car ownership influences only the probability of choosing “carsharing only” compared to the reference category (“car ownership only”). It did not have a significant impact on the category “no car / no carsharing”. This suggests that the carsharing variable is not just a general proxy of features found in central urban neighbourhoods (where

carsharing vehicles are mainly located) but has an independent influence on a subset of people, allowing them to live without owning a car by choosing carsharing. However, the variable was also not significant for the category “car ownership *and* carsharing” (i.e., household using carsharing as a second car) for both attitude segments. This suggests that the *location* of vehicles for households adding carsharing as a supplement to their household cars matters less than those using it as primary car access. A possible explanation is that some households use carsharing to access a vehicle, for example, near their work location to conduct business on non-business trips on working days, notably if they commute to work by transit. This could be further investigated with a joint mobility tool ownership model that would include transit passes, as done by Becker et al. (2018).

Furthermore, the fact that the variable is significant for only one of the two latent segments (representing 54 % of the sample) suggests that the availability of carsharing vehicles in one’s neighbourhood does not mean that everyone treats it as an alternative to car ownership. However, Chapter 9 suggests that even the most dedicated car lovers select carsharing in the most central neighbourhoods when the number of accessible carsharing vehicles is very high. In terms of policy implications, this suggests that increasing the availability of carsharing vehicles in underserved areas will, at first, only influence a subset of people with preferences for sustainable mobility (and thus likely aware of carsharing as an option). More *promotion* of the availability of the service and how it works could help move carsharing from an unconsidered or unknown alternative to a considered alternative for households. While carsharing is offered by private operators, the benefits of broader adoption rates are collective (e.g., reduced car ownership and use, better use of congested on-street parking spaces in cities, etc.). Thus, public policies could help its uptake by a more significant proportion of households. Finally, while there is considerable overlap in Montréal between the free-floating carsharing service zone and the location of station-based carsharing, only the latter’s influence was considered in the models. A simple dummy of whether a household lives in the free-floating zone would be too coarse to capture the service’s influence adequately. More precise indicators of the availability of free-floating vehicles (which are unlikely to be uniformly distributed within the serviced area at any given time) should be developed to better assess the impact on household car ownership / carsharing decisions.

Table 10.1 Summary of the association between the built environment and car ownership from the three main contributions

	C1 (Chapter 5)	Contribution 2 (Chapter 6)							Contribution 3 (Chapter 7)					
Modelling Unit	DA	1adultHH			2+adultsHH				Class 1: Car-oriented			Class 2: Non-car oriented		
Dataset	Census & Reg. Data	2018 Montréal Origin-Destination Survey							City of Montréal Mobility Survey 2019					
n	3156	16384			30123				883			1050		
Model	SDEM	Gradient Boosting Decision Trees (GBDT)							Latent-class MNL					
Outcome	Avg. VEH / HH	1adultHH: 0 or 1+ veh.			Car(s) / adult in HH (3 categories) ^a REF: < 1 veh. per adult				Joint CO/CS: Car only (REF)					
					0 Veh.	1+ veh/ad.			Car & CS	CS Only	No car / No CS	Car & CS	CS Only	No car / No CS
	Sign of correlation	Corr.	Rank	RI	Sign of corr. vs REF cat.	Rank	RI		Sign of correlation					
Pop. density [pers. / km²]	(-)	(-)	2	16.9%	(+)	(-)	1	16.20%	NS	NS	NS	NS	(+)	NS
Entropy [0-1] 5 categories	(-)	(-)	12	3%	(+)	(-)	8	5.20%	/	/	/	/	/	/
Density of 4-ways intersections	/	(-)	13	2.9%	(+)	(-)	12	3.70%	/	/	/	/	/	/
Distance to CBD	/	(+)	10	3%	(-)	(+)	9	5.10%	/	/	/	/	/	/
Walk dist. to metro stat. [km]	/	(+)	3	11%	(-)	(+)	3	10.20%	/	/	/	/	/	/
Metro station (dummy)	(-)		/	/					/	/	/	/	/	/
Sum of daily bus trips	(-)		/	/					/	/	/	/	/	/
Number of bus stops	/	(-)	14	3%	(+)	(-)	13	3.10%	/	/	/	/	/	/
Transit access to job @ 8 AM	/	/	/	/	/	/	/	/		(+)		NS	NS	NS
Number of carsharing vehicles	(-)	(-)	6	7%	(+)	(-)	6	6.40%	NS	NS	NS	NS	(+)	NS
Number of bikesharing stations	/	(-)	11	3%	(+)	(-)	14	3%	/	/	/	/	/	/
Number of grocery stores	(-)	(-)	7	6%	(+)	(-)	11	3.90%	/	/	/	/	/	/

Note: DA = Dissemination area; HH = household. " / " = the variable was not used in the model; NS = the variable was found not significant; RI = Relative influence. ^a The 3 categories were: 1) No car, 2) less than one car per adult and 3) one or more car(s) per adult

The influence of some tested variables could not be adequately assessed. One example is **accessibility to bikesharing stations**. While bikesharing might not be a direct substitute for car ownership, its presence within neighbourhoods contributes to increasing the number of alternatives available for daily travel. However, in the case of Montréal, its effect is confounded by a high correlation with the number of carsharing vehicles and the number of grocery stores accessible. Bikesharing and carsharing stations are clustered within the same neighbourhoods and absent from the same ones. For this reason, bikesharing was only included in the second contribution (GBDT, Chapter 7), where multicollinearity was less of an issue than in traditional regression and discrete choice models. Results from Chapter 7 indicate that all three variables contribute to facilitating living with fewer cars and were negatively associated with car ownership. The presence of bikesharing may have a synergetic effect with the high availability of carsharing vehicles. Carsharing might be the trigger to live with fewer cars (as suggested by the review presented in the section 3.6.2) while bikesharing can further help households who decide to live car-free or with only one car by providing an additional convenient mobility option for short trips within the city. However, further investigation is needed to assess the impact of those shared mobility services if they are expanded to more suburban settings.

Attitudes and car ownership / carsharing

Measuring and including attitudes in modelling can move some previously unobserved factors to the observed realm, thus refining behavioural understanding of travel-related decisions. It can help explain why, in a similar context, similar households exhibit very different levels of car ownership and carsharing membership (and likely, travel behaviour), as illustrated in Chapter 8 and Chapter 9. Chapter 8 has confirmed and expanded (to carsharing decisions) previous findings from S. H. Kim and Mokhtarian (2018) on the moderating role of attitudes on the relationship between sociodemographic and built environment characteristics and car ownership / carsharing decisions. The method confirmed the hypothesis that car-oriented households were less influenced in their decisions by both sociodemographic and built environment characteristics than non-car-oriented households.

The use of vehicle registration data as a complement to the census in the Canadian context

Unlike the British, Australian, and American censuses (American Community Survey), the Canadian census *does not* collect information about household car ownership. This shortcoming was circumvented by obtaining specifically for this thesis's research project a unique dataset of all registered vehicles aggregated at the smallest standardized Canadian census division, the Dissemination Area, for the census years. The dataset was obtained from the SAAQ (Québec's motor vehicle registration authority). Chapter 6 is the first paper ever published using this dataset from the province of Québec. This opens several avenues for future research. Additional aggregate analyses could be conducted, for example, by using successive census years within a Spatial Panel model to investigate the evolution of car ownership rates. Alternatively, this also makes it possible to expand the work of Chapter 6 and the study of Goetzke and Weinberger (2012) by considering neighbourhood car ownership levels to explore spatial dependence arising from endogenous social interaction effects on household car ownership. A third possible use could be as an instrumental variable to test the bidirectional effect between car ownership and some variables, such as attitudes, as was done by Moody and Zhao (2019).

10.3 Summary of limitations

The first limitation of this thesis is that all contributions were conducted with datasets **from the same region** (Montréal area), and all but one focused on the inner part of the region: the Island of Montréal. This aspect limits the generalization of results to other contexts. Reproduction of results using data covering more suburban areas from other cities in North America and other countries is highly recommended. Multi-city analysis should also be conducted. This is particularly important for the findings about buffer sizes and non-linear effects of built environment features reported in Chapter 7.

Attitudes are rarely included in regional travel surveys, as is the case with Montréal's Origin-Destination survey conducted every five years and used in Chapter 7 and Chapter 9. This means researchers must rely on ad hoc surveys with smaller sample sizes and too often not representative of the population of the studied region. This non-representativeness seems most substantial on key sociodemographic aspects like education (higher response rate among highly educated people) and the travel behaviour decisions being investigated, like car ownership. This issue seems widespread

in the research reviewed in Chapter 3 using attitudes (e.g., Xinyu Cao et al., 2007a, 2007b; S. H. Kim & Mokhtarian, 2018; Moody & Zhao, 2019; Van Acker et al., 2014). This was also the case for the City of Montréal Mobility 2019 used in Chapter 8 and Chapter 9, which, in addition, was non-geographically representative of the surveyed area (suburban neighbourhoods were underrepresented). This is problematic since those variables on which those surveys depart most from the reference population are also some of the most correlated with travel-related attitudes. This limitation does not preclude the study of relationships between variables to refine our understanding of travel-related decisions but limits inference to the general population to predict the impacts of transport policies using scenarios. Another limitation specific to car ownership is that attitudes are measured at the individual level and (most often) only for the respondent. In contrast, car ownership and, to a lesser extent, carsharing decisions are household-level decisions (refer to the section 8.4.1 for a more extensive discussion of the issue).

Controlling for residential self-selection is often presented as critical to obtaining a valid estimate of the relationship between travel behaviour (including car ownership) and built environment characteristics (Xinyu Cao et al., 2009; Mokhtarian & Cao, 2008; van Wee & Cao, 2022). The first contribution presented in Chapter 6, the modelling of car ownership rates at the aggregate level, did control for some aspects of residential self-selection through the inclusion of a spatial error term in the final model. That term allows control of unobserved contextual effects, for which one possible explanation is residential self-selection, where like-minded households cluster within the same neighbourhoods. The Gradient boosting decisions trees models used in Chapter 7 did not control for residential self-selection. This likely confounds some of the effects observed for the included built environment attributes. Chapter 8 used a latent segmentation of households based on the individual attitudes of the respondent as a form of control of residential self-selection. Chapter 9 suggests evidence of residential self-selection. Latent profile analysis (LPA) was used to cross-compare attitudinal profiles and neighbourhood types. It revealed that more car-oriented households were overrepresented in suburban neighbourhoods while less car-oriented households were more present in central neighbourhoods.

One aspect sometimes mentioned but often neglected in the debate about *how much* residential self-selection confounds the built environment's impact on travel is that it assumes an equilibrium between preferred neighbourhood types and observed residential choice. In short, the equilibrium

hypothesis means that building more active travel and transit-oriented developments would have only little impact on a region's aggregate car ownership and car use.

However, as evidenced by higher real estate prices in central locations, including in “trendy” and highly walkable and transit-oriented neighbourhoods, there is likely a strong latent demand for such living places and their associated lifestyles. This is backed by research investigating those questions in the Canadian context (Frank et al., 2014; Y. Huang, Parker, & Minaker, 2021). Those two studies show significant rates of mismatches. For households currently living in car-oriented neighbourhoods, 10 to 37 % reported high preferences for walkable or transit-oriented neighbourhoods. In short, this means that in the presence of unmet demand, concentrating a higher proportion of a region's new housing within walkable and transit-oriented areas could allow many households to find and afford homes to better align their mobility behaviour (and car ownership choices) with their preferences for sustainable travel. The implication is that the often-reported dampening effect of residential self-selection on the relationship between the built environment and car ownership and travel behaviour is likely weaker on the aggregate when there is latent demand. In such a context, the hypothesis is that not controlling for it might not be as problematic.

Residential parking was not included (except in Chapter 9) despite the literature review showing clear indications of its critical role in household car ownership decisions. Yes, in the simplest form, access to residential parking could have been included as an exogenous variable in the three contribution models when available in the datasets. However, the decision not to include it was based on its known endogeneity with car ownership, as detailed in the sections 3.2.3 and 0. Off-street parking availability might be an essential feature sought by car-owning households when choosing a home (Car ownership → Residential choice). This means that a household's current car ownership level likely influences the choice of having or not having off-street parking when deciding to relocate to a new home. As for off-street parking crowdedness, population density and design have been recognized to act as imperfect proxies. Results from Chapter 7 indicate that population density had the strongest influence within the gradient boosting model when measured within a 400 m buffer. This suggests that at this resolution, population density *might* act as a better proxy for very localized on-street parking crowdedness, with higher density associated with more constraints on finding on-street parking. This should be further investigated. Buffer sizes smaller than 400 m should be tested in future research to get closer to a proxy value that best approximates what happens on the curb of the street people live on.

Finally, all the models applied in the five papers presented in this dissertation focused on the number of cars owned by households without any consideration for the *types* of vehicles (categories, brand, model, fuel type, etc.). This assumes that all vehicles are considered interchangeable by households and are treated as having the same influence on travel behaviour. The main reason for considering vehicle types as beyond the scope of this dissertation is data limitations: all the datasets used in this research project do not contain the information about the types of vehicles. However, with trends in vehicle specialization (household owning multiple vehicles, each for specific usage), with the rapid rise in popularity of SUVs and other light trucks in the last 25 years and with the vehicle electrification policies being deployed in many jurisdictions, the impact on the overall fleet transformation cannot be estimated with the methods proposed here. This has all sorts of implications. For example, the models cannot be used to assess vehicle emission trends resulting from this fleet transformation. This is a blind spot of this work that should be addressed in future research.

10.4 Avenues for future research

Some of those recommendations for future research apply to car ownership and mobility tool ownership but could also enhance research on other aspects of travel behaviour.

What is not needed

Before digging into what future research should explore, it is important to remind researchers and future Ph.D. students what does not need more research. For example, there is no further need for cross-sectional aggregate models of car ownership. However, dynamic aggregate models at fine geographical scale with time-series data could still provide insights into the evolution of the spatial distribution of car ownership rates within cities.

There is also no further need for discrete choice models of household car ownership that do not include attitudes or do not estimate simultaneously residential choice and/or travel behaviour. In short, there is a need for more causal evidence, not more evidence of association between already tested variables and car ownership. Finally, in terms of data collection, there is not much need for small-scale non-representative cross-sectional surveys unless they are used for validation of multi-items attitudinal scales. Data collection and future research projects should be guided by precise

and well-defined research questions that presently require more attention. Some avenues are detailed in the next paragraphs.

Expand mobility tools ownership modelling.

With the proliferation of options in increasingly multimodal cities, this becomes necessary and can provide additional evidence of their interdependencies with car ownership decisions. Studies using discrete choice experiments have investigated stated preference for bundles of mobility tools with advanced modelling methods that integrate attitudes-based heterogeneity (W. Li & Kamargianni, 2019; Liao et al., 2020; Matyas & Kamargianni, 2021). There is, however, a critical need to model *observed* choices of mobility tool ownership with advanced frameworks to further refine our understanding of people's preferences in real-world situations. Specifically, understanding what influences people to choose a particular combination of tool ownership/membership in their mobility portfolio. This includes exposure to mobility resources. Both free-floating and station-based carsharing must be included in future research, alongside bikesharing membership and transit passes.

Understanding the influence over time of the evolving availability of those services within a region is also critical. For this reason, questions about subscriptions to the various mobility services should be included in large-scale travel surveys if that is not already the case.

Better consideration of parking.

Too few studies modelling car ownership have included precise measures of off-street and on-street parking availability despite the results of Z. Guo (2013a) suggesting an impact likely larger than income (at least in NYC). This is highly relevant for transport policies as both types of parking can be influenced by regulations that do not require massive investment, unlike transit infrastructure. Parking regulation can nonetheless have a tremendous impact on people's car ownership and use decisions, as reported in the section 3.4.2.5. The challenge of parking regulation is likely more political than financial. Furthermore, off-street parking availability also seems to influence substitution patterns between car ownership and carsharing, as illustrated in Chapter 9. This should be further investigated.

The two forms of parking each presents unique challenges for successful integration in vehicles and mobility tools ownership modelling. The critical challenge for off-street residential parking is

the strong endogeneity issue with car ownership. One suggestion to address this issue is to model residential choice and car ownership jointly and to include the availability of residential parking as a key attribute of the residential choice. A three-level nested logit approach could be used. Still, a more complex modelling option could offer even more vital insights into this complex choice dynamic (e.g., access to off-street parking likely matters less for a car-free household looking to stay that way when relocating than for multiple cars households). This requires information about residential parking availability in travel surveys.

On-street parking's main issue relates to finding precise indicators to capture the level of hassle for households to find parking spots as close to their home as possible. Exact measures of on-street parking are more relevant in cities' central neighbourhoods built before the automobile, where off-street is less common and where the curbs are crowded. However, this level of crowdedness can be highly variable from one street to another, depending on various factors. These indicators must be calculated through automated methods. Using a manual evaluation of on-street parking crowdedness with Google Street View, as was done by Z. Guo (2013a), is unrealistic for any study that does not explicitly focus on the effect of parking or when large-scale travel surveys are to be used.

However, on-street parking is less likely to suffer from endogeneity bias with car ownership decisions than residential parking. That is: the ease or difficulty of parking on a specific street is *a priori* unknown to a household looking to relocate on that street. One can have intuitions simply by looking and experiencing parking crowdedness when visiting the potential future home. However, it is likely that an adequate assessment of the day-to-day hassle of finding parking can only be done once someone moves in. Thus, the hypothesis is that on-street parking crowdedness is less likely to affect someone's choice of residential location. Although, this should be validated empirically.

Incorporation of attitudes

As previously mentioned, attitudes have been increasingly incorporated in transportation research over the last 20-25 years, including, but to a lesser extent, in car ownership modelling. First, as suggested by others, there is a critical need for better, more standardized, robust, and validated measures of attitudes and other psychological constructs. Following the practice used in psychological research, this means measuring latent psychological constructs using validated

multi-item scales for which reliability was assessed in various contexts (an example is the validated scale of “car pride” proposed by Moody (2019)). Identifying scales using the least number of items while still preserving the reliability of the measured construct is critical if attitudes are to be incorporated in large-scale travel surveys (or add-ons of those surveys) where each additional question is costly. In short: ensuring we measure the right thing in the right way. The analyses presented in Chapters 7 and 9 were limited to a small set of attitude indicators toward transportation and the car. However, for future car ownership and mobility tool ownership modelling, it would be useful to include attitudes toward *all* modes, including toward shared mobility options like carsharing and bikesharing, to fully understand the behavioural mechanism shaping those medium-term decisions. To the best of my knowledge, this has not yet been done.

Furthermore, more advanced methods than were used in this thesis, such as hybrid choice models (also called integrated choice and latent variable models; ICLV), where attitude latent variables and the choice of car ownership/carsharing are estimated simultaneously, could provide a more accurate estimate of the role of attitude on the joint decisions by reducing measurement biases. Understanding what influences people’s residential choices and *how* much transportation preferences matter when deciding where to live relative to other preferences and for *whom* is also important. As location greatly affects car ownership decisions, one question that requires further investigation is: do people genuinely understand the impact of specific locations on the *cost* of transportation over the duration of a mortgage? This includes the potential savings from a neighbourhood where the family could live with no car or only one car instead of owning one car per adult. Discrete choice experiments could provide answers about how people’s decisions might be influenced by providing complete information on the integrated cost of car ownership and residential location. Surveys of recent movers with retrospective questioning could help identify the influence of travel preferences and transportation costs on people’s recent decisions.

Finally, in addition to all the previous recommendations, there is a critical need to explore the causal impact of factors that can be leveraged through policies and **lead to changes in car ownership**. Focusing on factors leading to car ownership reduction is critical. Still, factors leading to an increase in car ownership also need to be understood to identify transport policies to prevent people from adding cars to their fleets. This requires true longitudinal data (same households surveyed multiple times) where *changes* in the built environment are incorporated as explanatory variables. Most, if not all, true panel data models reviewed in Chapter 3 considered built

environment features as constant over time (often due to historical data unavailability). On the one hand, changes in features like density, diversity and design are happening more slowly and are less likely to affect people's behaviour directly. On the other hand, other variables such as accessibility to and by transit, access to carsharing vehicles, bicycle infrastructure, changes to on-street parking (e.g., removal of whole parking lanes to make room for priority bus lanes or bike lanes) and local commercial opportunities (e.g., local grocery stores) are changing on much faster timeframes. Assessing the influence of those aspects on travel behaviour and longer-term car ownership and mobility tools ownership decisions is paramount for research to offer quality policy recommendations to cities as to what works best to help them quickly curb car ownership and car use. Measurement of the same attitudes at multiple points in time is also necessary. This could help untangle how mobility resources and accessibility changes are perceived and if they lead to changes in attitudes. If those changes in attitudes lead to changes in behaviour and how social interactions influence the diffusion of those changes. Appropriate modelling methods able to incorporate all those elements and identify the causal direction of influence are necessary.

CHAPTER 11 CONCLUSION AND PERSPECTIVES

11.1 Summary

The number of registered vehicles has increased faster than the population allowed to drive them in many countries and regions. Québec and Canada are no exception and are contributing to that trend. This is likely fuelled by demographic changes, the resilience of the system of automobility and the persistence of car-oriented transportation and urban planning policies. Unfortunately, while the car can provide accessibility benefits to its owner, the system of automobility itself is responsible for a wide range of societal, environmental, and economic consequences. There seems to be an increased desire to reduce car use in cities to alleviate some of those consequences. However, while extensive evidence shows that automobile ownership considerably influences travel behaviour, notably mode choice and distance travelled, goals to curb its growth seem absent from the transportation planning process. This was illustrated in 0 in a case study of Québec's automobility indicators, transportation and urban planning documents and planned infrastructure projects (Laviolette et al., 2020). Planning documents adequately recognized the main issues in transportation but expressed an uneven acknowledgement of car dependency as a source of problems across documents. The priority given to road expansion projects, despite a simultaneous push for public transit infrastructure, is not consistent with the objectives and visions of the planning documents. This suggests a political resistance to change and a strong influence of institutional car dependency in the planning process. Moving toward a more sustainable transportation system might prove very difficult.

This context motivated this thesis's objective to improve the understanding of factors influencing household car ownership. A review of the literature revealed four gaps, three of which are addressed by specific contributions and the fourth by the entirety of the thesis.

The first gap is linked to the general objective: no published review of factors influencing car ownership at the time of submitting this thesis was found. The second gap is the need for more investigation of spatial dependence effects on car ownership and which factors contribute to this observed spatial dependence. The third gap is linked to high variability and imprecision in how built environment variables are computed to be used in car ownership models. Notably, the absence of investigation of the zone size or buffers used to calculate the variables and if those

variables exhibit non-linear effects (“threshold effects”) on household car ownership. The fourth gap pertains to the rapid rise in popularity of carsharing services and the lack of investigation on how carsharing is jointly considered with car ownership by households.

A general methodological framework was proposed to answer research questions derived from those gaps (Chapter 4). At the basis of this framework is the development of an integrated spatial database that fuses together numerous datasets. This allowed for the computation of the different representations of car ownership used as outcome variables in the three modelling methodologies. The database also allowed multiple explanatory variables to be tested and incorporated into the developed models of car ownership and mobility tool ownership.

The first contribution presented in Chapter 6 confirmed the strong effect of spatial dependence on aggregate car ownership between small geographical units using advanced spatial modelling. It tested sociodemographic and built environment variables as sources of contextual effect and confirmed the presence of unexplained spatial autocorrelation in car ownership rates. This suggests that spatial dependence should be tested and, if significant, controlled for in car ownership modelling as it can affect modelling results and policy recommendations.

In the second contribution (Chapter 7), a machine learning method known as gradient boosting decision tree (GBDT) was applied to the large-scale 2018 Montréal Origin-Destination survey to test model sensitivity to different buffer sizes and identify potential “threshold” effects of built environment features on household car ownership. Results confirm that no one-size-fits-all buffer best captures the effect of all built environment variables. Accessibility measures to opportunities and mobility resources were very sensitive to the size of the buffers. Furthermore, all tested variables presented threshold and non-linear effects on car ownership, thus invalidating the assumption of linear-in-parameter relationship assumed in many discrete choice models.

The third contribution aimed to expand the scope of car ownership modelling by integrating carsharing as an alternative way to access a car within the choice set to investigate the moderating effect of attitudes on sociodemographic and built environment characteristics. This is accomplished by using a latent-class discrete choice model allowing for heterogeneity in the joint choice to be modelled by using attitudes only in the segmentation process. The method identified two latent attitudinal segments (car-oriented and non-car-oriented) with different responses to built environment features on their car ownership and carsharing choices. Notably, the density and the

availability of carsharing vehicles within walking distance only affected respondents who were in the non-car-oriented segment, while accessibility by transit to work destinations affected the car-oriented segment. In terms of policy implications, this suggests that improvement in accessibility to mobility resources might not affect everyone in the same way, but that they are worth pursuing.

Chapter 9 extended the analysis of Chapter 8 by building a neighbourhood typology and a latent segmentation of attitudes, both using latent profile analysis (LPA). The method confirmed a strong association between neighbourhood types and attitude profiles. This can be explained either by residential self-selection, residential determinism, where the built environment influences attitudes, or a little bit of both. Results also indicate the presence of an important mismatch between attitudes and residential locations (30 % of “car-lovers” live in the two most central neighbourhood types). Results from multinomial logistic models indicate that the built environment (neighbourhood types) still affects car ownership and car ownership/carsharing decisions when sociodemographic, attitudes and access to off-street parking are controlled for. Furthermore, attitudes had an influence on car ownership levels in every neighbourhood type, from suburban to the most central.

Finally, knowledge acquired from the three main contributions and from the extensive literature review presented in Chapter 3 led to the development of a conceptual framework of factors influencing car ownership (Chapter 10).

11.2 Perspectives

Bringing car ownership growth to a halt and reducing the numerous negative consequences of extensive car use will likely prove very difficult for most countries and regions deeply entrenched in car dependency. Independent and robust research on factors influencing household car ownership decisions can provide valuable insights to guide societies toward a more sustainable mobility system. This thesis contributed empirical evidence on which factors can minimize the need for car ownership and facilitate car-free and car-light living. However, simply preventing households from adding cars to their fleet is unlikely to be enough. Future research should focus on revealing the causal mechanism through which voluntary car ownership reduction occurs (“demotorization”, partial or total). This is critical to identify which strategies and policies should be tested and implemented to bring the concept to reality. For this to be a success, a household

shedding a car must perceive it as an act of liberation from the burden of automobile ownership and not a constraint on personal mobility. Many possible avenues exist. The City of Montréal Mobility survey used in this thesis revealed that 20 % of respondents would like to reduce the number of cars they own. Among those, about half (46 %) said they were waiting for the vehicle to “die”. This suggests studying the impacts of voluntary car scrappage programs (“cash for clunkers”) where households opting in could be offered various incentives to facilitate their transition to living with one fewer car, including easy access to other mobility tools. Experimental design studies should be developed to evaluate the long-term effect of such programs and their scaling potential.

In general, transforming urban mobility to reduce the need for car ownership will require changes in attitudes (toward the car, but also toward its alternatives) and lifestyles. More research is still needed to understand what leads to *changes in attitudes* and how those changes can then influence the hierarchy of choices: residential location, car ownership and short-term travel behaviour decisions. However, this requires increasingly robust and complex survey design, measurement methods and modelling techniques to disentangle those relationships. As suggested by other researchers (e.g., Bohte et al., 2009; Chorus & Kroesen, 2014; Kroesen, 2019; Kroesen & Chorus, 2018), longitudinal design with attitudes measured at several points in time models able to test the directional effects are needed. Multi-waves, large sample data collection survey able to capture a wide range of changes in context (e.g., massive infrastructure changes, residential and work relocation), behaviour and vehicle ownership is prohibitively expensive and will require substantial funding.

Despite those costs, it is becoming critical to better understand the complex attitude–behaviour–context mechanism as cities are looking for new, innovative, cost-efficient strategies to facilitate the transition toward more sustainable mobility behaviour. This includes a variety of soft travel behaviour change strategies whose effectiveness should be evaluated when implemented in tandem with changes in built environment characteristics. Those changes can happen at the neighbourhood level (e.g., new cycling and transit infrastructure, provision of carsharing and bikesharing) or at the individual level (e.g., residential location or work relocation). Finally, knowing what leads to change in attitudes might also help identify strategies to minimize opposition to any project or policy perceived as a threat to a lifestyle deeply entangled with the possession and use of an automobile. This opens the door for transdisciplinary research involving researchers from various

disciplines (e.g., engineering, urban planning, social psychology, sociology, economy) along with stakeholders from civil society and government agencies to tackle the roots of car dependency.

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ANNEX A TRANSLATION OF CHAPTER 5 - ARTICLE 1: RELENTLESS AUTOMOBILITY: AN ANALYSIS FROM THREE PERSPECTIVES

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ABSTRACT

The phenomenon of "peak-car", the growth in the use of active and collective modes and a renewed interest in more dense, mixed and human scale urban developments, all raise the question of the decline of car mobilities. A three-perspective analysis framework is proposed to assess, on the one hand, whether this decline is real and, on the other hand, whether it is accompanied by a paradigm shift in transport and urban planning that would indicate the end of *automobility*. The question is applied specifically for the province of Québec and its two metropolitan areas, Montréal and Québec. As a first perspective, the analysis of motorization and automobile use indicators reveals a sustained increase in car mobility over the past two decades. As a second perspective, the analysis of official planning documents and framework policies for mobility and urban development reveals an adequate understanding of mobility issues, but an uneven recognition of dependence on the automobile. In addition, none of the municipal and metropolitan documents presents specific objectives for reducing car use or car ownership. Finally, from a third perspective, the priority given to some infrastructure projects are not consistent with the objectives and visions of planning documents. Indeed, the benefits expected from ambitious public transit projects are compromised by highway development projects in Montréal as well as in Québec City. The justifications for these road projects come from a classic planning paradigm widely shown to be outdated and inadequate. The priority given to them seems to stem from political resistance to a paradigm shift. Taken together, these three perspectives tend to show that despite certain positive signs, the decline in automobile mobility, which would be based on a real paradigm shift in transportation and urban planning, does not seem to have started in Québec. **Keywords:** Car dependency, automobility, urban planning, transport policy, transportation infrastructure

Introduction

The environmental, societal, and economic consequences of *automobility* – the car-centric mobility paradigm – are well documented (e.g. Gärling & Steg, 2007; Hérán, 2011). This paradigm will have to change rapidly in the face of the climate emergency. Starting in 2009, several studies began to report a slowdown in the growth of automobile mobility (measured in vehicle-kilometres travelled; VKT) (P. Goodwin, 2012; P. Goodwin & Van Dender, 2013; Millard-Ball & Schipper, 2011; Newman & Kenworthy, 2011; Puentes & Tomer, 2008). This phenomenon, known as "peak-car", has generated a great deal of interest and many factors have been put forward in an attempt to explain its causes: economic factors, changes in mobility practices among young people, densification, improvements in public transit and active travel infrastructure, the influence of information technologies, demographic changes, etc. (P. Goodwin, 2012). In their most recent book about car dependency, Newman and Kenworthy (2015a) give great importance to the re-urbanization of cities through densification and a shift in transport policies toward sustainable modes to explain this phenomenon. On the other hand, more recent studies present a somewhat less optimistic picture. For example, Focas and Christidis (2017) conclude that it would be premature to speak of a paradigm shift in car mobility in Europe. In the United States, Mislinski (2019) observes a rebound in the growth of total VKT since 2013 (even controlling for population growth), with the rebound not yet reaching 2005 levels. Leard et al. (2019) even conclude that VKT will continue to grow at the same rate as before the levelling-off.

In parallel with these trends in the evolution of automobile mobilities, there is a great diversification of mobility options in European and North American cities. For example, there has been a significant renaissance in cycling, encouraged by the rapid development of cycling infrastructure and bikesharing systems. (Buehler & Pucher, 2012; Pucher & Buehler, 2017) and bikesharing systems (Fishman, 2016) including in Québec and Montréal (Morency et al., 2017; Vélo Québec, 2016a, 2016b). Many North American cities have reported an increase in public transit supply and ridership since 2000 (Boisjoly et al., 2018), a trend also observed in Québec (Gouvernement du Québec, 2018a). Access to the automobile is also changing with a tenfold increase in the supply of carsharing services and members of these services around the world (Shaheen, Cohen, et al., 2018). This trend is particularly marked in Montréal (Wielinski et al., 2019).

Since the evolution of mobility patterns is intimately guided by land use development and the development of transportation infrastructure, the main objective of this work is to investigate **whether the automobile-centred approach to transportation and land use planning, which has prevailed for decades, is being transformed.** From this central question, several research sub-questions arise. First, in the case of the metropolitan regions of Québec City and Montréal, is *automobility*, as measured here by automobile use and ownership, declining? Next, are the planning documents that public authorities are adopting coherent and sufficient to support a transition toward more sustainable and less car-centric mobility practices? Finally, are the prioritized major infrastructure projects and government strategies consistent with the vision, objectives and targets of these planning documents? Our hypothesis is that a positive answer to all these questions could mean a complete paradigm shift marking the end of *automobility*. A positive answer to only some of these questions would instead mark a partial paradigm shift that could confirm what Banister (2008, p. 74) identifies as *schizophrenic* paths. That is, a situation where one recognizes the existence of issues, plans to resolve them, but ultimately continues to do what one has always done without adopting strategies or actions that can fundamentally change the situation.

To answer these questions, we propose an analytical framework with **three perspectives.** The **first perspective** consists of a diagnosis of the situation and aims to quantify the evolution of car mobility in terms of levels of use and motorization using statistical and survey data. The **second perspective** of analysis is an evaluation of the response of public authorities to transportation issues in their official planning documents. The **third perspective** is an evaluation of the coherence between planning documents, major infrastructure projects and government strategies prioritized to improve mobility on the territory. The province of Québec, and more specifically the metropolitan regions of Montréal and Québec City, are taken as a case study.

The remainder of the paper is organized as follows. First, a review of the existing literature on the limitations of past planning approaches, the analysis of public policy coherence and the assessment of expected impacts of infrastructure projects is proposed. This is followed by a detailed presentation of the analytical framework in three perspectives. The analysis of each perspective is then presented, followed by a discussion of what can be drawn from the analysis with respect to the stated research questions.

Literature review

According to Metz (2013), the “peak-car” phenomenon marks a transition from the third to the fourth era of travel. In this fourth era, the average distance travelled per day and per person (especially by car) have stopped growing¹⁷, having reached saturation (Metz, 2010). The future growth of total distances travelled by societies will be mainly due to demographic changes. However, does this leveling-off of car mobility mean a decline in *car dependency*? And more broadly, is it a sign or even the result of the beginning of a *paradigm shift in mobility*?

Gabriel Dupuy (1999)’s perspective is that car dependency goes beyond the mobility system alone, encompassing a system of organization of our society ranging from supply chains to the organization of individuals’ activities according to their access to the automobile (the “club” effect). Based on Dupuy’s perspective, it can be argued that a sustained, deep and permanent decline in automobile mobility is only possible through a profound transformation of our societies. This means that a major shift in the foundations of transportation planning, land-use planning, and demand management must occur. This transformation of the planning paradigm must also be accompanied by strong political commitments to prioritize projects and public policies to promote sustainable mobility that are sufficiently supportive to overcome car dependency (Banister, 2008).

Indeed, the classical planning approach long favoured by planning authorities assumes ever-increasing automobile demand. To meet this demand, which manifests itself in the form of congestion, the solution is therefore to increase road capacity. This “predict and provide” approach treats car traffic as a liquid (Newman & Kenworthy, 2015b), a flow whose movement on the network is to be optimized by increasing its speed. Such a planning approach neglects the various effects of induced demand, which are widely recognized and have been demonstrated by several empirical studies today (e.g. Cervero, 2003; Duranton & Turner, 2011; P. Goodwin, 1996). It also neglects the two-way and long-term effects between the development of transport infrastructure and land use (Masson, 1998; Wegener, 2014). In short, by planning essentially for the car, such an approach greatly favours its ownership and use to the detriment of sustainable modes by reducing density, segregating uses, scattering activity locations and increasing distances.

¹⁷ Metz (2013) points out that this stabilization excludes air travel, which is still growing strongly.

The growing externalities, especially environmental, the inability to solve congestion issues and improve the quality of life of the conventional approach have been known for many years already (Newman & Kenworthy, 2015b). More recent planning exercises are therefore based on a desire to change the development paradigm by focusing on integrated transportation and urban planning strategies (Masson, 1998) and on development projects that rely on structuring public transit investments and mixed densification of the built environment. Transit-Oriented Development (TOD) is one of the approaches that exemplify this new paradigm of urban development and is at the heart of Montréal's Metropolitan Planning and Development Plan (MPDP) (Douay & Roy-Baillargeon, 2015).

Consistency of planning approaches and infrastructure projects

Despite the objectives and ambitions for change set out in planning documents in both North America and Europe, numerous works have illustrated that the achievement of a coherent overall strategy between the different planning levels and prioritized projects seems to face many obstacles. In an analysis of transportation planning in France, Héran (2017) criticizes the sectoral approach to planning, i.e., the prioritization of a single mode at a given location. He confirms that this approach is incapable of producing overall coherence. For example, the "all public transport" strategies that succeeded the "all car" approach are questioned since they generate a form of duality of approaches where public transport is prioritized only in dense areas and where it is considered that the car should still be maintained in the suburbs since it is the only possible mode of transport. The nuisance of motorized transport is thus largely underestimated. Héran (2017) also reports another example relevant to the present analysis in Québec in the "Schéma de cohérence territoriale (SCoT)" of Lille (France), which claims to want to reduce road congestion by investing in public transit and encouraging active modes while pursuing the development of the road network.

Buhler et al. (2018) have used *textometrics* to analyze urban policy discourses within planning documents. The authors apply this automated method to two editions, separated by about 10 years (2000 and 2010), of the Urban Travel Plans ("Plan de développement urbain"; PDU) of 18 French agglomerations, for a total of 36 documents to identify contrasts in the discourses that would be difficult to observe by human reading. The analysis thus reveals two types of discourse on the automobile. The first is more concerned with substituting and limiting the car, while the second focuses on adding and promoting alternatives to the car, but without questioning its place in the

city. A comparison of the two editions also reveals a shift toward a greater willingness to act, but expressed in more abstract terms, which could be explained by a desire on the part of the agglomerations not to reveal all their cards in anticipation of future negotiations on certain infrastructure projects with higher levels of government. Such a strategy had already been revealed by the study of the planning documents of three French agglomerations by Reigner and Hernandez (2007) who sought to analyze the interactions of the agglomerations with the State, which owns the higher-level road networks, in the articulation of the objectives, actions and projects of their PDU. To this end, Reigner and Hernandez carried out an exhaustive inventory of all the projects mentioned in the local planning documents in order to reveal the travel models toward which the representatives of these agglomerations wish to move. The overall picture thus reveals a desire for connectivity of the upper road networks on the periphery to bypass and access the city with, at the same time, the wish to develop a sustainable and attractive urban core where the car is controlled. This duality of approaches (also mentioned by Kaufmann (2003) and Hérán (2017)) is not, however, openly stated in the planning documents, illustrating the political strategy of local representatives to hide their cards in order to maximize their chances of seeing their projects implemented.

Transportation policies in Québec have already been the subject of several critical works and analyses. For example, Paulhiac and Kaufmann (2006) have looked at transportation and planning policies in the Montréal region based on the logic of action of urban transportation policies in Europe in order to determine whether the city can be a "model" in the North American context as are Bern and Zurich in Switzerland. The authors base their analysis on the characteristics of the city (density, strong centrality, high share of public transport use) to determine that Montréal is closer to European cities than to other Canadian and American cities. With respect to the relationship between transportation and urban planning in public policies of recent decades, the authors point out that the authorities are betting heavily on the development of new infrastructure and their structuring virtues. Despite this belief and the desire to improve public transit, the authors note the lack of integrated strategic planning for transportation and development at the time. Paulhiac and Kaufmann (2006) conclude that despite the presence of what is identified as a favourable reference framework for public transit in the city, significant improvements to the supply of public transit have not materialized, regularly coming up against the issue of funding for public transit, which is largely the responsibility of other levels of government. Scanu (2014)

conducted an analysis of the discourses of urban actors who participated in the public consultation processes surrounding the development of Québec City's Sustainable Mobility Plan (2011). Drawing on the theoretical perspective of social problems and the principles of narrative and discursive coalition, the author illustrates that there are three narratives of sustainable mobility, each held by a distinct group of actors. There is a vision of sustainable mobility (built around a future tramway) as a vector of economic growth, real estate development and local and international attractiveness and there is a people's vision more focused on the needs of equity, accessibility and diversity of the city's current citizens. The first vision, supported by the committee responsible for drawing up the plan and by the economic elites, leads the author to suggest that the use of the word "sustainable" would be a way for the economic elites to hide the real motivations of economic growth behind an environmental discourse.

In an analysis similar to the present one, Legacy et al. (2017) explore the governance issues and policy clashes in transportation planning between various levels of government in Australia. From a theoretical perspective, the authors use path dependency principles in transport planning to explain road capacity expansion decisions in three case studies: Sydney, Melbourne and Perth. Transportation and land-use planning documents, government press releases, social media and a few key stakeholder interviews are used to inform the analysis. On the one hand, the authors observe the creation of a consensus turn to prioritize public transport to increase accessibility in transport and land use planning documents at the metropolitan level in the early 2000s. At the same time, a top-down antagonism seems to have emerged in recent years as political decisions at the federal and state government levels favour the development of major road infrastructure. Opaque processes and biased evaluation mechanisms seem to guide these projects, which run counter to local planning objectives, but also to the principles of public consultation and consensus-based decision-making that should emerge. The authors see this as an attempt by political elites to reintroduce the car-centred solutions of the past. A similar application of the path dependency principle as a method of analyzing discursive barriers to sustainable mobility in New Zealand concludes that once pro-road policies are established, the arguments of government organizations are accepted by people as the norm, thus inhibiting the emergence of opposition to recent and future road projects (Imran & Pearce, 2015).

In short, the analysis of the coherence between political discourse, planning documents and prioritized transportation projects and policies is a recurring theme in the scientific literature,

which makes it possible to identify parallels between the situation in Québec and elsewhere in the world. However, the combination of an analysis of mobility trends, planning documents from three different levels of government and planned infrastructure projects as a tool for reflecting on a possible paradigm shift in mobility in Québec does not seem to have been achieved.

Expected impacts of infrastructure projects

Without attempting to conduct an in-depth evaluation of each public transit development project selected for this study, it is appropriate to determine whether, in their general concept, these projects can contribute to the achievement of sustainable mobility targets, particularly the reduction in automobile use and the increase in the use of public and active modes. Based, for example, on Litman (2019)'s work, it is estimated that improving public transit services has many direct and indirect benefits for society, the environment and the economy, particularly through a reduction in automobile travel and a transformation of urban development and land use.

Evaluations of specific new light rail projects in Portland, OR (USA), which may be similar to the development of the “Réseau express métropolitain” (REM) in the Montréal area, indicate, for example, that the corridors that received the intervention became denser, that households in these corridors made significantly more trips on foot and by public transit, and that there was a smaller increase in VKT by car compared to similar freeway corridors without the intervention (Ewing & Hamidi, 2014). The authors confirm the importance of an integrated approach to the development of compact, mixed-use neighbourhoods to capture the multiplier effects of transit investments and thus support a *slowdown in the* growth of automobile use. This effect is possible because of the combined influence of variables in the built environment on mobility behaviour (Ewing & Cervero, 2010).

Finally, since road capacity expansion projects are also proposed in parallel with these transit projects, it is important to know what impacts are generally expected from this type of project. As illustrated above, it is unlikely that these projects will contribute to reducing congestion, if only in the very short term. It is also unlikely that they will achieve the objectives of reducing the number of automobile trips and the modal share of the automobile because of the principle of the *Fundamental law of road congestion* (Duranton & Turner, 2011). Considering also the effects on urban developments by highway infrastructure (Cervero, 2003), their implementation is likely to increase car ownership and compromise the expected benefits of public transit projects.

Analytical framework

To explore the question of the decline or survival of automobile mobility, we propose to evaluate the state's response to the problem posed by the massive use of the automobile and the difficult implementation of sustainable mobility. To do so, a three-perspective analysis framework is developed to reproduce the process that planning authorities follow to respond to this major challenge of the 21st century. The proposed analytical framework is illustrated in Figure A.1.

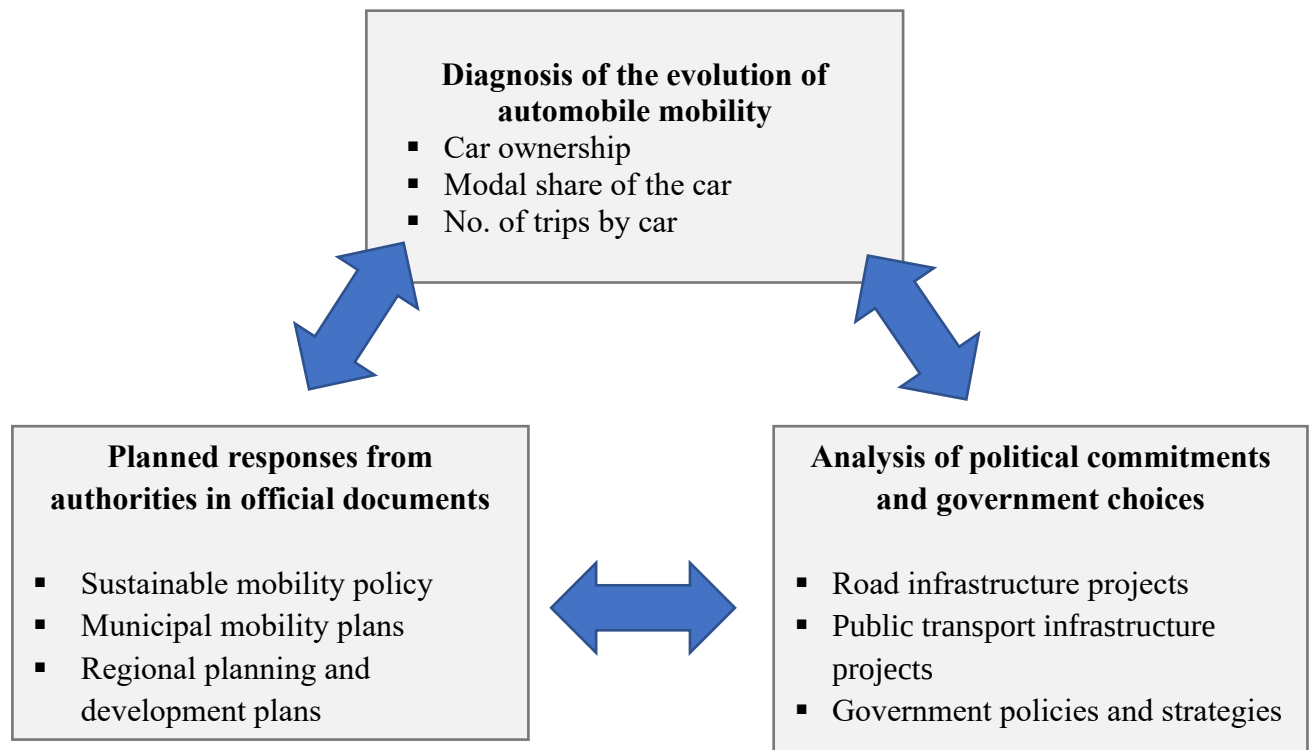


Figure A.1: The three-perspective framework of automobility analysis

Perspective 1: Diagnosis of mobility and motorization

To diagnose the state of mobility by automobile, three key indicators are selected according to the data available for the study area. One indicator is chosen to characterize the evolution of car ownership and two other indicators are used to characterize car use.

For motorization, **the indicator** chosen is the number of passenger vehicles¹⁸ (cars and light trucks¹⁹) registered in Québec per thousand adults (16 years and older, i.e. the legal driving age). It is estimated by combining registration data from the *Société d'assurance automobile du Québec* (SAAQ) for the period 2000 to 2017 (SAAQ, 2022)²⁰ and annual population estimates from Statistique Canada (2022). To complete the analysis, an attempt is made to compare the evolution of car ownership rates between Québec, Canada and the United States. This comparison is made on the basis of vehicles per 1000 inhabitants and not per adult since this is the format in which the American data is available. The data for Québec and Canada are those compiled annually by Statistique Canada (2018a) from provincial data. This compilation of registered vehicles includes all cars and light trucks under 4500 kg, which includes passenger vehicles and vehicles for commercial, industrial or institutional use. For the United States, the data on vehicles per capita comes from the work of Sivak (2017) which obtained the number of "light-duty vehicles" (cars, pickups, SUVs and vans) from the Federal Highway Administration.

To quantify recent changes in automobile use, it is not possible to use the number of VKT annually since the survey that provided this indicator for Québec and Canada was discontinued in 2009 (Ressources Naturelles Canada, 2011). To compensate for this limitation, the **first indicator** chosen is the modal share of driving trips. Three sources of data are used: (1) data on the mode of transportation most regularly used for commuting to work from the 2001 and 2016 Canadian censuses (Statistique Canada, 2017c), (2) highlights from the 2003, 2008 and 2013 Origin-Destination (OD) surveys in the Montréal region²¹ (AMT, 2013) and highlights from the 2006, 2011 and 2017 Québec City area OD surveys (Ministère des Transports du Québec, 2008, 2015a, 2019a). These OD surveys are household-based telephone surveys conducted every five or six years with a sample size of approximately 4.5% for Montréal and 9% for Québec City. This type of survey provides an accurate picture of mobility for an average fall weekday in the survey area. A province-wide survey of this type is not yet available. Finally, the **second indicator** of

¹⁸ The SAAQ (Société d'assurance automobile du Québec) identifies "passenger vehicles" as those owned by individuals and dedicated to personal, non-commercial use.

¹⁹ The SAAQ classifies sport utility vehicles (SUVs), pickup trucks and small vans as "light trucks".

²⁰ Data are not available by administrative region before 2000.

²¹ Data from the 2018 O-D survey are not available as of the writing of this article (May 2020).

automobile use is the total number of trips made by automobile. The same three sources as the modal share indicator are used.

Perspective 2: Planned responses from authorities in official documents

Three types of official documents guiding the development of the transportation system and land use planning are selected for this analysis.

The **first type of document** is the Government of Québec's Sustainable Mobility Policy 2018-2030 (SMP; Gouvernement du Québec, 2018c). This is the first document of its kind at the provincial level. The policy covers the movement of people and goods by all modes of transportation and for the entire territory of the province.

The **second type of document** is the Metropolitan Planning and Development Plan (MPDP). The plans for the Montréal (CMM, 2012) and Québec City (CMQ, 2013) regions are analyzed. For Montréal, the plan covers transportation planning, land development, urban planning criteria and the protection of agricultural and natural environments throughout the territory of the *Communauté métropolitaine de Montréal* (CMM), which is made up of 82 municipalities. For Québec City, the plan covers the planning and development of the territory and transportation in an integrated manner on the territory of the *Communauté métropolitaine de Québec* (CMQ) made up of 28 municipalities.

The **third type of document** is the Transportation Plan (Montréal) or the Mobility Plan (Québec City). The City of Montréal's transportation plan dates from 2008 (Ville de Montréal, 2008) and the City is currently working on a new integrated mobility and urban plan. Québec City's Sustainable Mobility Plan has been in effect since 2011 (Ville de Québec, 2011). These plans cover the administrative limits of these cities.

For each of these documents, four elements are identified and analyzed. The first is the framing of the problem, i.e., the diagnosis of the situation regarding the use and ownership of private cars. This involves answering the question: is the issue of car dependency identified and highlighted? In this sense, is the increase in car ownership, the increase in car use, the evolution of the urban form and the consequences of the overuse of the car identified?

The second element is the definition of the vision for each of the documents (or the main orientations in the absence of a clearly stated vision). The third element is the list of objectives

related to motorization and personal travel, more specifically the reduction of automobile use and the increase in the use of active and public modes. Finally, the fourth element is the list of quantified targets related to the identified objectives.

Perspective 3: Analysis of political commitments and government choices

The third and final step of the proposed framework is to analyze the main transportation infrastructure projects prioritized by government authorities since the adoption of these plans and policies. The objective is to assess the consistency between the prioritized projects and the vision, objectives and targets established in the official planning documents reported in the second analysis perspective. To meet this objective, the main road infrastructure projects for the Montréal and Québec City regions are identified from the Ministère des Transports du Québec (2019c). As public transit projects are not carried out or funded by a single government agency, there is no official list of completed, in progress or under study projects for the entire province. To identify the main projects considered, the document *Les 12 travaux du transport collectif au Québec* (The 12 works of public transit in Québec) produced by the organizations Trajectoire Québec and Équiterre (2018) is used. Projects are selected if they meet the following inclusion criteria:

Criteria for inclusion of projects

- Major infrastructure projects to increase road capacity or public transit supply. Existing infrastructure rehabilitation projects that do not add road capacity are excluded.
- The "Major" refers to the costs of the project and the expected impacts of the project on urban mobility and on land use development.
- The project must have government approval and be under construction or in advanced planning stage (with significant funding already allocated).

To limit the projects analyzed, a maximum of two major road infrastructure projects and two major public transit projects per region are selected.

Project analysis method

The following questions help guide the analysis of these projects:

- Are these projects mentioned in the planning documents analyzed?

- Based on the scientific literature on the recognized impacts of these types of projects, is it considered likely or unlikely that they will contribute to the achievement of the vision set out in the five planning documents?
- Based on the scientific literature on the recognized impacts of this type of project, will they contribute to the achievement of the objectives and targets identified in the planning documents (positive impact) or will they delay their achievement (negative impact)?
- If it is felt that the projects will delay the achievement of the visions, objectives and targets (negative impact), what are the stated arguments for proceeding with these projects?
- Are these arguments typical of the resilience of a traditional approach to transportation planning and the political issues associated with automobile dependence?

Selected projects

Project #1: Montréal Region - Extension of Highway A-19

The extension of Highway 19 has been studied by the Ministère des Transports since its inauguration in the 1970s. The project to complete the highway was re-launched in 2010 by the government to transform an 8-kilometre section of the current Route 335 (1 lane per direction) into an "urban highway" with 2 lanes of traffic in each direction and a lane reserved for public transit, carpooling and electric vehicles between Highway 440 in the city of Laval and Highway 640 in Bois-des-Fillion, on the North Shore (Ministère des Transports du Québec, 2019d). The project also includes a multifunctional path for pedestrians and cyclists.

In 2018, the government confirmed the final configuration and officially gave the green light to the project by granting the environmental decree to begin preparatory work (Ministère des Transports du Québec, 2019d). Preliminary estimates indicate costs between 500 and 600 million Canadian dollars and its completion is planned for 2025 (La Presse canadienne, 2018). The project was selected for analysis because it meets the established criteria and is the most important confirmed project for increasing road capacity in the Montréal region.

Project #2: Montréal Region - Extension of the Montréal Metro Blue Line

The extension of 5 stations and 5.8 km of the Montréal Metro Blue Line to the east has been discussed since the 1980s (Corriveau & Caillou, 2018). The project recently reached important milestones with the confirmation of funding by the provincial and federal governments in the summer of 2019 and the launch of its Office of project management in the spring of 2019 to carry out the plans and specifications (Gouvernement du Canada, 2019a; Ministère des Transports du Québec, 2019e). Preparatory work is scheduled to begin in 2020, infrastructure work in 2021, and commissioning is planned for 2026 (STM, 2019). Project costs are estimated at C\$4.5 billion. (Radio-Canada, 2019b). The project meets the selection criteria and is one of the two largest public transit projects underway in the Greater Montréal area.

Project #3: Montréal Region – Réseau express métropolitain (REM)

The largest public transit project under construction in Québec is the Réseau express métropolitain (REM) piloted and financed in large part by the Caisse de dépôt et placement du Québec (CDPQ). The REM is a 26-station, 67-km automated light rail transit project serving the northern, western (including the Montréal Airport) and southern suburbs of Montréal. Construction of the project began in 2018 and full operation is scheduled for 2023. The project is financed by CDPQ, the federal government and the provincial government and its cost is estimated at C\$6.3 billion (CDPQ Infra, 2019). The project meets the selection criteria and represents the largest project to add public transit services in the Montréal region.

Project #4: Québec City region - Third road link between the North shore and the South shore

The third link project in the Québec City region aims to connect, via a tunnel, Highway 40 on the north side of the St. Lawrence River east of Québec City and Highway 20 on the south side of the river east of the city of Lévis. Although the first feasibility studies for this project were carried out in the 1970s, it has recently returned to the government agenda and is presented on the Ministère des Transports' website as a government priority (Ministère des Transports du Québec, 2019b). A project office was created in 2017 and the project has recently (April 2019) passed an important stage, becoming a "project in planning" for which a sum of 325 million Canadian dollars has been set aside in Québec's infrastructure plan 2019-2029 for preliminary studies and for the production

of plans and specifications documents (Gouvernement du Québec, 2019a). Work is expected to begin before 2022. However no completion date has been set at this time. A technical feasibility study for the final chosen route of a tunnel passing under the eastern tip of Île d'Orléans estimated the cost of the project at more than 4 billion Canadian dollars (Massicotte, 2016). The project meets the selection criteria and is the largest road capacity expansion project currently being planned in the province.

Project #5: Québec City region – Réseau structurant de transport collectif (RSTC)

Québec City's structuring transportation network is a public transit network project that includes a 23-km tramway route, a 17-km trambus route and an improved 16-km Métrobus network with dedicated infrastructure (Ville de Québec, 2019b). The project was unveiled in March 2018 by the City of Québec (Ville de Québec). After fifteen months of negotiations, an agreement was reached in August 2019 between the City and the provincial and federal governments to ensure full funding of the project (Gouvernement du Canada, 2019b). Initial work on the project has begun and final delivery is scheduled for 2026. Total costs for the entire project are estimated at 3 billion Canadian dollars (Ville de Québec, 2019a). The project meets the selection criteria and is the largest public transit project in the Québec City region.

Additional analysis

In addition to the major projects, the total amount of investment planned in public transit and road transportation rehabilitation and development projects for the next ten years (2019-2029) by the Québec government is compared as an indicator of government intentions. Finally, the Québec strategy for the electrification of transportation, which applies to all types of transportation (public and private, collective and individual) (Ministère des Transports du Québec, 2022) is also briefly discussed in relation to the research questions.

Perspective 1: Changes in car ownership and use

Car ownership indicators

The evolution of car ownership (vehicles per 1000 adults) from 2000 to 2017 for the province of Québec, the administrative region of Capitale-Nationale (Québec City), the administrative region

of Montréal (Island of Montréal) and the administrative regions of Laval, Montérégie, Lanaudière and Laurentides, which include the municipalities that make up Montréal's suburbs, is illustrated in Figure A.2.

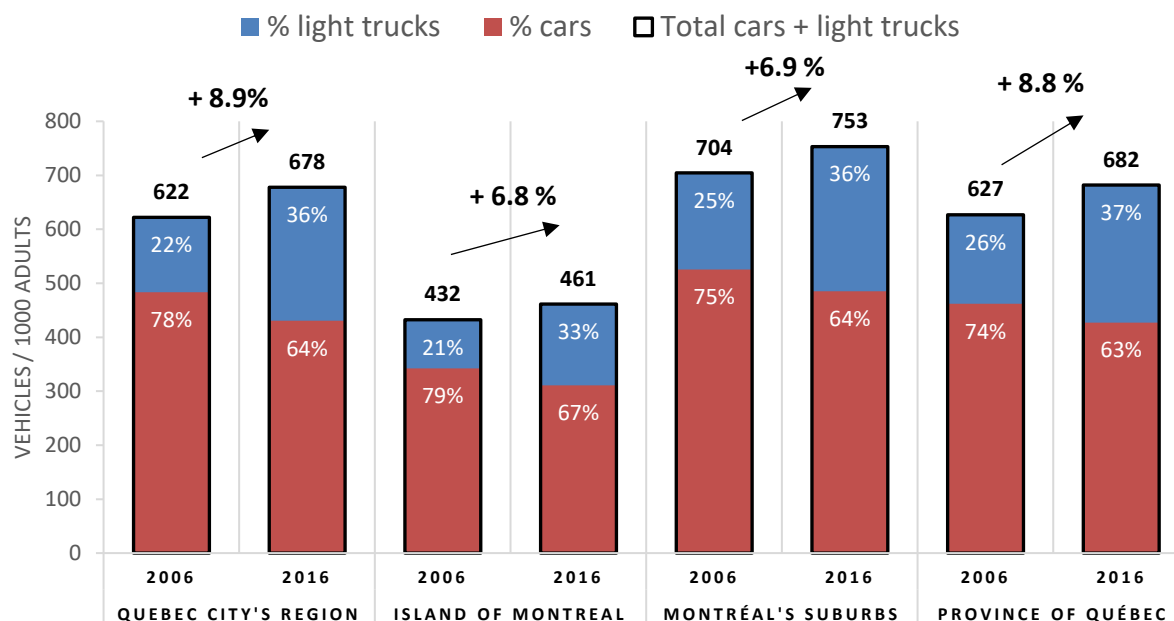


Figure A.2 Car ownership rates in 2000 and 2016

Source: Number of passenger vehicles from SAAQ (2018) and population estimates from Statistique Canada (2022). Calculations by the authors.

For the entire province, between 2000 and 2017, the number of cars and light trucks for personal use increased by 38%, adding an average of 77,000 vehicles annually to the roads. For the same period, the adult population increased by 16.5%. Figure A.2 also allows us to observe a lower growth in car ownership on the Island of Montréal. It also illustrates the transformation of the vehicle fleet, as the proportion of light trucks in passenger vehicles increased from 24% to 39% province-wide between 2000 and 2017. This strong trend is driven by the increasing popularity of sport utility vehicles (SUVs) and *pickup trucks* in vehicle sales in the province, including in more urbanized areas such as Québec City and Montréal (Pineau & Whitmore, 2018). The popularity of this type of vehicle is not unique to Québec, as they are gaining market share in both North America and Europe (Kommenda, 2019).

To complete the analysis, a comparison is made between the evolution of car ownership (in vehicles per 1000 inhabitants, commercial and private use) in Québec, Canada and the United States (Figure A.3).

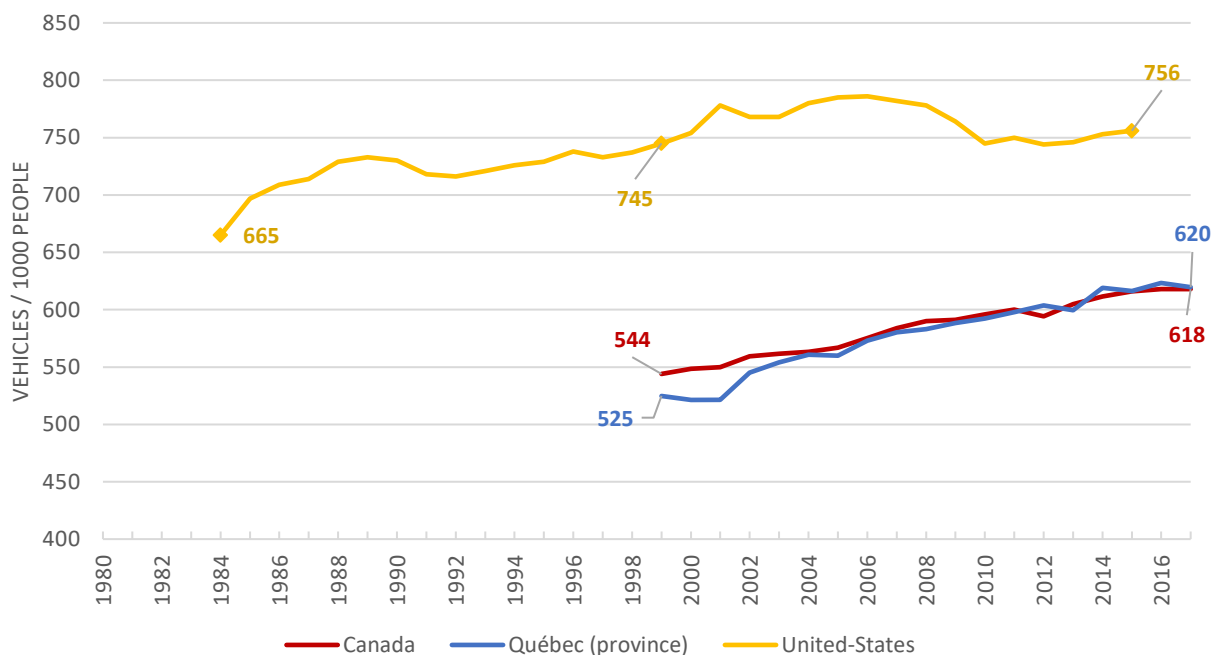


Figure A.3 Changes in car ownership rates (vehicles per 1000 people). Québec, Canada and the United States.

Data sources: Statistics Canada (2018b) and Sivak (2017).

The first observation is that the rate of motorization is much higher in the United States than in Canada and Québec, and it seems to have peaked in 2007, only to fall back and remain relatively stable thereafter. The second observation is that this phenomenon of motorization levelling off is not observed either in Québec or in Canada.

In sum, the data analyzed allows us to conclude that there has been sustained growth in car ownership since the beginning of 2000 and suggest that the plateau in car ownership does not yet appear to have been reached. This is problematic because car ownership is an important predictor of car use (de Jong et al., 2004). It positively favours driving over alternative modes and is associated with higher distances travelled (e.g., Caulfield, 2011; Dieleman et al., 2002). This trend of increasing car ownership risks exacerbating the many externalities that result from the massive use of cars for travel.

Automobile use indicators

The first indicator for analyzing usage is the modal share of the automobile and sustainable modes. Statistics are first presented for commuting to work from the sample data (25%) of the 2001 and 2016 censuses. Results for the province of Québec, Montréal's Census Metropolitan Area (CMA) and Québec City's CMA are shown in Figure A.4

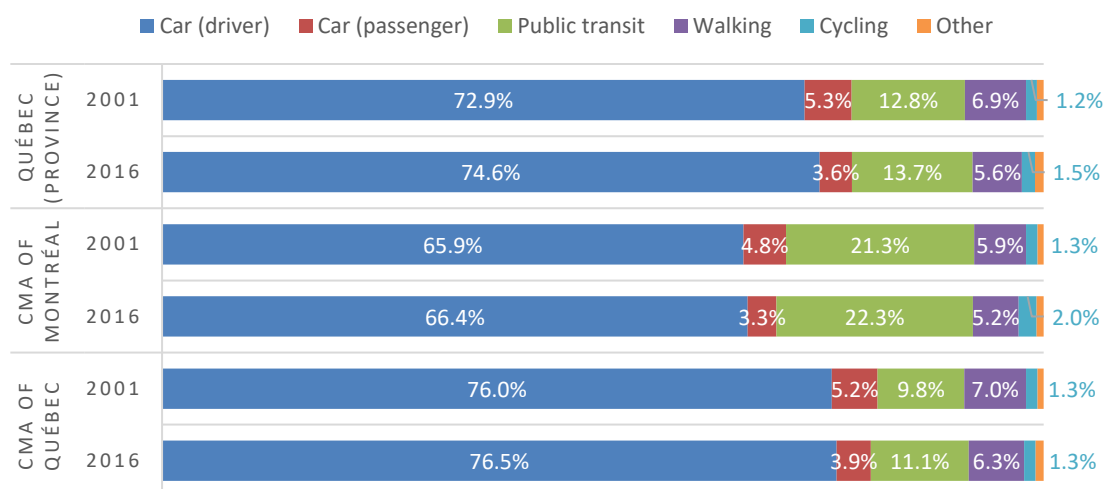


Figure A.4 Modal split of commuting. Sample data (25%) from the 2001 and 2016 censuses.

Source: Statistique Canada (2017c), processing by the authors.

The figure shows some positive trends over 15-year period, such as a slight increase in the share of home-to-work trips made by public transit in the three regions analyzed (+0.9% for the province, +1% for Montréal and +1.3% for Québec City) and an increase in the share of trips made by bicycle for the province as a whole (+0.24%) and for Montréal (+0.7%), but not in the Québec City region.

Unfortunately, if these gains are due to a modal shift away from driving, the results are not observable in these data since the modal share of the car also increased for the province and the two studied regions (+1.7% for the province, +0.5% for Montréal and Québec). Instead, there was a decline in the share of trips made by car as a passenger (-1.7% for the province, -1.6% for Montréal and -1.3% for Québec). A decline in walking was also observed (-1.3% for the province, -0.7% for Montréal and -0.7% for Québec City), which could be explained by a greater increase in the number of jobs in the suburbs than on the Island of Montréal (AMT, 2013) and a decrease in commuting trips whose origin and destination are located in the urban core (Savage, 2019).

It remains difficult to estimate precisely the factors that could explain these changes. Nevertheless, it seems that a reduction in the modal share of the driving is possible in the North American context. In the Vancouver CMA, the modal share of the driving for commuting went from 79.2% in 2001 to 69.3% in 2016, a decline of 9.9% in 15 years. A similar trend was observed in Toronto, although to a lesser extent, as the share of driving commuting trips fell by 3.9% during this period, from 71.4% in 2001 to 68.0% in 2016 (Statistique Canada, 2017c).

Thus, the observed *status quo* in the share of trips made by car is not good news, since the growth in population and *economic activity* means an increase in the absolute number of single-occupancy car trips. This is demonstrated by the **second indicator** tracking changes in car use. The Figure A.5 shows the changes between 2001 and 2016 in the population as well as the number of commuting trips by each mode.

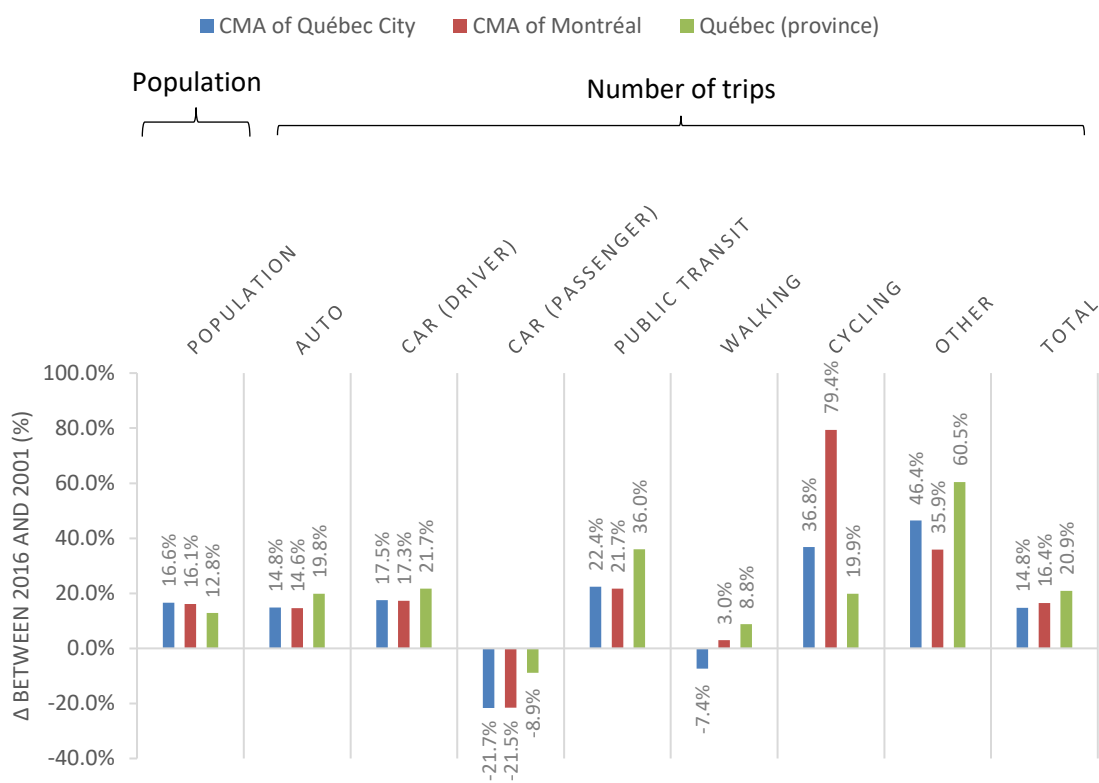


Figure A.5 Changes in population and number of trips by mode between 2001 and 2016

Data source: Population (Statistique Canada, 2016) and travel (Statistique Canada, 2017c).

The data from the Figure A.5 data are incomplete, however, since they do not take into account the diversification of travel patterns and the decline in the relative importance of commuting. To

compensate for this limitation of the census data, data from the Montréal and Québec City Origin-Destination surveys are used.

The share and number of trips made by each mode of transportation during the morning rush hour in Greater Montréal (comparable territories in 2003, 2008 and 2013) are shown in Table A.1

Table A.1 Modal shares, number of trips and changes in the number of trips. Greater Montréal region in 2003, 2008 and 2013.

Montréal Area - MODES - Morning peak period (6 a.m. to 9 a.m.)							
	All	Auto	Public transit	Dual mode	Other collective modes^a	Other	Active travel modes
Modal shares							
2003C	100%	62.5%	16.1%	2.1%	8.8%	0.1%	10.2%
2008C	100%	59.9%	17.9%	2.9%	8.7%	0.2%	10.5%
2013C	100%	62.1%	17.4%	3.2%	6.8%	0.3%	10.3%
Number of trips							
2003C	2 018 000	1 262 000	325 000	43 000	178 000	3 000	206 000
2008C	2 083 000	1 247 000	372 000	60 000	181 000	5 000	219 000
2013C	2 310 000	1 434 000	401 000	73 000	156 000	6 000	239 000
Change in the number of trips							
2008/2003	3.2%	-1.2%	14.5%	39.5%	1.7%	66.7%	6.3%
2013/2008	10.9%	15.0%	7.8%	21.7%	-13.8%	20.0%	9.1%
2013/2003	14.5%	13.6%	23.4%	69.8%	-12.4%	100.0%	16.0%

Note: The "C" indicates that the comparison is made according to the same survey territory, i.e., 2003.

^a Includes paratransit, school bus and other buses.

Source: OD Survey 2013 (AMT, 2013).

The share of automobile use (drivers and passengers combined) remained fairly stable between 2003 and 2013, while the total number of trips made by car increased by 13.6%. In addition, the highlights of the 2013 O-D survey reveal an uneven distribution of growth in automobile use. The southern and northern suburbs showed a 25.8% increase between 2013 and 2003 in the number of car trips during the morning rush hour, compared to an increase of only 3.8% on the Island of Montréal (AMT, 2013). The O-D survey data also corroborate the decrease in car trips as

passengers observed in the census data, since the average vehicle occupancy rate went from 1.23 in 1998 to 1.20 in 2013 (over 24 hours) (AMT, 2013).

For the Québec City area, the number of trips made by each mode of transportation over 24 hours is presented in Table A.2.

Table A.2 Modal shares, number of trips and changes in the number of trips. Québec City region in 2006, 2011 and 2017.

Québec City Region - MODES – 24 hours								
	All	Driving	Passenger	Public transit	Dual mode	Other collective modes^a	Other	Active travel modes
Modal shares								
2006C	100%	59.9%	14.5%	6.7%	0.3%	4.8%	1.1%	12.7%
2011C	100%	62.6%	14.2%	7.6%	0.4%	4.5%	1.0%	9.7%
2017C	100%	63.3%	14.4%	6.6%	0.5%	3.8%	1.0%	10.4%
Number of trips								
2006C	2 031 900	1 217 900	294 500	135 600	5 700	98 200	22 200	257 800
2011C	1 905 100	1 191 900	271 100	144 600	8 400	86 100	19 400	184 300
2017C	2 125 900	1 346 500	305 500	139 900	10 500	81 400	20 600	221 500
Change in the number of trips								
2011/2006	-6.2%	-2.1%	-7.9%	6.6%	47.4%	-12.3%	-12.6%	-28.5%
2017/2011	11.6%	13.0%	12.7%	-3.3%	25.0%	-5.5%	6.2%	20.2%
2017/2006	4.6%	10.6%	3.7%	3.2%	84.2%	-17.1%	-7.2%	-14.1%

Note: C: The "C" indicates that the comparison is made according to the same survey territory, i.e., 2003.

^a Includes paratransit, school bus and other buses.

Source: O-D Survey 2017 (Ministère des Transports du Québec, 2019a)

In Québec City, these data show that the car gained ground between 2006 and 2017, when the number of trips taken by drivers increased by 10.6%, twice as fast as for all trips (+4.6%) (Ministère des Transports du Québec, 2019a). As in Montréal, the increase in trips made by car (over 24 hours) between 2006 and 2017 was much greater for residents of the northern (+29%) and southern (+44%) suburbs than for those of the Québec City agglomeration (+6.5%) and the main suburban city of Lévis (+6.6%). The car occupancy rate also decreased slightly, from 1.24 in 2006 to 1.23 in 2017 over a 24-hour period.

In short, for the two regions studied, despite an increase in public transit and active transportation (particularly cycling), there has also been a significant increase in single-occupancy car travel. This growth is mainly observable in the suburbs, particularly in the northern and southern shores of the two metropolitan areas. This situation is not surprising when compared to population growth. Thus, the work of Gordon et al. (2016) estimated that between 2006 and 2016, 77% of the population growth in the Montréal CMA occurred in the *car suburbs* and 6% in the suburban fringe (*exurban*)²². For Québec City, 62% of the CMA's population growth occurred in the *car suburbs* and 35% in the exurban areas. It is also relevant to draw a parallel with the increase in urban sprawl observed by Nazarnia et al. (2016) which is described as exponential in Montréal and very rapid in Québec City.

In sum, all the statistics show an increase in car ownership, an increase in car travel and relatively stable modal split over the last fifteen years, likely fuelled by suburbanization.

Second Perspective: Planned response by authorities in official documents

Issues and problems

Although they are not exhaustive, the statistics and findings presented in the previous section illustrate an increase in automobile mobility. The first element of the planning documents analyzed is the identification of issues related to car dependency. More specifically, the objective is assessing whether the increase in car use and ownership is identified as a source of problems. It is also necessary to evaluate whether the link between land use and road network development and the issues of increased car mobility are identified in the documents. The inventory for each document is detailed and then followed by a summary table.

²² See Gordon et al. (2016, p. 10) for definitions of the different types of neighbourhoods and the classification methodology used.

Sustainable mobility policy (SMP)

The concept of car dependency is not explicitly mentioned in the document and the wording remains cautious in identifying the car as a major issue (Gouvernement du Québec, 2018c). For example, it is stated that "The dynamics of growth in the number of trips are primarily observed on the road network..." (p. 39)²³. However, the government emphasizes the issues related to the current mobility system, particularly the negative impacts on citizens' health (p. 20) road safety issues (p. 20), traffic (p. 39), inequality issues (p. 21), environmental and climate change impacts (p. 21). The policy mentions some of the causes of the current problematic situation, such as the deficiency of public transit services and the lack of alternatives, as well as the impact of land use planning on mobility practices, indicating that it "favours the use of the automobile and restricts alternative modes" (p. 21). It also notes that "The growth of the economy, the decrease in household size, and the concomitant increase in car ownership rates and vehicle size are factors that contribute to this phenomenon [of increasing GHGs from the vehicle fleet]." (p. 21).

Metropolitan Planning and Development Plan (MPDP) - Montréal

Car dependency is highlighted a few times in the plan (CMM, 2012). For example, in a box on sustainable land-use planning approaches, it is emphasized that these approaches generally have the objective of reducing dependence on the automobile (p. 52). It is also stated that the creation of *Transit-Oriented Development* (TOD) neighbourhoods, the flagship orientation of the MPDP, will "improve public health by reducing dependence on the automobile and promoting active transportation" (p. 81). In its observations on recent changes in mobility in the region, the CMM points out the increase in automobile travel and the rise in car ownership (p. 128) and makes the connection between urban sprawl and the increase in distances travelled by automobile (p. 131).

Metropolitan Planning and Development Plan (MPDP) - Québec

The MPDP clearly recognizes that the type of urban development that has favoured the fragmentation of activity locations and urban sprawl over the past few decades has contributed to an increase in automobile dependency (CMQ, 2013, p. 9 and 13). It also states that this has had

²³ Note that all extracts from planning documents were freely translated from French by the first author. Any inconsistencies and spelling mistakes fall on the authors of the present paper.

numerous negative impacts on quality of life, household finances, public finances, the loss of natural space and accessibility issues (p. 13). The plan also notes the constant increase in travel, mainly by car (p. 25) and that "Although the Québec City metropolitan region has the highest ratio of highway kilometres per capita in Canada, its highway network is increasingly saturated." (p. 25). In the explanation of the plan's main principles, i.e., urban development integrated with sustainable mobility, the plan illustrates at the same time that the type of development carried out until now favoured the use of the automobile (p. 125).

City of Montréal Transportation Plan

This is the document that most explicitly expresses the issue of automobile dependency (Ville de Montréal, 2008). The issue is presented in the plan's vision (p. 13): "... Montréal wants to significantly reduce **its dependence on the automobile** through massive investments in public transit and active transportation modes such as...". Dependence on the automobile is also highlighted as having "unfortunately increased in recent years" (p. 70). Its reduction is a strong objective of the plan, the expression recurring fourteen times in the document.

The increase in car ownership is also recognized and identified as a source of problems as they seek to "...reduce the negative impacts caused by too much growth in car ownership on its territory" (p. 54). Although it is identified as being "better controlled than the rest of the metropolitan area, but still growing..." (p. 141). The city also readily acknowledges the contribution of transportation to climate change and environmental degradation due to "the ubiquity of the automobile" (p. 39).

Finally, the city does recognize the issues associated with the exodus to the suburbs, noting that "The population growth [of the outer suburbs] further increases the pressure to maintain and develop transportation infrastructure." (p. 53). In this sense, the City reiterates the importance of "integrating transportation planning from a metropolitan perspective with land use planning." (p. 60). The plan also states that "A priori, there is no need to increase highway capacity in the region." (p. 86) and emphasizes the link between highway development and its influence on land use planning (p. 86).

Sustainable mobility plan - Québec City

In its 2011 Sustainable Mobility Plan, Québec City recognizes that the increase in car ownership and the number of trips made by car is a major trend contrary to sustainable development (Ville

de Québec, 2011, p. 18). The plan also indicates that "The continued choice of the single-family home in the suburbs and the resulting dependence on the automobile lead to an increase in greenhouse gas emissions." (p. 18) and that therefore, "The growth of cities will have to be done more through densification..." (p. 17). The City also notes in the analysis of trends up to 2030 that "Expansion of road networks will be seen as a waste of resources, both in terms of land use, unproductive travel expenditures, and greenhouse gas emissions." (p. 17).

The Table A.3 lists, for the five documents analyzed, references to the notions of car dependency, increased car ownership and car use, and the link between urban development and increased car use.

Table A.3 Summary of automobile issues in planning documents.

Document	Dependence on the automobile	Increase in car ownership	Increase in car use	Negative consequences	Link to urban form
Sustainable mobility policy	No direct mention	Yes (p. 21)	Indirectly <i>through</i> increased congestion.	Environmental, social and economic (p. 20-22)	Yes (p. 21)
MPDP - Montréal	Yes, two mentions	Yes (p. 128)	Yes (p. 128)	GHG (p. 131), Congestion (p. 138)	Yes, that is the core of the plan.
MPDP - Québec	Yes, three mentions	No mention.	Yes (p. 25 and 132)	Environmental, social and economic (p. 13)	Yes (p. 9)
Transportation plan - Montréal	Yes, 14 mentions	Yes (p. 54 and 141)	Yes (p. 49)	Environmental, social and economic (p. 41)	Yes (p. 41 and 44)
Mobility Plan - Québec City	Yes, three mentions	Yes (p. 18)	Yes (p. 18)	Environmental, social and economic (p.18)	Yes (p. 17-18)

Thus, with the exception of the province's Sustainable Mobility Policy, all the documents explicitly recognize the issue of automobile dependency. All of them, with the exception of the Québec metropolitan area's MPDP, recognize that the increase in car ownership is an issue and all the documents underscore the increase in automobile use. These documents also recognize that a major change in the way mobility and land use are planned is necessary to achieve sustainable development objectives. The City of Montréal even speaks of "...a radical shift now." (Ville de Montréal, 2008, p. 39).

Vision, targets and objectives

Visions from the five planning documents are reported in Table A.4. The visions that most strongly indicate a reduction in automobile dependency and use are those of the Montréal Transportation Plan and the Montréal MPDP (**text in bold**). The visions of the Montréal MPDP, the Montréal Transportation Plan and the Québec City Mobility Plan emphasize the importance of developing active and public transportation, while the SMP's vision speaks more broadly of sustainable mobility and an efficient transportation ecosystem (underlined text). Finally, all the visions except for the Montréal Transportation Plan mention a link between land use planning and mobility (*text in italics*).

Table A.4 Visions of planning documents.

Document	Vision
Sustainable mobility policy (SMP)	"In 2030, <u>Québec is a North American leader in sustainable and integrated 21st century mobility.</u> <i>On a territory developed with sustainable mobility in mind</i> , it has an <u>efficient, safe, connected and low-carbon transportation ecosystem</u> that contributes to Québec's prosperity and meets the needs of citizens and businesses." (Gouvernement du Québec, 2018c, p. 6)
MPDP - Montréal	"Going Global: Building a Competitive, Attractive, Supportive and Responsible Community" and the statement specifically regarding transportation development: "By 2025, the community is one of the major intermodal transportation hubs in North America through the interconnectivity of road, air, sea and rail modes. <i>These networks support the region's development to great advantage</i> and are recognized as safe, reliable and seamless. Above all, the <u>community has made the shift to public transit</u> by adequately developing an accessible, rapid, attractive and flexible network that meets the needs of users and significantly reduces automobile use . It is at the top of the list of the most efficient metropolitan regions in terms of controlling the production of greenhouse gas emissions." (CMM, 2012, p. 31)
MPDP - Québec	The MPDP of the Québec City agglomeration does not have an explicit vision statement. Instead, it is based on three priorities from which 13 strategies are derived: " Structure by building a <i>more coherent</i> metropolitan region in <i>terms of land use patterns and sustainable mobility</i> ." "Attract by providing quality living environments and employment sites in sufficient quantity to accommodate growth and by complementing the development of our identity elements." "To endure by <i>limiting the pressures of urbanization</i> on natural and agricultural environments, using our resources wisely, and ensuring the safety, public health, and well-being of citizens." (CMQ, 2013, p. 9)
Transportation Plan - Montréal	"To ensure the mobility needs of all Montréalers, by making our agglomeration a pleasant place to live as well as a prosperous economic hub that respects its environment. To do this, Montréal wants to significantly reduce its dependence on the automobile through <u>massive investments in public and active modes of transportation</u> such as the tram, metro, high-performance buses, trains, bicycles and walking, as well as in better adapted uses of the automobile such as <u>carpooling, carsharing and taxis</u> ." (Ville de Montréal, 2008, p. 13)
Mobility Plan - Québec	"The purpose of the Sustainable Mobility Plan is to contribute to making Québec City an attractive, prosperous and sustainable region that is illustrated, in particular, by a <i>strong integration of land use and transportation</i> and whose population <u>favours active and collective modes of travel</u> ." (Ville de Québec, 2011, p. 27)

Subsequently, the objectives and targets selected from the five documents analyzed (Table A.5) are those directly related to the following elements: reducing motorization, reducing automobile use, increasing the use of sustainable modes of transportation (public, active, alternative) and reducing the consequences (congestion, pollutant and GHG emissions, health impacts) associated with the current level of automobile use.

Table A.5 Objectives and targets of planning documents.

Objectives (or orientations) ^a (Or = Orientation, Obj = Objective)	Targets (or criteria) ^b (C = target, Cr = criteria)
1. Sustainable Mobility Policy 2018-2030 (Gouvernement du Québec, 2018b, Synthesis document, p.1-2)	
Or-1: Mobility at the service of citizens	C-1: 70% of the Québec population has access to at least four sustainable mobility services.
	C-2: 20% reduction in average travel time between home and work.
Or-2: Lower carbon footprint mobility	C-4: Decrease by 20% the share of trips made by single-occupancy vehicles province-wide.
	C-5: 40% reduction in oil consumption in the transportation sector below 2013 levels
	C-6: 37.5% reduction in GHG emissions from the transportation sector below 1990 levels.
Or-3: Mobility to support a strong economy	C-9: Reduction of congestion-related costs for businesses in the Montréal and Québec City metropolitan regions. Not quantified.
	C-10: 20% reduction in gross household spending on transportation (in constant 2017 Canadian dollars).
2. MPDP - Montréal (CMM, 2012, document sommaire, p.15)	
Obj-1.1: Direct 40% of housing development to access points of the metropolitan transit system	Cr-1.1: 40% of housing development in TOD area.
Obj-2.1: Identify a public transport network that can structure urbanization	No numerical targets.
Objective 2.2: Increase the modal share of trips made by public transit in the morning peak period to 30% by 2021	Cr-2.2: Public transit modal share ↑ to 30% by 2021.
Obj-2.3: Optimize and complete the road network to support the movement of people and goods	Cr-2.3.3: Reduction of congestion-induced delays. No numerical targets.
Obj-2.4: Promote active mobility on a metropolitan scale	No numerical targets.

Note: ^a The SMP has no objectives, only guidelines and numerical targets.

^b MPDPs do not use the word *target*, but rather *criteria* to be met or achieved.

Table A.5 Objectives and targets of planning documents (continued)

Objectives (or orientations) ^a (Or = Orientation, Obj = Objective)	Targets (or criteria) ^b (C = target, Cr = criteria)
3. MPDP - Québec (CMQ, 2013, p. 32)	
Obj-2.2.1: <i>Direct development to encourage the use of public and active modes of transportation</i>	Cr-2.2.1: Double the modal share of public transit used by 2031 in the CMQ territory. Target of 20% in the morning rush hour and 14% on a daily basis.
Obj-2.2.2: <i>Increase the connectivity of public transit, adapted transportation services and active transportation infrastructure in the region</i>	Cr-2.2.2: Increase the modal share of active travel to 15% by 2031. Double the modal share of cycling from 1% to 2% by 2031.
4. Transportation plan - Montréal (Ville de Montréal, 2008, pp. 70, 98-99, 109, 127)	
Or-A1: Implement better public transportation services	C-A.1.1: Increase transit ridership by 8% by 2012 and 26% by 2021.
Or-A2: Encourage active modes	No numerical targets.
Obj-2.1: To significantly increase peak period walking by 2021	
Obj-2.2: <i>To become, in the years to come, the cycling city par excellence...</i>	
Or-B1: The road network	C-B1.1: Decrease peak-period car trips to Montréal by 15% compared to anticipated trips in 2024 ^c . C-B1.2: Decrease anticipated automobile travel by 20% by 2021 (24-hour period) .
5. Mobility Plan - Québec City (Ville de Québec, 2011, pp. 37-39)	
Obj-1: Double the modal share of public transit in Québec City and Lévis by 2030	C-1: For the Québec City agglomeration, increase the modal share of public transit to 26% in the morning peak period and to 20% over 24 hours. For Lévis, increase the modal share of public transit to 11% in the morning peak period and to 5% over 24 hours.
Obj-2: Increase active travel by 2030	C-2: For the Québec City agglomeration, increase the modal share of active transportation (walking and cycling) to 17%.

Note: ^a The SMP has no objectives, only guidelines and numerical targets.

^b MPDPs do not use the word *target*, but rather *criteria* to be met or achieved.

^c This is an indirect target as the plan states that "Achieving the Transportation Plan's goals for travel by mode would result in a 15% decrease in automobile travel..."

A few observations can be drawn from these goals and targets. First, only the Sustainable Mobility Policy has a clear target for reducing single-occupancy vehicle trips (C-4). For the Montréal Transportation Plan, these "targets" (C-B1.1, C-B1.2) are rather what is expected by achieving the other objectives of the plan (see footnote 10). This lack of clear targets does not appear to be aligned with the Transportation Plan's vision of reducing automobile dependency (Table A.3). The same observation can be made of the Montréal MPDP, whose vision calls for a significant reduction in automobile use, although no objective in the plan refers to this. About the size of the vehicle fleet and household car ownership levels, no document includes a specific objective or target in this regard. However, it is noted that the provincial government, in its sustainable mobility policy, wishes to see a reduction in household spending on transportation (C-10). Considering that, on a provincial scale, 90% of household transportation expenditures are for private transportation and only 10% for public transportation (Statistique Canada, 2018b), a reduction of the order of 20% will inevitably involve a reduction in expenditures related to car ownership.

Inconsistencies can also be observed between targets in the same document, as is the case for the Sustainable Mobility Policy. Achieving the target of reducing average travel times (C-2) could be in direct contradiction with the target of reducing car trips. In fact, at the provincial level, the average commute time for driving is 23.4 minutes, behind active transportation (14 minutes), but far ahead of the 43.3 minutes for public transit (Statistique Canada, 2017b). Even for the Montréal metropolitan area, where congestion is often presented as endemic, the average commuting time is considerably shorter for driving (26.6 minutes) than for public transit (44.4 minutes) (Statistique Canada, 2017a)²⁴. While, in the long term, the densification and integrated land-use planning strategy could make it possible to achieve both targets, there are doubts as to whether they will be achieved by 2030.

In short, except for the Sustainable Mobility Policy, which presents a quantified objective for reducing automobile use, the other documents only identify objectives for increasing the use of sustainable modes (sometimes without numerical targets). While the issues related to car use are

²⁴ Census travel times are reported and not calculated.

generally well identified (Table A.3), it seems that the objectives and targets set do not reflect the ambition to reduce the consequences associated with these issues.

The next section will therefore seek to assess whether the projects planned for the next decade will contribute to achieving the objectives of these documents and to the goal of reducing car-based mobility (use and ownership).

Third perspective: Prioritized infrastructure projects and government strategies

The purpose of adopting a transportation plan, sustainable mobility plan or sustainable mobility policy is to guide the implementation of strategies, policies and projects that achieve the targets and visions set. In reality, the complex dynamics of a three-tiered government system (municipal, provincial and federal), each with its own area of jurisdiction that must be managed with a limited budget, makes the coordination required for the successful implementation of the plans and policies adopted a challenge. In addition to these implementation issues, there is the inherent reality of a democratic system where political priorities change with electoral cycles and follow various social, ideological and technological changes.

In such a context, it is not surprising that the projects and actions to be carried out do not follow exactly the prioritization stated in the plans and policies or are simply not carried out. The issue addressed in this third analysis perspective is that of consistency between the type of projects prioritized and the visions, objectives and targets of the planning documents. Based on the scientific literature on the general impacts expected from road and transit infrastructure projects, the estimated contribution of each project (positive, negative, or uncertain) to the achievement of the objectives and targets of planning documents is presented in Table A.6.

Table A.6 Expected contribution of projects to the objectives of planning documents.

Contribution: (P) positive, (N) negative, (I) uncertain.		Projects				
	Objectives / Targets	P1: A-19 (HW)	P2: Blue line (PT)	P3: REM (PT)	P4: 3 rd link (HW)	P5: RSTC (PT)
Sustainable mobility policy	C-1: 70% have access to 4 sustainable mobility services	P ¹	P	P	P ^a	P
	C-2: 20% reduction in commuting time	N	I	I	I ^b	I
	C-4: -20% to single-occupancy vehicle modal share	N	P	P	N	P
	C-5: -40% of oil consumption in transport	N	P	P	N	P
	C-6: -37.5% of GHG emissions from transport	N	P	P	N	P
	C-9: ↓ of the costs associated with congestion for businesses	N	I	I	I ^b	I
	C-10: ↓ of 20% of household expenditure on transport.	N	P	P	N	P
MPDP - Montréal	Obj-1.1: 40% of household growth in TOD areas	N	P	P		
	Obj-2.1: To identify a structuring public transport network	N	P	P		
	Obj-2.2: To increase the modal share of public transport in the AM peak to 30% (2025)	N	P	P		
	Obj-2.3: Optimize and complete the road network	P	N	N		
	C-2.3.3: ↓ of delays due to congestion	N	I	I		
	Obj-2.4: Promote active mobility on a metropolitan scale	N	P	P		
MPDP - Québec City	C-2.2.1: Double the PT modal share (2031) in the CMQ.				N	P
	C-2.2.2: ↑ 15% LD modal share and *2 bicycle modal share (2031).				N	P
Transport Plan - Montréal	C-A.1.1: ↑ 26% increase in PT ridership (2021)	N	P	P		
	Obj-2.1: ↑ peak period walking trips (2021).	N	P	P		
	Obj-2.2: To become the cycling city par excellence	N	I	I		
	C-B1.1: ↓ 15% auto trips to MTL in PPAM p/r to those anticipated (2021).	N	N	P		
	C-B1.2: ↓ 20% of anticipated 24-hour auto trips (2021).	N	P	P		
Mobility Plan - Québec City	C-1A: For QC agglomeration, ↑ to 26% in PPAM and 20% over 24h modal share of PT.				N	P
	C-1B: For Lévis, ↑ to 11% in PPAM and 5% over 24 h the modal share of PT.				N	I
	C-2: For Québec City agglomeration, ↑ to 17% to modal share of AT.				N	P

Note: ^a To the extent that these projects include a dedicated carpool and bus lane, it can be estimated that the addition of PT service where none existed before may allow more citizens to have access to an additional sustainable mobility service.

^b Depending on the state of urban development on the south shore of Québec City at the time of the tunnel's opening, it is possible that the new link will temporarily reduce travel times and the costs associated with congestion. However, these gains will not tend to last over time (Cervero, 2003). PT = Public Transit; AT = Active travel

Public transport infrastructure projects

The first consideration is whether these projects were included in the planning documents. For Québec City, the general concept of building a structuring public transit network was directly included in the city's sustainable mobility plan (Ville de Québec, 2011, p. 53), although its final form has obviously evolved since 2011. The MPDP refers to the Mobility Plan when it mentions the development of a structured public transit network (CMQ, 2013, p. 139). For Montréal, the extension of the metro's blue line was planned as one of the 21 projects included in the transportation plan (Ville de Montréal, 2008, p. 18). As for the REM, its final form proposed by the CDPQ could not be foreseen in 2008. However, the project does complete two projects planned at the time, namely the construction of a light-rail between downtown and the Montréal Airport and the increase in public transit capacity in the Champlain Bridge-Bonaventure corridor (Ville de Montréal, 2008, pp. 18-19). In the MPDP, the projects are listed less specifically, as the plan only mentions "the extension of the Metro" and the creation of an "airport shuttle" (CMM, 2012, p. 136).

The literature review carried out illustrated that the development of public transport projects on rail (light rail and tramway) generally promotes an increase in the use of these modes as well as active modes. In the longer term, they also reduce the average number of trips made by car for households near these new corridors. Densification and diversification of land use near stations are, however, essential to achieve the multiplier effect of these projects (Ewing & Hamidi, 2014). Nevertheless, while these projects are a step in the right direction, it is less certain that they alone will reduce the absolute number of trips made by car on a metropolitan scale or reduce congestion levels. It is possible, however, that the influence of these projects will slow the growth of car use as in Portland (Ewing & Hamidi, 2014) and slow the growth of vehicle volumes in highway corridors directly influenced by these projects, as was the case for the light rail system in Denver (Bhattacharjee & Goetz, 2012).

Projects to increase road capacity

As with public transit projects, it is necessary to validate whether these projects were included in the planning documents. For the Québec City region, the sustainable mobility plan does not mention the 3rd link over the St-Lawrence river and states: "A priori, there is no need to increase

highway capacity in the region. Nor is it necessary to reduce the number of highway lanes." (Ville de Québec, 2011, p. 86). Instead, the City recommends transforming certain sections of the highway into urban boulevards (p. 87). At the metropolitan level, the MPDP does not specifically mention the 3rd link, but it does include a section entitled "Road investments that will also contribute to the region's sustainable mobility," which then supports the planned projects by the Ministry of Transports that aim to increase the road capacity. The document emphasizes that the automobile will remain the main mode of travel in the region (CMQ, 2013, p. 141).

In the Montréal region, the Montréal transportation plan does not mention the extension of Highway 19, as it is not located within the City's administrative limits. It is also emphasized that "Montréal is not aiming to increase road capacity to access the island..." (Ville de Montréal, 2008, p. 128). The city would rather rethink the sharing of space in order to favour active and collective modes of transportation. However, the plan does propose the extension and connection of several arterial road segments, mainly at the eastern and western ends of the Island (p. 137). At the metropolitan level, the MPDP includes contradictory elements. For example, in a box on development, transportation and public health, it is stated that "In parallel with the increase in public transit supply, a policy of non-expansion of the urban highway network to prevent induced traffic also contributes to the modal shift toward public transit..." (CMM, 2012, p. 83). Yet, it is stated later in the plan that "As with public transit systems, significant investment in the highway system will therefore be required to maintain and develop it." (p. 138). The statement is followed by a table listing four highway extension or completion projects (including the A-19), two-lane addition projects and numerous rehabilitation and optimization projects (Table 27, p. 139).

As briefly illustrated in the literature review, there is ample theoretical and empirical evidence that adding road capacity (including a new road link) does not reduce congestion issues and favours an automobile-oriented type of urban development. In the case of the 3rd link, twelve experts consulted by the *Journal de Québec* have confirmed that the project will not be an exception to what has been observed elsewhere (S. Martin, 2017). On the page dedicated to the project, the Ministère des Transports du Québec (2019f) states that the project will make it possible to "reduce congestion during rush hours, promote the use of public transit and optimize the transportation of goods". Public transit would thus be favoured by the inclusion of bus, carpooling and electric vehicles exclusive lanes. It should be noted that the report of the multi-criterion analysis used by the Ministry of Transport to identify the corridor and the choice of a tunnel (rather than a bridge)

has not been made public at the time of publication of this article (July 2020) (Radio-Canada, 2019a). In addition, economic and environmental arguments were also put forward by the Ministry of the Environment, who emphasized that by contributing to the economic development of the region, the project would be part of a sustainable development perspective that would make it possible to fight against climate change (Porter, 2019).

The justifications for the extension of Highway 19 in the Montréal region are not very different from those for the 3rd link in Québec City. It is also a good example of the resilience of car dependency within institutions. Indeed, the Ministry of Transport was forced by the *Bureau d'audiences publiques sur l'environnement* (BAPE)²⁵ in 2014 to conduct a more in-depth analysis between two-lane highway scenarios and urban boulevard scenarios, notably because "[The commission] believes that, in the wake of the shift set out in its planning documents, the Ministry must give more room to active and collective modes of transportation and strategically orient its actions toward this objective." (BAPE, 2015, p. 126). In its subsequent comparative analysis, however, the Department concludes that the choice of an urban boulevard would have increased the number of signalized intersections and slowed traffic, thereby reducing roadway capacity to a point that does not achieve acceptable levels of service." (MDDELCC, 2018, p. 9). Such a conclusion confirms the difficulty for the government apparatus to move away from a traditional transportation planning paradigm where optimization of vehicle flows guides the decision process. In short, while the evaluation documents demonstrated that improvements to this corridor were necessary, particularly in order to improve public transit services (BAPE, 2015), we question, in light of the established literature, the potential of the project in its chosen final form to contribute to the achievement of the objectives of the planning documents. Furthermore, by choosing a highway that doubles the current car traffic capacity, it is difficult to imagine how it will be possible to "...promote modal transfer and reduce the environmental and economic costs associated with road congestion" as put forward by the Ministère des Transports du Québec (2018) in its announcement of the project. Indeed, as an example, Bhattacharjee and Goetz (2012, p. 268) pointed out that the induced demand generated by the increase in interstate highway capacity at

²⁵ Québec's independent commission responsible for the environmental evaluation of all major projects.

the same time as the development of Denver's light rail system was one of the factors that contributed to light rail's inability to reduce the congestion balance on those same highways.

Evolution of road transport expenditures vs. public transport

Since it is not possible to evaluate all road and public transit infrastructure projects, an indicator is proposed to evaluate government priorities: the share of investments in the road network versus that in public transit infrastructure. These investments are listed annually in the Québec's infrastructure plan and, according to a compilation made for the 2018-2028 plan, 69% of transportation investments are directed toward developing and maintaining the road network and 31% toward public transit infrastructure (L'Alliance TRANSIT, 2018). In the 2019-2029 update of the infrastructure plan, which occurred one year after the sustainable mobility policy came into effect, the proportion of investments rose to 73% for the road network and declined to 27% for public transit (L'Alliance TRANSIT, 2019).

The case of transportation electrification

The provincial government adopted a broad transportation electrification strategy in 2015, prior to the adoption of its more comprehensive Sustainable Mobility Policy (Ministère des Transports du Québec, 2015b). Since 99% of Québec's electricity is generated from renewable sources (Ministère des Transports du Québec, 2015b), transportation electrification is presented as a wise choice for the province. Its objectives are to reduce GHG emissions from the transportation sector, reduce dependence on fossil fuels and promote economic development. The strategy focuses on one hand on public transit and freight transportation. But on the other hand, it aims to transform the fleet of private cars *through* a series of measures to encourage the purchase and use of electric vehicles. A rebate on the purchase of new 100% electric and plug-in hybrid personal vehicles of up to 8,000 Canadian dollars has been offered since 2012 (Gouvernement du Québec, 2019b). Since May 2019, an additional rebate of 5,000 Canadian dollars has been added by the Canadian government (Gouvernement du Canada, 2019c). Financial support is also available for the installation of charging stations at home and automobile use is encouraged through access to dedicated lanes and toll-free access to bridges (Ministère des Transports du Québec, 2022). For the Government of Québec, the total rebates granted amounted to 280 million Canadian dollars from 2012 to April 2019 (Transition Énergétique Québec, 2019).

While it can be agreed that fleet electrification is part of the solution to reducing some of the impacts of car dependency, the strategy in its current form and the message sent by the government through the efforts and money that are being deployed are questioned, particularly with regard to the objectives of planning documents. Looking only at the Sustainable Mobility Policy, it seems unlikely that encouraging the purchase and use of private electric cars will contribute to achieving the targets of reducing the modal share of driving (C-4), reducing travel times (C-2) and reducing household spending on transportation (C-10). In sum, we argue that in its current form, the transportation electrification strategy encourages the pursuit of a mobility system development model based on automobile ownership and use, contributing to the maintenance of societal dependence on the automobile. This inconsistency of Québec's private transportation electrification strategy with sustainable mobility objectives could be considered a "transportation taboo," a term proposed by Gössling and Cohen (2014) to identify what currently seems untouchable in transportation policy.

Conclusion

The three-perspective analytical framework proposed in this paper sought to determine whether automobile mobilities are in decline in Québec and whether this decline is accompanied by a transformation of transportation and land-use planning mechanisms. The framework was applied to the province as well as to its two metropolitan areas, Montréal and Québec City. The first analysis showed that Québec does not seem to have experienced the "peak-car" phenomenon observed in the United States, Australia and several European countries. In fact, automobile use and car ownership have continued to increase in the province and at the metropolitan level over the past two decades, sustained by significant growth in the suburban areas of Montréal and Québec City despite growth in the use of public transit and bicycles in the urban core.

The second perspective of analysis revealed an unequal recognition of the issues related to automobile dependence and the growth of car-based mobility (use and ownership) by planning authorities. Explicit recognition of these issues decreases with the increase in the planning scale, being more present at the level of municipal transportation and mobility plans than at the level of the Metropolitan Planning and Development Plans (MPDP) than in the provincial Sustainable Mobility Policy. Paradoxically, the most ambitious targets for *reducing* car use and ownership are identified in the Provincial Sustainable Mobility Policy. The municipal plans and the MPDPs only

set targets for increasing the use (modal share or ridership) of active and public modes. This paradox is particularly striking for the City of Montréal's Transportation Plan, which places the reduction of car dependency at the heart of its vision but does not set any direct objective for reducing automobile mobility. On a more reassuring note, the five documents clearly state the link between the urban development of the last few decades and the increased use of the automobile and the increase in motorization. They also indicate that integrated planning of these two components is essential to achieve sustainable mobility objectives.

The third perspective highlighted the main transportation infrastructure projects in relation to the visions and objectives of the planning documents. First, with the exception of the third road link project between the north and south shores of the Québec City region, all the projects were included (albeit partially for the REM) in the MPDPs and in municipal plans. Subsequently, based on the existing literature, it can be argued that the public transit projects (Blue line extension, REM and Québec's city structural transit network; RTSC) are aligned with the visions of the planning documents and should contribute to the achievement of some of the targets set. To achieve the multiplier effects of these projects, they must be accompanied by integrated, dense and mixed-use urban development in their respective corridors. However, it must be noted that it is unlikely that these projects, on their own, will be able to achieve an absolute reduction in automobile mobility. It is nevertheless important to remember that these public transit projects, like other documented projects around the world, have the potential to generate a wide range of social, environmental, and economic benefits resulting from increased accessibility. Through the influence on urban development, they have the potential to at least slow the growth of automobile mobility.

Finally, it is believed from the literature that the highway projects (3rd link and A-19) are not aligned with the visions of the planning documents and will *not* contribute to the achievement of almost all the goals of the planning documents. The increased highway capacity of these projects is likely to induce short- and long-term automobile demand that could compromise the gains expected from the public transit projects planned for each region. It is therefore very surprising and incoherent to note the presence of the A-19 extension in the Montréal's MPDP. Furthermore, the promises to include dedicated lanes for public transit in both projects to qualify them as "sustainable mobility" projects may be associated with a strategy aimed at making them socially and environmentally acceptable rather than with a real desire to plan mobility differently. In general, these environmental arguments are added to economic development arguments that are

typical of political and institutional resistance to a change in the mobility paradigm. A situation described by Newman and Kenworthy (2015b, p. 143) which underscores the difficulty for a city (in this case, a province) to move away from a road-based development paradigm where new road projects are justified on the basis of time, fuel and other community benefits. This situation is compounded by the context of a government agency (in this case, the Ministry of Transportation) dedicated almost exclusively to road development and offering politicians and decision-makers biased assessments in favour of automobile development (Newman & Kenworthy, 2015b, p. 144).

In sum, the continued growth of car-based mobilities, the absence of objectives and tools for reducing the place of the automobile in most planning documents and the simultaneous pursuit of infrastructure projects with opposite effects illustrate the difficulty of implementing a paradigm shift in transportation planning that can truly reverse current trends. The difficulties for the government to fully realize this paradigm shift through the implementation of an ambitious sustainable mobility policy adopted in April 2018 underline the political impact of car dependency. This situation in Québec amounts to confirmation of what Dupuy suggested in a recent interview for FLUX magazine (G. Dupuy & Gallez, 2018, p. 107) that car dependency is "... above all a problem that arises for all public policies that claim to be virtuous in regulating mobility. I would say that it is a political problem."²⁶

²⁶ Translation by the first author.