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POLYTECHNIQUE MONTRÉAL
affiliée à l'Université de Montréal

How Much Carsharing Do We Need? A System-Level Evaluation of Its Environmental Implications for Urban Mobility

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Thèse présentée en vue de l'obtention du diplôme de *Philosophiæ Doctor*
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How Much Carsharing Do We Need? A System-Level Evaluation of Its Environmental Implications for Urban Mobility

présentée par **Yonsorena NONG**
en vue de l'obtention du diplôme de *Philosophiæ Doctor*
a été dûment acceptée par le jury d'examen constitué de :

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DEDICATION

English

To my father Kunthara, my mother Kethya, and my sisters Thya and Thyda, whose quiet love and patience supported me at every step.

To those who believed in me when I doubted myself.

Français

À mon papa Kunthara, à ma maman Kethya et à mes sœurs Thya et Thyda, dont l'amour discret et la patience m'ont accompagnée à chaque étape.

À celles et ceux qui ont cru en moi lorsque je doutais de moi-même.

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RÉSUMÉ

L'autopartage est largement promu comme une stratégie permettant de réduire les impacts environnementaux du transport urbain. Pourtant, les études empiriques et de modélisation rapportent des résultats très divergents : certaines mettent en évidence des réductions substantielles des émissions, tandis que d'autres observent des bénéfices limités, voire une augmentation des déplacements motorisés. Cette divergence s'explique par le fait que la performance environnementale de l'autopartage dépend de plusieurs déterminants opérant à différentes échelles et difficiles à dissocier analytiquement. Ces déterminants incluent la manière dont l'accès à l'autopartage modifie la demande de mobilité selon les groupes d'usagers, la façon dont les impacts de fabrication et de fin de vie des véhicules sont répartis sur le service de mobilité rendu, ainsi que la capacité physique des flottes partagées à répondre à la demande dans la structure spatiale et temporelle des déplacements réels. Si les évaluations de cycle de vie intégrées à des modèles de transport peuvent, en principe, représenter simultanément ces mécanismes, elles tendent souvent à en masquer les contributions individuelles, ce qui complique l'interprétation des différences de résultats entre contextes et études.

Cette thèse adopte une perspective de cycle de vie fondée sur les déterminants afin de clarifier dans quelles conditions l'autopartage génère des bénéfices environnementaux, pour quels usagers ces effets se produisent, et pourquoi ils peuvent ne pas se matérialiser en pratique. Plutôt que de proposer un modèle intégré unique, la thèse analyse séparément, sous des hypothèses contrôlées, la composition comportementale et la structure d'adoption, l'efficacité matérielle et la faisabilité opérationnelle, puis en synthétise les implications. Cette structure vise à compléter les évaluations intégrées en explicitant les déterminants qu'elles doivent représenter et les conditions dans lesquelles leurs résultats peuvent être interprétés.

La thèse est organisée en trois études empiriques. Le Chapitre 3 examine les implications environnementales des réponses comportementales à l'autopartage et la manière dont la composition des adopteurs et la structure d'adoption façonnent les résultats environnementaux à l'échelle du système. Il s'inscrit dans l'approche dominante de la littérature en appliquant des élasticités comportementales issues d'études empiriques, mais l'étend à une population synthétique basée sur les activités de la grande région de Montréal, avec une résolution spatiale explicite et une comptabilité complète des impacts sur le cycle de vie. Les ajustements de mobilité issus de la littérature sont appliqués comme scénarios à deux catégories d'adopteurs : les individus disposant d'un accès intermittent à un véhicule du ménage et ceux sans accès à une voiture privée. L'adoption est modélisée comme un processus de montée en charge struc-

turé plutôt que comme un choix binaire, ce qui permet de suivre l'évolution des émissions à l'échelle du système selon différents ordres d'adoption et contextes spatiaux. Les résultats montrent que les impacts environnementaux dépendent principalement de l'identité des adopteurs et de la séquence d'adoption. L'adoption par les usagers occasionnels de la voiture réduit de manière cohérente les empreintes carbone sur le cycle de vie par substitution des déplacements en voiture privée, tandis que l'adoption par des usagers sans accès préalable à une voiture augmente les émissions en raison d'un surcroît de déplacements motorisés, même lorsque les flottes partagées sont électrifiées. Une adoption aléatoire produit des trajectoires quasi linéaires, tandis qu'une adoption structurée selon la demande de déplacement et la densité résidentielle génère des réponses agrégées non linéaires. Ces résultats montrent que les évaluations moyennes par usager sont insuffisantes pour l'interprétation à l'échelle du système et que la structure d'adoption constitue une hypothèse critique, souvent implicite, des évaluations à grande échelle.

Le Chapitre 4 se concentre sur l'efficacité matérielle à travers l'usage des véhicules sur leur durée de vie. S'appuyant sur le constat que les gains environnementaux apparaissent principalement lorsque l'autopartage remplace des déplacements existants en voiture privée, cette étude se limite aux automobilistes et analyse l'influence de la distance annuelle parcourue et du kilométrage total réalisé sur la durée de vie des véhicules sur l'intensité carbone du cycle de vie. À partir d'un vaste ensemble de données de véhicules retirés de la circulation au Québec, l'analyse montre que le kilométrage de fin de vie varie fortement entre conducteurs et est fréquemment inférieur aux valeurs représentatives utilisées dans les analyses de cycle de vie conventionnelles. Les conducteurs à faible et moyenne intensité d'usage sous-utilisent particulièrement les véhicules privés par rapport à des durées de vie réalisables. Lorsque ces usagers satisfont des besoins de mobilité similaires à l'aide de véhicules partagés, les impacts de fabrication et de fin de vie peuvent être répartis sur une quantité plus importante de service de mobilité effectivement rendu, réduisant ainsi l'intensité environnementale par personne-kilomètre. À l'inverse, les conducteurs à fort kilométrage atteignent déjà un usage élevé avec des véhicules privés et tirent donc des gains d'efficacité matérielle plus limités de l'autopartage. Ces effets sont accentués pour les véhicules électriques, dont les impacts de production et de fin de vie plus élevés les rendent particulièrement sensibles à la sous-utilisation. Ce chapitre établit ainsi l'usage des véhicules sur leur durée de vie comme un déterminant central de l'efficacité matérielle, et non comme un simple paramètre de modélisation.

Le Chapitre 5 examine si les niveaux d'usage des véhicules requis pour obtenir des gains d'efficacité matérielle sont réalisables sous des contraintes spatiales et temporelles réelles. À partir d'un jeu de données détaillé sur la demande quotidienne de déplacements dans le centre de Montréal, le chapitre met en œuvre un cadre d'affectation spatiale et temporelle de flotte permettant d'évaluer si des véhicules électriques partagés peuvent desservir des trajets initialement réalisés en voiture privée sous des contraintes d'accès réalistes. La demande de déplacement est maintenue fixe et les changements comportementaux ne sont pas modélisés. L'usage réalisé des véhicules et la couverture des trajets émergent plutôt de règles explicites de faisabilité et d'hypothèses de dimensionnement de flotte. Les résultats montrent qu'un usage élevé des véhicules n'est pas garanti par conception et dépend de la distribution spatiale de la demande, des seuils d'accès et de la configuration de la flotte. La réduction de la taille de la flotte peut accroître l'usage moyen par véhicule, mais cet effet n'est environnementalement bénéfique que dans la mesure où une part substantielle des trajets demeure faisable. Lorsque trop de trajets deviennent inaccessibles, la mobilité se reporte vers la voiture privée et les émissions à l'échelle du système augmentent. Des hypothèses supplémentaires intégrant la variabilité de la vitesse de marche liée à l'âge et le déploiement de véhicules autonomes illustrent comment les conditions d'accès et les stratégies de repositionnement influencent la faisabilité et les impacts sur le cycle de vie.

Pris ensemble, les trois chapitres montrent que la performance environnementale de l'autopartage est gouvernée par l'alignement de trois déterminants. Les réponses comportementales déterminent si l'autopartage substitue des déplacements existants en voiture privée ou induit une demande motorisée supplémentaire, tandis que la composition des adopteurs et la structure d'adoption façonnent les résultats à l'échelle du système et leur trajectoire de montée en charge. L'efficacité matérielle dépend de la capacité à répartir les impacts de fabrication et de fin de vie sur un volume suffisant de service de mobilité effectivement rendu, plutôt que de les concentrer dans des véhicules sous-utilisés. La faisabilité opérationnelle détermine si les flottes partagées peuvent physiquement atteindre un nombre suffisant de trajets, dans le temps et dans l'espace, pour soutenir ce service en pratique. Chaque déterminant est nécessaire, mais aucun n'est suffisant pris isolément.

Pour les politiques publiques et la planification, cette thèse montre que l'autopartage doit être considéré comme un instrument climatique conditionnel plutôt que comme une solution universelle. Les bénéfices environnementaux apparaissent principalement lorsque l'adoption provient d'usagers occasionnels de la voiture et de conducteurs à faible ou moyenne intensité d'usage, lorsque les véhicules électriques partagés sont utilisés pour satisfaire efficacement des besoins de mobilité existants, et lorsque les conditions de service permettent de desservir les trajets de manière fiable. Ces résultats soutiennent des stratégies de déploiement ciblées, un dimensionnement de flotte informé par des critères environnementaux et une intégration étroite avec des systèmes multimodaux. Plus largement, la thèse fournit une base analytique transparente pour interpréter les impacts de l'autopartage et pour concevoir des modèles intégrés qui demeurent interprétables, évolutifs et ancrés dans les contraintes du monde réel.

ABSTRACT

Carsharing is widely promoted as a strategy for reducing the environmental impacts of urban transportation. Yet empirical and modelling studies report highly inconsistent results: some find substantial reductions in emissions, while others report limited benefits or even increases in motorised travel. This divergence reflects the fact that carsharing's environmental performance is shaped by multiple determinants operating at different scales and often difficult to disentangle analytically. These determinants include how access to carsharing reshapes travel demand across user groups, how vehicle manufacturing and end-of-life impacts are distributed across delivered mobility, and whether shared fleets can physically fulfil demand within the spatial and temporal structure of real-world travel. While integrated life-cycle assessments coupled with transport modelling can, in principle, represent these mechanisms simultaneously, doing so often obscures their individual contributions and makes it difficult to explain why outcomes differ across contexts and studies.

This dissertation adopts a determinant-based life-cycle perspective to clarify under what conditions carsharing yields environmental benefits, for whom these effects occur, and why they may fail to materialise in practice. Rather than proposing a single integrated model, the dissertation analyses behavioural composition and adoption structure, material efficiency, and operational feasibility separately under controlled assumptions, and then synthesises their implications. This structure is intended to complement integrated assessments by clarifying the determinants they must represent and the conditions under which their results can be interpreted.

The dissertation is organised into three empirical studies. Chapter 3 examines the environmental implications of behavioural responses to carsharing and how adopter composition and adoption structure shape system-level outcomes as adoption expands. It follows the dominant approach in the literature by applying empirically derived behavioural elasticities, but extends it to an activity-based synthetic population of the Greater Montréal Area with explicit spatial resolution and full life-cycle impact accounting. Literature-based travel adjustments are applied as scenario inputs to two adopter categories: individuals with intermittent access to a household vehicle and individuals without access to a private car. Adoption is treated as a structured scaling process rather than a binary outcome, allowing system-level emissions to be traced under alternative adoption orders and spatial contexts. Results show that outcomes depend primarily on who adopts and in what sequence. Adoption by occasional car users consistently reduces life-cycle carbon footprints through substitution of private-car

travel, whereas adoption by carless users increases emissions due to additional motorised travel, even when shared fleets are electrified. Random adoption produces smooth, near-linear scaling, whereas structured adoption based on travel demand and residential density produces non-linear aggregate responses. These findings show that average per-user assessments are insufficient for system-level interpretation and that adoption structure is a critical, often implicit assumption in large-scale evaluations.

Chapter 4 focuses on material efficiency through vehicle lifetime use. Building on the finding that environmental gains arise primarily when carsharing replaces existing private-car travel, this chapter restricts attention to private-car users and examines how annual driving distance and realised lifetime mileage shape life-cycle carbon intensity. Using a large dataset of deregistered vehicles from Québec, the analysis shows that lifetime mileage varies widely across drivers and is frequently lower than the representative values assumed in conventional life-cycle assessments. Low- and mid-mileage drivers in particular underuse private vehicles relative to feasible lifetimes. When these users rely on shared vehicles to fulfil similar mobility needs, manufacturing and end-of-life impacts can be distributed across a larger amount of realised mobility service, reducing environmental intensity per person-kilometre. High-mileage drivers, by contrast, already achieve high lifetime vehicle use with private cars and therefore exhibit limited material efficiency gains from carsharing. These effects are amplified for electric vehicles, whose higher production and end-of-life impacts make them especially sensitive to underuse. This chapter establishes vehicle lifetime use as a central material efficiency determinant rather than a fixed modelling parameter.

Chapter 5 examines whether the vehicle-use levels required for material efficiency gains are feasible under real spatial and temporal constraints. Using a detailed daily travel-demand dataset for central Montréal, the chapter implements a spatial and temporal fleet-assignment framework that evaluates whether shared electric vehicles can serve private-car trips within realistic access constraints. Travel demand is held fixed and behavioural change is not modelled. Instead, realised vehicle use and trip coverage emerge from explicit feasibility rules and fleet-size assumptions. Results show that higher vehicle use is not guaranteed by design and depends on the spatial distribution of demand, access thresholds, and fleet configuration. Reducing fleet size can increase average use per vehicle, but this is environmentally beneficial only insofar as a substantial share of trips remains feasible; when too many trips become unreachable, travel reverts to private cars and system-level emissions increase. Additional assumptions incorporating age-related walking-speed variability and autonomous-vehicle dispatch illustrate how access conditions and repositioning strategies affect feasibility and life-cycle outcomes.

Across the three chapters, the dissertation shows that carsharing's environmental performance is governed by the alignment of three determinants. Behavioural responses determine whether carsharing substitutes existing private-car travel or induces additional motorised demand, while adopter composition and adoption structure shape system-level outcomes and their scaling trajectories. Material efficiency depends on whether manufacturing and end-of-life impacts are distributed across sufficient realised mobility service, rather than being concentrated in underused vehicles. Operational feasibility determines whether shared fleets can physically reach enough trips, in time and space, to sustain that service in practice. Each determinant is necessary, but none is sufficient on its own.

For policy and planning, the dissertation demonstrates that carsharing should be treated as a conditional climate strategy rather than a universal solution. Environmental benefits arise primarily when adoption comes from occasional and low- to mid-mileage private-car users, when shared electric vehicles are used to deliver existing mobility needs with high lifetime use, and when service conditions allow trips to be served reliably. These results support targeted deployment, environmentally informed fleet sizing, and integration with broader multimodal systems. More broadly, the dissertation provides a transparent analytical foundation for interpreting carsharing impacts and for designing integrated models that remain interpretable, scalable, and grounded in real-world constraints.

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LIST OF SYMBOLS AND ACRONYMS

ABM	Agent-based Model
AV	Autonomous Vehicle
BEV	Battery Electric Vehicle
COPERT	COmputer Programme to calculate Emissions from Road Transport
CO	Carbon Monoxide
CO_2	Carbon Dioxide
EoL	End-of-Life
EV	Electric Vehicle
FF	Free-floating Carsharing System
GHG	Greenhouse Gas Emissions
GMA	Greater Montréal Area (Montréal's Census Metropolitan Area)
GPS	Global Positioning System
GREET	Greenhouse gases, Regulated Emissions, and Energy use in Technologies
GTFS	General Transit Feed Specification
HBEFA	Handbook Emission Factors for Road Transport
HC	Hydrocarbons
ICEV	Internal Combustion Engine Vehicle
IPCC	Intergovernmental Panel on Climate Change
LCA	Life Cycle Assessment
LCI	Life Cycle Inventory
LCIA	Life Cycle Impact Assessment
LTM	Lifetime Mileage
MATSim	Multi-Agent Transport Simulation
MOVES	Motor Vehicle Emission Simulator
NMC811	Nickel-Manganese-Cobalt (811)
NO_x	Nitrogen Oxides
OD	Origin–Destination
OSM	OpenStreetMap
P2P	Peer-to-peer Carsharing System
PKT	Person-Kilometres Travelled
$PM_{2.5}$	Fine Particulate Matter ($\leq 2.5\ \mu$m)
PM_{10}	Particulate Matter ($\leq 10\ \mu$m)

RT	Round-trip Carsharing System
SAAQ	Société de l'assurance automobile du Québec
SO_2	Sulfur Dioxide
UNEP	United Nations Environment Programme
VKT	Vehicle-Kilometres Travelled
VMT	Vehicle Miles Travelled
WLTC	Worldwide Harmonized Light Vehicles Test Cycle

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CHAPTER 1 INTRODUCTION

1.1 Motivation

Cities around the world face increasing pressure to reduce environmental impacts from transport, a sector that remains among the most difficult to decarbonise. Even as Electric Vehicle (EV) become more common and efficiency standards tighten, total vehicle-kilometres travelled continue to rise in many regions due to population growth, urban expansion, and persistent dependence on privately owned cars [3, 4]. These trends underscore that technological improvements alone are unlikely to deliver the deep emission reductions required to meet climate targets.

In this context, shared mobility has attracted growing interest as a complementary strategy. Among shared modes, carsharing holds particular appeal because it allows households to access a car without owning one. In principle, this can reduce private vehicle holdings, support more multimodal travel patterns, and concentrate EV where they can be used more effectively. From a resource-use perspective, shared fleets may also activate dormant vehicle capacity in a world facing mounting pressure on material and natural resources.

These possibilities make carsharing attractive to policymakers. Yet effective policy design requires more than enthusiasm for sharing. Carsharing systems that perform well in dense, transit-rich neighbourhoods may perform differently when deployed at broader scales. Policies developed around niche markets or early adopters may not translate when adoption expands, and universal promotion risks producing outcomes that diverge from expectations. Empirical evidence already suggests mixed patterns: some users reduce driving while others increase it; some shared fleets achieve high utilisation while others remain underused.

These contrasting outcomes point to a deeper challenge: *carsharing does not offer a guaranteed environmental benefit.* Instead, performance depends on a combination of factors that vary across local contexts, including who adopts the service, how intensively vehicles are used, and whether operations can sustain effective service delivery. Understanding these dependencies, and the limits they impose on environmentally meaningful expansion, is essential for cities that hope to use carsharing as a credible component of their decarbonisation strategy. This need for clarity motivates the work undertaken in this dissertation.

1.2 Problem statement

Despite increasing interest in carsharing, current research offers only a partial basis for understanding its environmental implications when adoption expands. The issue is not a lack of evidence, but the difficulty of interpreting findings derived from small-scale services or early adopters when designing policy for broader deployment.

Behavioural studies. Existing behavioural research shows that carsharing can influence car ownership, driving distance, and mode choice [5, 6]. However, these effects vary sharply across user groups, including principal car owners, occasional drivers, and individuals without car access, and across neighbourhoods. Many studies rely on self-selected samples or localised programmes, which can limit how directly findings translate to city-wide adoption.

It is important to note that many behavioural studies report central tendencies, including average or typical user responses, and such results remain valuable. They provide an accessible summary of what happens in observed settings and are often the most feasible way to communicate behavioural effects. The remaining challenge is that policy design for large-scale deployment requires understanding how outcomes change when the population composition of adopters shifts. For environmental assessment, this implies that heterogeneity across plausible adopter groups must be examined explicitly and translated into life-cycle impacts. As a result, it remains unclear how different types of user groups and adoption structure would shape the system-levl environmental impacts if carsharing were prevalent at scale.

Operational studies. Operational research provides insight into how vehicle availability, spatial imbalance, relocation, charging, and idle time shape how shared fleets function [7–13]. These factors do not directly convert mobility activity into emissions, but they constrain how effectively shared fleets can deliver trips and accumulate mileage. Empty kilometres, charging strategies, and achievable utilisation levels arise from these service-delivery conditions. Many operational studies optimise cost or service performance rather than environmental metrics. They are often calibrated to existing fleets and less frequently used to examine how service feasibility and vehicle utilisation constraints evolve as adoption expands. This makes it difficult to know whether vehicle utilisation patterns that appear environmentally favourable under simplified assumptions are attainable under explicit spatial and temporal constraints.

Environmental and life cycle assessment (LCA). Life Cycle Assessment (LCA) studies quantify emissions from vehicle production, operation, maintenance, and End-of-Life (EoL) [14–16]. Yet many assessments rely on static or idealised assumptions about vehicle utilisation pattern, fleet size, and behavioural or operational conditions [17]. Such simplifications can obscure the influence of vehicle utilisation pattern, a central determinant of material efficiency strategy, on environmental performance. Without linking vehicle utilisation to behavioural composition or to service-delivery constraints, environmental outcomes may be overestimated or underestimated in ways that are difficult to diagnose.

Fragmentation and policy risk. These research strands provide valuable insights, but they often address different questions and operate with different assumptions. Behavioural studies describe demand-side changes, operational studies describe supply-side feasibility, and LCA studies quantify environmental burdens. Without a coherent way of relating these domains, it is difficult to judge whether carsharing will reduce or increase emissions when adoption expands. Relying on small-scale evidence or optimistic assumptions about user behaviour, vehicle use, or operational feasibility can lead to unrealistic expectations. Universal promotion of carsharing as an environmental solution may therefore be ineffective, or counterproductive, when deployed without considering local mobility conditions and the limits imposed by user profiles and service delivery.

These observations motivate the need for a structured framework that clarifies *how*, *where*, and *under what conditions* carsharing supports environmental and climate goals. Multiple determinants influence its performance, including behavioural responses, material efficiency strategies, and operational conditions, as well as other external drivers such as pricing, governance, or urban form. It is neither feasible nor necessary to analyse all determinants simultaneously in a single assessment. A transparent analytical approach is required that specifies which pathways are examined, why they are central to environmental outcomes, and how results should be interpreted as adoption expands.

This dissertation focuses on three determinants that strongly influence environmental performance under large-scale adoption: (i) behavioural heterogeneity, (ii) a material efficiency strategy centred on vehicle consolidation and lifetime functional use of vehicle, and (iii) operational feasibility as a service-delivery constraint. The first two determinants function as causal mechanisms that can translate mobility patterns into environmental impacts, while the third determines whether the conditions required for material efficiency mechanisms are feasible under explicit access and assignment rules. Under controlled and comparable assumptions at city-wide population scale, the aim is not to predict the performance of a specific operator, but to clarify the conditions under which carsharing is environmentally advantageous and the situations in which expectations should be tempered. This provides a transparent basis for interpreting carsharing's role in urban climate policy.

1.3 Research gaps and hypotheses

Despite substantial research on carsharing, three interlinked gaps limit our ability to evaluate its system-level environmental implications under large-scale adoption. These gaps do not correspond one-to-one with the empirical chapters. Instead, they motivate the staged analytical strategy and the hypotheses guiding this dissertation.

1.3.1 Gap 1: Behavioural heterogeneity and scalability

Empirical studies demonstrate that carsharing affects mode choice, annual distance driven, and car ownership. However, these effects vary widely across user groups, including principal car owners, occasional drivers sharing a household car, individuals without car access, multimodal travellers, and suburban residents. Existing evidence is dominated by early-adopter samples or localised datasets, which can limit how directly behavioural patterns translate to city-wide adoption. Moreover, behavioural studies rarely translate these differences into LCA outcomes.

What remains limited is population-scale, scenario-based evidence that applies empirically grounded behavioural relationships within an explicit adoption structure to a large urban population, in order to examine how behavioural heterogeneity shapes environmental outcomes as adoption expands.

> **H1:** The environmental outcomes of large-scale carsharing depend strongly on the distribution of behavioural responses across user groups.

1.3.2 Gap 2: Operational performance, system constraints, and scaling

Operational studies provide rich descriptions of how shared fleets behave, including utilisation patterns, relocation, charging, and idle time. These patterns do not in themselves constitute a mechanism that converts mobility and operational activity into emissions, but they constrain whether operation that avoids vehicle underutilisation and enables material-efficiency gains is feasible in practice. However, many operational models prioritise cost or reliability rather than environmental outcomes and do not incorporate utilisation-dependent environmental intensity or behavioural diversity. Fewer studies examine how feasibility and supply–demand balance evolve under large-scale adoption.

> **H2:** Under large-scale adoption, operational constraints and supply–demand balance can limit or erode environmental gains that appear under simplified or small-scale assumptions.

1.3.3 Gap 3: Environmental assessments with static or idealised utilisation assumptions

LCA studies quantify environmental impacts but often rely on static assumptions regarding annual vehicle mileage, average user behaviour, or idealised service conditions. These simplifications may not capture vehicle utilisation patterns implied by behavioural diversity or by service-delivery constraints. Limited representation of utilisation dynamics can lead to inconsistent or incomplete assessments of material efficiency.

> **H3:** Environmental assessments that represent vehicle use (annual distance and implied Lifetime Mileage (LTM)) as an outcome of behavioural or operational processes yield different system-level outcomes than assessments based on static or average use assumptions.

1.3.4 Positioning of the hypotheses and scope of hypothesis testing

These gaps motivate a staged analytical design. Instead of combining behavioural change, material efficiency strategy, operational feasibility, and life-cycle impacts within a single fully integrated model, each determinant is evaluated under controlled assumptions using methods suited to its scale, while a harmonised LCA framework is applied across all chapters.

Chapter 3 focuses on plausible adopters and examines how behavioural responses across user groups and scaling structure shape environmental outcomes when supply is unconstrained. Chapter 4 isolates vehicle utilisation pattern with material efficiency strategy under fixed demand and idealised access. Chapter 5 evaluates operational feasibility in an electric free-floating context, deriving realised vehicle use and trip coverage from spatial and temporal assignment rules, fleet size, and accessibility constraints.

Integrated assessment is valuable for forecasting, optimisation, and scenario planning in many settings. At the same time, combining determinants too early can make it harder to interpret which assumptions drive results. Behavioural effects can be confounded with operational availability, vehicle utilisation can appear to improve due to modelling architecture rather than a material efficiency mechanism, and environmental outcomes may be difficult to attribute to identifiable drivers. The staged design adopted here seeks to clarify each determinant on its own terms before they are interpreted jointly in the conclusion.

This choice also defines how the hypotheses are supported. Hypothesis H1 is evaluated directly through within-study scenario comparisons across adopter groups. In contrast, Hypotheses H2 and H3 concern contrasts with alternative assumptions that are not implemented as matched counterfactual baselines within the same modelling context for every chapter. Their support therefore rests on within-study evidence that demonstrates sensitivity to service-delivery and material efficiency mechanism, combined with careful comparison to established assumptions and findings in the literature. This scope is made explicit to avoid overstating the extent of within-context hypothesis testing.

1.4 Conceptual and analytical framework

The conceptual framework of this dissertation clarifies how two causal mechanisms and one operational constraint jointly shape the environmental performance of carsharing at the system level. The two causal mechanisms are *behavioural change* and a *material efficiency strategy*. The third determinant, *operational feasibility*, acts as a service-delivery constraint that conditions whether material efficiency gains implied by favourable demand patterns can be realised in an operating system.

These determinants are selected because they strongly influence life-cycle environmental outcomes and can be examined consistently within a shared-mobility and LCA framework. They are not assumed to operate independently in real-world systems. Instead, they are conceptually distinct elements whose individual roles must be understood before their combined implications can be meaningfully interpreted.

The first layer of the framework concerns **behavioural change**. Behavioural responses determine who adopts carsharing and how mobility choices shift relative to private-car use. These demand-side responses shape both the volume of travel to be served and its distribution across modes and spatial contexts. Behavioural change therefore constitutes a direct mechanism through which carsharing can increase or decrease environmental impacts, depending on which users adopt the service and how their travel patterns adjust.

The second layer concerns a **material efficiency strategy**. This mechanism focuses on how vehicle-related resources are allocated to deliver mobility services, and on how embedded production and EoL impacts are distributed across that service output. When a fixed level of travel demand is delivered using fewer vehicles over their service lifetimes, embedded impacts are amortised across a larger functional output per vehicle, reducing environmental intensity per unit of service. Material efficiency is conceptually distinct from behaviour because it concerns how vehicles are consolidated to meet existing mobility needs, rather than how much people travel.

The third layer concerns **operational feasibility**. This determinant reflects supply-side service-delivery constraints that determine whether, and under what conditions, a shared fleet can provide the required mobility service. Factors such as spatial and temporal alignment between vehicles and users, vehicle availability, access rules, and empty travel shape the level of vehicle use that can be achieved in practice. Operational feasibility does not constitute a causal mechanism in itself; instead, it bounds whether behaviourally favourable demand and material efficiency potential can be realised under real service conditions.

These three determinants feed into a harmonised LCA, which quantifies how behavioural change, material efficiency, and operational conditions jointly shape the environmental performance of carsharing. LCA thus serves as the common evaluative platform across the empirical chapters, allowing results derived under different assumptions to be interpreted within a consistent life-cycle perspective.

1.4.1 Research objective

The overarching objective of this dissertation is:

> *To determine under what behavioural, material efficiency, and operational conditions large-scale carsharing can reduce life-cycle environmental impacts at the system level, and where the limits and potential misinterpretations of such benefits arise as adoption expands..*

Rather than seeking to predict the performance of any specific carsharing service, the dissertation aims to clarify the mechanisms and constraints that govern environmental outcomes under large-scale deployment. This includes identifying how different adopter profiles influence demand-side substitution or rebound effects, how vehicle lifetime use affects the distribution of embedded emissions, and how spatial and temporal service-delivery constraints bound the vehicle utilisation levels required for material efficiency.

To achieve this objective, the dissertation adopts a staged analytical design. Behavioural change, material efficiency, and operational feasibility are examined separately under controlled assumptions using methods suited to their respective scales, while a harmonised LCA framework is applied across all analyses. This approach prioritises interpretability and transparency over exhaustive realism, allowing the influence of each determinant to be examined without confounding effects.

The objective is therefore not to deliver a single aggregate estimate of carsharing's environmental impact, but to clarify boundary conditions, trade-offs, and leverage points that are relevant for policy design, fleet planning, and interpretation of existing empirical evidence. By doing so, the dissertation provides a structured basis for assessing when carsharing is likely to contribute to urban decarbonisation and when additional expansion is unlikely to yield further environmental gains or may produce counterproductive effects.

1.4.2 Research contributions

This dissertation contributes to the study of carsharing and its environmental implications by clarifying how behavioural responses, material efficiency, and operational feasibility shape system-level environmental outcomes under large-scale adoption. Rather than proposing a single integrated predictive model, the work develops a determinant-based analytical approach that makes explicit which mechanisms are examined, under what assumptions, and how their effects should be interpreted when scaling beyond niche deployments.

A central premise of the dissertation is that system-level environmental results can be difficult to interpret when multiple determinants are combined prematurely or represented implicitly. Behavioural change, utilisation, and operational feasibility are often acknowledged in the literature, but their respective roles are frequently conflated or embedded within modelling choices that obscure causal attribution. By examining these determinants separately under controlled assumptions and then synthesising their implications, the dissertation contributes a clearer basis for interpretation, comparison, and policy relevance.

The main contributions are fourfold.

1. **A harmonised life-cycle accounting basis across determinants.**

   The dissertation applies a consistent, cradle-to-grave LCA framework across all empirical chapters. Behavioural responses across user groups and adoption structure (Chapter 3), material efficiency strategy based on lifetime functional use of vehicles (Chapter 4), and operational feasibility under spatial and temporal constraints (Chapter 5) are evaluated using … using a harmonised life-cycle accounting framework with a common annual system reference, while allowing mobility demand and functional units to vary where required by the behavioural or operational scope of each theme.

2. **Population-scale evidence on behavioural heterogeneity and adoption structure.**

   Chapter 3 extends existing behavioural evidence by applying empirically documented behavioural adjustments to a metropolitan-scale synthetic population. Instead of focusing on average adopters, the analysis examines how environmental outcomes evolve as adoption expands across plausible user groups and spatial contexts. By structuring adoption by baseline travel demand and residential density, the chapter shows that system-level outcomes depend not only on behavioural effect sizes, but also on who adopts first and where adoption occurs. This clarifies why behavioural results observed in average user studies cannot be extrapolated mechanically to large-scale policy scenarios.

3. **Explicit treatment of material efficiency strategy based on lifetime functional use of vehicles.**

   Chapter 4 isolates the material efficiency mechanism by grounding vehicle lifetime functional use in empirical relationships between annual driving distance and lifetime functional use (i.e., LTM). Rather than assuming a representative vehicle or fixed utilisation rate, the analysis shows how heterogeneity in a material efficiency strategy based on lifetime functional use of vehicles alters the allocation of production and EoL emissions across private and shared mobility options. This contribution is not a critique of average-based assumption, which remains useful for many purposes, but a demonstration that variation in LTM becomes decisive when evaluating carsharing as a consolidation strategy. The results identify which user profiles are most sensitive to changes in lifetime functional use of vehicles and under what conditions material efficiency gains are plausible.

4. **Operationally grounded bounds on achievable vehicle utilisation pattern and coverage.**

   Chapter 5 introduces spatial and temporal feasibility as an explicit constraint on environmental performance. By deriving realised vehicle use and trip coverage from a trip-to-vehicle assignment model, the chapter shows how fleet size, access rules, and repositioning options bound the vehicle utilisation levels required for material efficiency gains. The analysis does not aim to predict observed operator behaviour or to identify an economically optimal fleet. Instead, it characterises the trade-offs between vehicle underuse and unmet demand under defined feasibility rules, and it demonstrates how operational constraints can limit or reshape the environmental potential identified under idealised assumptions.

Together, these contributions advance understanding of carsharing not by offering a single summary estimate of its environmental impact, but by clarifying the mechanisms and constraints that govern its performance at scale. The dissertation shows that environmental outcomes depend on adopter composition and their behavioral responses, a material efficiency strategy based on lifetime functional use of vehicles, and service feasibility, and that these determinants must be examined explicitly if carsharing is to be assessed credibly as a climate strategy rather than as a universally beneficial intervention.

1.4.3 Methodological overview

The methodological approach of this dissertation is designed to evaluate, in a transparent and interpretable way, how carsharing affects the environmental impacts of urban mobility when adoption expands. The central methodological challenge is that the key determinants under investigation—behavioural change, material efficiency through vehicle use, and operational feasibility—operate at different analytical scales and rely on different types of data and modelling logic.

In this dissertation, each empirical chapter isolates one determinant under controlled assumptions, applies methods suited to its scale and data availability, and generates inputs for a harmonised LCA accounting. This design choice does not attempt to replicate the full complexity of real-world carsharing and is therefore appropriate to the methodological objectives of the dissertation. It does not imply that determinants operate independently in real systems, but reflects the practical need to examine their effects in a way that preserves interpretability and avoids conflating mechanisms that are difficult to disentangle empirically.

Across all chapters, environmental performance is evaluated using a consistent LCA framework. Behavioural responses, material efficiency strategy, and operational outcomes are therefore compared on a common environmental basis, even though they are derived using different analytical tools. The following subsections describe the role of LCA in the analysis and summarise how each empirical chapter operationalises its respective determinant.

Life-cycle assessment as the evaluative backbone

LCA provides the common environmental accounting framework across all empirical chapters. In this dissertation, LCA is used to quantify the environmental impacts associated with providing urban mobility in Montréal over a one-year period. While the analysis covers a full set of life-cycle impact categories, results presented in the main text focus on climate change potential, as this is the most commonly reported and policy-relevant indicator in the carsharing literature. Results for additional impact categories are available in the Appendix.

The accounting framework, temporal horizon, and study area are held broadly consistent across chapters. However, the functional unit and population under consideration vary with the objective of each empirical theme. While a common annual time horizon and study area are maintained across chapters, the functional unit is adapted to the analytical objective of each theme. In the behavioural analysis (Chapter 3), the functional unit reflects realised urban mobility over one year, allowing total travel demand to change in response to adoption. In contrast, the material efficiency and operational analyses (Chapters 4 and 5) evaluate the environmental implications of providing a given level of realised carsharing service under fixed total travel demand. Chapters 4 and 5 therefore share a consistent functional unit, while Chapter 3 intentionally departs from demand invariance to isolate behavioural effects.

Environmental burdens are quantified across vehicle life-cycle stages, including vehicle manufacturing, operation, maintenance where relevant, and EoL treatment. A consistent system boundary is applied across chapters, and the same background life-cycle inventory data for electricity, fuels, and vehicle production are used throughout. Although intermediate indicators such as emissions per person-kilometre are reported where useful, all comparisons are anchored to the same annual mobility demand.

This common LCA framework is essential because carsharing affects not only how people travel, but also how vehicles are used over their lifetimes. Consolidating travel onto fewer vehicles can increase lifetime functional use and reduce environmental intensity per unit of service, while underused shared vehicles can concentrate embedded emissions in fewer kilometres of delivered mobility. LCA translates the behavioural, vehicle utilisation pattern, and operational outputs of each chapter into comparable environmental outcomes under a shared accounting structure.

Different LCA implementation tools are used across chapters to match data availability and modelling requirements. Chapter 3 implements life-cycle calculations in openLCA (v2.6), while Chapters 4 and 5 rely on a Python-based implementation using carculator (v1.8.5). This transition reflects the need for tighter integration between operational simulation outputs and Life Cycle Inventory (LCI) in the latter chapters. Across all implementations, the same background database (ecoinvent v3.8, cut-off system model) is used for vehicle production, electricity, fuels, and EoL processes, ensuring consistency in underlying life-cycle data despite differences in computational framework.

Scaling behavioural change scenarios to system-level under unconstrained supply (Chapter 3)

Chapter 3 examines the behavioural determinant by applying empirically documented behavioural adjustments to a metropolitan-scale synthetic travel-demand dataset for the Greater Montréal Area. The chapter addresses the question:

> How does behavioural heterogeneity across plausible adopter groups translate into system-level life-cycle environmental outcomes when carsharing adoption is scaled under unconstrained service availability?

Behavioural adjustments are introduced exogenously, based on effect sizes reported in the literature, for two adopter categories: occasional drivers with intermittent access to a household vehicle and individuals without access to a car. These adjustments modify mode choice and total travel distance, reallocating trips among private cars, carsharing, public transport, and active modes.

Methodologically, carsharing is treated as fully available. Any individual designated as an adopter is assumed to have all relevant trips served without operational constraints. This assumption isolates behavioural effects by holding supply unconstrained. Environmental outcomes are then evaluated using LCA to compare life-cycle emissions before and after adoption at both individual and population scales. The chapter does not estimate behavioural parameters or predict adoption, but clarifies how different adopter compositions and adoption scaling structures shape environmental outcomes when scaled to a full urban population.

Material efficiency under fixed demand and idealised access (Chapter 4)

Chapter 4 isolates the material efficiency determinant by holding behaviour and service availability constant and examining how vehicle lifetime use affects environmental intensity. The analysis focuses on private-car users, consistent with the finding from Chapter 3 that substitution of existing private-car travel is the primary channel for greenhouse-gas reduction. The central question is:

> Under fixed travel demand and idealised access, how does heterogeneity in vehicle lifetime use affect life-cycle environmental intensity, and under what utilisation conditions are material efficiency gains from carsharing plausible in principle?

The chapter combines empirical data on deregistered vehicles from Québec with analytical representations of shared-fleet lifetime use. Relationships between annual driving distance and lifetime mileage are used to characterise utilisation heterogeneity across user profiles. Under the assumption of ideal access, all trips by adopters are served, and no additional behavioural change or operational constraint is introduced.

Within this controlled setting, changes in environmental performance arise from consolidating travel demand onto fewer vehicles with higher lifetime functional use. LCA is used to quantify how production and EoL impacts are distributed across service output and how carbon intensity per person-kilometre varies across user groups. The chapter therefore establishes the utilisation conditions under which material efficiency gains are plausible in principle, providing a reference point for assessing whether such conditions can be achieved once operational constraints are introduced.

Operational feasibility and realised vehicle use pattern (Chapter 5)

Chapter 5 introduces spatial and temporal service-delivery constraints through a trip-to-vehicle assignment framework applied to dense areas of Montréal Island. The central question is:

> Under explicit spatial and temporal service-delivery constraints, can shared electric fleets achieve sufficient trip coverage and realised vehicle use to sustain the material efficiency gains identified under idealised conditions?

The chapter uses observed private-car travel demand and assigns trips to shared vehicles based on spatial proximity, time overlap, access rules, and fleet size. Behaviour is not modified and vehicle use is not imposed by assumption. Instead, realised annual distance per used vehicle, trip coverage, and, where applicable, empty travel are derived directly from assignment outcomes.

When fleet size is small relative to demand and access constraints, some trips cannot be served and remain private. When fleet size is large, vehicles may remain underused. In dispatch-enabled configurations like Autonomous Vehicle (AV), repositioning increases feasible coverage but introduces additional vehicle kilometres that must be evaluated explicitly. These operational outputs are translated into environmental outcomes using the same LCA framework, allowing the chapter to characterise how feasibility constraints bound achievable utilisation and system- level environmental performance.

1.4.4 Staged integration through synthesis

Across the three empirical chapters, the methodological progression moves from behaviour-driven scenarios with unconstrained supply, to idealised material efficiency under fixed demand, and finally to operationally constrained service delivery. The synthesis chapter integrates these insights without collapsing them into a single predictive model. Instead, it interprets how behavioural changes across user groups, material efficiency strategy, and operational feasibility jointly condition the environmental performance of large-scale carsharing, while keeping the scope and assumptions of each analytical stage explicit. Figure 1.1 summarises this staged integration by showing how the three empirical studies build on one another, progressing from behavioural potential, to material-efficiency requirements, and finally to operational feasibility under real-world constraints.

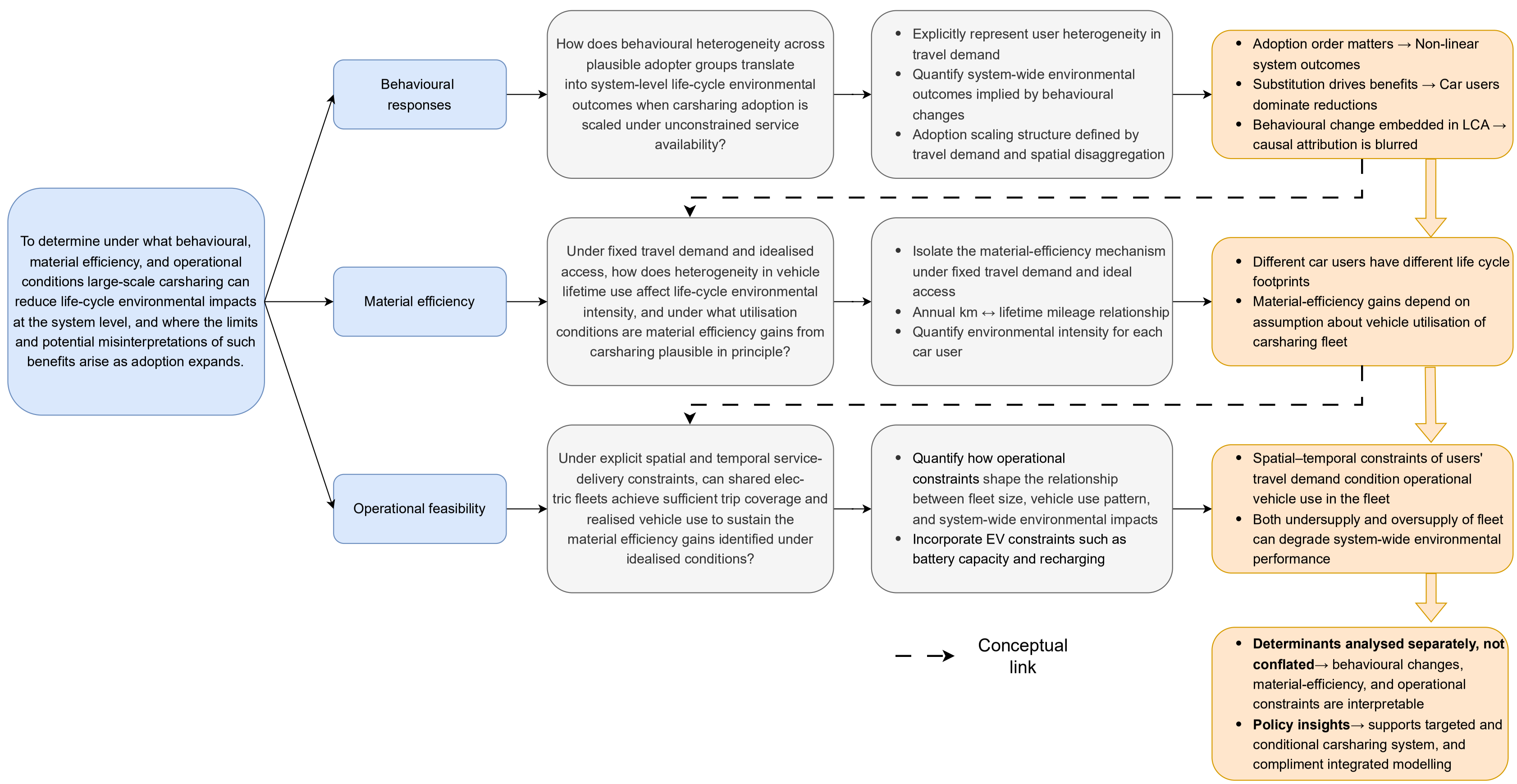

Figure 1.1 Staged analytical structure of the dissertation, illustrating how behavioural responses (Chapter 3), material efficiency through vehicle lifetime use (Chapter 4), and operational feasibility (Chapter 5) are examined sequentially and synthesised without collapsing into a single predictive model.

1.5 Dissertation structure

The dissertation is organised into six chapters. Chapter 1 introduces the research motivation, gaps, hypotheses, and analytical approach. Chapter 2 reviews behavioural, material efficiency, and operational perspectives in the literature. Chapters 3 to 5 present the three empirical analyses, each addressing one determinant under controlled assumptions. Chapter 6 synthesises the findings, discusses their implications for policy and research, and outlines limitations and future directions.

CHAPTER 2 LITERATURE REVIEW

Chapter note.

This chapter reviews prior research on the environmental implications of carsharing and clarifies the specific knowledge gaps that motivate the analytical structure of this dissertation. Its role is not only to summarise existing findings, but also to establish the evidentiary basis for the research gaps and working hypotheses formulated in Chapter 1.3.

2.1 Chapter overview

The literature on carsharing and shared mobility can be grouped into three broad perspectives that are often treated separately. Behavioural studies examine how carsharing affects car ownership, mode choice, and travel demand at the user or household level. Operational and system-design studies focus on fleet management, spatial-temporal allocation of vehicles, and service reliability from an operator perspective. Environmental assessments, typically based on LCA, quantify Greenhouse Gas (GHG) emissions and other impacts associated with vehicles, energy use, and infrastructure. Each perspective has matured considerably in recent years, including through several synthesis papers and reviews [6, 18, 19].

Viewed through the lens of this dissertation, these perspectives correspond to two main determinants, namely behavioural change and material efficiency, together with one overarching service-delivery constraint, operational feasibility. The review therefore focuses on how existing work has characterised these determinants, where their treatment remains partial or inconsistent, and how this motivates the staged analytical design adopted here.

The review proceeds in five steps. Section 2.2 introduces the main carsharing service models and their operational attributes. Section 2.3 summarises the environmental outcomes reported in the literature. Section 2.4 synthesises the behavioural, operational, material efficiency, and built-environment determinants through which these service models influence environmental outcomes. Sections 2.6 and 2.6.4 summarise the methodological approaches and data sources used across these strands of literature. Section 2.7 then consolidates persistent gaps and links them to the overall research agenda of the dissertation, thereby connecting the broader research context to the staged analytical design.

2.2 Types of carsharing

Carsharing is not a single service but a family of service models that differ in booking rules, parking arrangements, operational control, and data infrastructure. These design choices shape where and when vehicles are available, how intensively they are used in operation, and what kinds of relocation and support activities are required. In turn, these operational characteristics condition behavioural responses, the level of vehicle use that can be achieved across the fleet, and the resulting environmental performance of carsharing systems.

Following established typologies [5,6], this section distinguishes four main business-to-consumer (B2C) models: Round-trip Carsharing System (RT), Free-floating Carsharing System (FF), Peer-to-peer Carsharing System (P2P), and a corporate or closed-user-group marketplace model. Electrification acts as a cross-cutting overlay in each case. The aim here is operational and definitional rather than evaluative. The environmental mechanisms associated with these models are developed in Section 2.4, and the empirical evidence is reviewed in Section 2.3.

2.2.1 Round-Trip, Station-Based (RT)

In round-trip or station-based RT systems, users begin and end their booking at the same designated station. Reservations are typically required, with dedicated parking spaces reserved for the fleet. Access is controlled through membership credentials and advance bookings; short-notice reservations are possible when supply allows [5].

Operationally, RT systems emphasise reliability at known locations. Vehicles can be assigned to station catchment areas and are rarely relocated outside of maintenance or exceptional events. This yields (i) low relocation needs, (ii) relatively stable station-level utilisation profiles, and (iii) temporally concentrated demand around weekends, evenings, and planned trips. For electrified RT fleets, depot- or station-based charging can be integrated into operations, simplifying the representation of charging logistics, associated overhead kilometres, and electricity mix in LCI.

RT models therefore illustrate how carsharing can redistribute vehicle-kilometres among users with different travel needs while maintaining relatively simple operational patterns. Examples include Zipcar in North America and the UK, Mobility Carsharing in Switzerland, and the long-standing station-based service of Communauto in Montréal [5, 19].

2.2.2 One-Way, Free-Floating (FF)

One-way or free-floating FF systems permit point-to-point trips within a geofenced home area. Vehicles can be picked up and dropped off on-street or in mixed public and private parking without returning to the origin station [5]. The value proposition is high spontaneity and flexibility for short urban trips, including first and last mile connections to public transport.

Maintaining acceptable availability in FF fleets requires continuous balancing of supply and demand. Vehicles tend to accumulate in attractor zones (for example central business districts and transit hubs), while peripheral or uphill areas can become undersupplied. Operators respond through vehicle relocation, incentive schemes, or adjustments to the home area. As a result, FF systems exhibit (i) medium to high relocation intensity, (ii) sensitivity to spatial imbalance, and (iii) potential additional parking search and turnover effects. These features increase both operating costs and overhead vehicle-kilometres that must be considered when assessing environmental performance.

Electrified FF systems face additional complexity. Charging typically relies on a mix of public or on-street chargers, off-street hubs, and sometimes mobile recharging crews. The timing and location of charging influence the effective carbon intensity of electricity and may introduce further empty kilometres for repositioning vehicles to chargers [6]. Examples include SHARE NOW in several European cities, GIG Car Share in the San Francisco Bay Area and Sacramento, and Communauto FLEX in Montréal.

2.2.3 Peer-to-Peer (P2P)

Peer-to-peer P2P platforms mediate access to privately owned vehicles during idle periods. Private owners list their vehicles, set availability windows and prices, and renters book them through the platform. Fleet composition is heterogeneous in terms of age, technology, and segment, and vehicles are typically parked at the owner's home or workplace.

Platform control over operations is weaker than in B2C models. Relocation is limited; vehicles return to the owner or are left at negotiated locations. Telemetry and data quality can be heterogeneous, depending on whether vehicles are equipped with dedicated telematics devices or rely on manual odometer readings. Efficient use of fleet thus depends strongly on platform scale, geographic concentration of supply and demand, and pricing.

From an environmental-accounting standpoint, P2P raises distinct questions about allocating production and EoL burdens between private and shared use, dealing with heterogeneous vehicle efficiencies, and handling incomplete or noisy data on travel patterns. Examples include Getaround and Turo in North America and Europe, and SnappCar in several European countries.

2.2.4 Corporate / Closed-User-Group Variants

Corporate or closed-user-group carsharing restricts access to a defined set of users, such as employees of a firm, members of a municipal administration, or staff at a university campus. Vehicles are usually parked at depots or dedicated bays, and bookings are managed through internal systems or platform interfaces. Duty cycles often follow workday schedules, with predictable peaks around office hours and off-peak idle periods.

Operationally, these fleets typically exhibit (i) low relocation needs, (ii) temporally concentrated vehicle use during specific demand windows, and (iii) strong data quality and maintenance control. Because vehicles are owned or leased by a single organisation, records of mileage, trip purpose, fuel or electricity use, and maintenance can be centralised. For Battery Electric Vehicle (BEV) deployments, depot charging and managed dwell time facilitate low-carbon charging strategies and simplified infrastructure planning.

Corporate and closed-user fleets thus serve as examples of contexts where carsharing-like pooling is implemented within a controlled institutional environment, with relatively high data quality and strong scheduling control. Examples include municipal pool-car programmes, university campus fleets, and enterprise carsharing offerings by operators such as Mobility or Ubeeqo/Europcar.

2.2.5 Electric Carsharing (Cross-Cutting Overlay)

All of the service models described above can operate hybrid or BEV fleets. Electrification introduces additional design variables, including charging siting (depot versus on-street), power levels, dwell-time management, and time-of-use electricity mix, that interact with both operational feasibility and environmental performance [6].

In station-based and corporate fleets, charging can be concentrated at depots or stations, where vehicles return regularly and dwell time is more predictable. This tends to simplify charging logistics, making it easier to plan capacity, limit empty-kilometres for charging, and exploit periods of lower grid carbon intensity. In FF fleets, by contrast, vehicles are more dispersed, and charging often relies on public or on-street infrastructure. Operators may need mobile crews to retrieve, charge, and redeploy vehicles, increasing overhead kilometres and staff travel. Historically, fully electric FF systems such as Autolib' in Paris have demonstrated both the environmental potential of combining electrification with sharing and the operational vulnerability of such models to parking policy, vandalism, and relocation requirements.

From an environmental perspective, electric carsharing couples the use-phase advantages of zero-tailpipe emissions with the higher production-phase impacts associated with electric powertrains and batteries. Whether this combination delivers net climate benefits depends critically on functional use of vehicle, the electricity mix, and the operational requirements of the service. Electrification therefore heightens the relevance of the material efficiency mechanism: the extent to which each shared vehicle and its battery provide functional mobility over their LTM. This dependency makes the interaction between operational performance and LCA particularly salient. The attributes of the various carsharing models reviewed in this dissertation are summarised in Table 2.1 and Table 2.2.

Notes. This typology is operational rather than evaluative. Its purpose is to clarify how different service designs structure vehicle availability, relocation needs, and data flows. These structural attributes act as background conditions that can either enable or constrain high

Table 2.1 Operational attributes of RT vs. FF carsharing models.

Attribute	RT (Station-Based)	FF (Free-Floating)
Booking & return rule	Return to same station; reserved slots	One-way; end anywhere in home area
Parking model	Dedicated station parking	Mixed on-street/off-street within zone
Typical trip patterns	Planned trips; medium duration; errands/weekend	Short, spontaneous urban trips; first/last mile
Relocation intensity	Low (usually none)	Medium–high (active rebalancing)
Spatial control	High (fixed stations)	Medium (geofenced home area)
Temporal control	Medium–high (reservations)	Medium (demand-responsive)
Data/telemetry quality	High (operator-controlled)	High (operator-controlled)
Electrification readiness	High (depot or at-station charging)	Medium (public or on-street charging logistics)
Environmental accounting notes	Low relocation; clear station overheads	Include relocation and empty-kilometres

functional use of vehicles in the fleet and multimodal substitution. The next section (Section 2.3) summarises the environmental outcomes reported for these services, and Section 2.4 connects them to the behavioural, operational, material efficiency, and built-environment determinants that drive these outcomes.

2.3 Environmental impacts of carsharing

This section synthesises the environmental outcomes reported in the literature across major indicator families. The goal is to summarise what studies find, regardless of whether the underlying method is behavioural and transport based, emissions modelling, or LCA. As emphasised in several recent reviews [18–20], the environmental evidence base for carsharing is methodologically heterogeneous and context dependent. Studies differ in system boundaries, functional units in the case of LCA, assumptions about user behaviour and patterns of vehicle use to deliver mobility service, and the degree to which operational overheads are represented.

- **Non-LCA empirical studies** estimate environmental impacts using observed or self-

Table 2.2 Operational attributes of P2P vs. Corporate/Closed carsharing models.

Attribute	**P2P**	**Corporate / Closed**
Booking & return rule	Owner-set availability; varied return rules	Member-only; depot or defined bays
Parking model	Owner or home location; ad hoc	Reserved depot or bays on premises
Typical trip patterns	Varied; depends on owner supply	Duty-cycle trips (work-related)
Relocation intensity	Low (platform-mediated)	Low (central scheduling)
Spatial control	Low–medium (dispersed owners)	High (single or few sites)
Temporal control	Low (owner calendars)	High (workday peaks)
Data/telemetry quality	Medium (heterogeneous devices)	High (enterprise systems)
Electrification readiness	Low–medium (home charging variability)	High (depot or workplace charging)
Environmental accounting notes	Heterogeneous vehicle technology and age	Centralised records; predictable duty cycles

reported changes in Vehicle-Kilometres Travelled (VKT), car ownership, travel diaries, mode-shift substitution patterns, or fuel consumption. Emission factors may be drawn from tools such as Motor Vehicle Emission Simulator (MOVES) (U.S.), Handbook Emission Factors for Road Transport (HBEFA) (Europe), COmputer Programme to calculate Emissions from Road Transport (COPERT), or regional carbon-intensity tables. These studies typically provide behaviourally rich insights but often exclude vehicle production and upstream energy burdens, and they may represent relocation and other operational overheads only in a simplified way.

- **LCA studies** extend system boundaries to incorporate vehicle manufacturing, energy supply chains, infrastructure, and EoL phases, often using harmonised inventory databases (for example ecoinvent or regionalised inventories). These works provide more comprehensive accounting but usually rely on assumed or average pattern of vehicle use, behavioural substitution drawn from empirical studies, or idealised relocation rules, rather than modelling them explicitly and dynamically.

Although these approaches differ in scope and boundary definitions, taken together they delineate the full spectrum of environmental pathways through which carsharing can reduce, shift, or, under certain conditions, increase environmental burdens. This section reports and contextualises the empirical findings within that broader landscape. Methodological distinctions and their implications for interpretation are revisited in Section 2.6.

Table 2.3 provides an overview of the environmental indicator families most frequently used in carsharing research, illustrating the range of metrics and studies that inform current assessments.

Table 2.3 Indicator families commonly reported in carsharing environmental studies (LCA and non-LCA).

Indicator family	**Typical categories or metrics**	**Representative studies**
Climate impacts	CO_2, GHG emissions (CO_2-eq.)	[17, 18, 21–25]
Energy use	Cumulative energy demand; direct fuel use; electricity mix; primary energy factors	[21, 25–27]
Air pollutants and photochemical formation	NO_x, SO_x, CO, HC, $PM_{10}/PM_{2.5}$; ozone formation potential	[18, 26]
Acidification, eutrophication, and toxicity	Terrestrial, freshwater, and marine eutrophication; terrestrial acidification; human and ecotoxicity	[28]
Ozone depletion	Upstream refrigerants; electricity and battery supply-chain emissions	[28]
Resource and material depletion	Mineral, metal, and fossil resource depletion; cumulative material demand	[21, 25, 27]
Infrastructure and land use	Parking footprint; curb allocation; station siting; congestion exposure	[27, 29]

2.3.1 Climate impacts: CO_2 and GHG emissions

Across both LCA and non-LCA studies, many analyses report potential reductions in GHG and CO_2 emissions when carsharing replaces private car ownership or reduces VKT. Early large-scale surveys in North America by Martin and Shaheen [24, 30] documented substantial reductions in VKT and emissions among users who shed one or more household vehicles.[1] Similar patterns were found in Switzerland, where Mobility Carsharing members showed significant reductions in car ownership and driving [30].

[1]The 2011 study reported that 50% of carsharing adopters either sold a vehicle or postponed a vehicle purchase, leading to an estimated average reduction of 0.58 vehicles per household and corresponding reductions in VKT and fuel consumption.

However, several studies find heterogeneous or mixed effects. In free-floating systems, Firnkorn and Mueller [23] observed that while some users replaced private car trips with carsharing, others increased total car travel by using shared vehicles for trips previously made by walking, cycling, or transit. In European contexts, studies such as [31] show that GHG impacts can range from large reductions to moderate increases depending on substitution patterns, vehicle-shedding behaviour, and initial car-ownership levels.

LCA-based studies extend behavioural and operational analyses by incorporating production, maintenance, and EoL burdens. Several assessments [17, 21, 32] report potential reductions of roughly 35–65% per person-kilometre compared with private car use, particularly under conditions of high and efficient use of shared fleets. Other studies, however, show that these gains can diminish substantially when induced demand or mode shifts from public transit occur [17]. In the North American context, Chen and Kockelman [25] found that individual carsharing members can reduce their transport-related GHG emissions by about 51% after joining a carsharing programme. Arbelaez Vélez [18] further demonstrated that reported GHG outcomes vary widely across cities and methodologies, reflecting differences in electricity mix, changes in VKT, relocation intensity, allocation rules, and underlying emission accounting assumptions.

For electric carsharing, results depend heavily on the carbon intensity of electricity and temperature effects. Lausselet et al. [22] showed that in Nordic contexts, shared BEVs can yield GHG reductions relative to shared Internal Combustion Engine Vehicles (ICEVs) if lifetime mileage is high, but cold-weather energy demand and battery replacements can narrow advantages. Similar sensitivities are reported in [14, 15, 33], which find that BEV advantages shrink when electricity mixes include higher shares of marginal fossil generation, although these studies focus on passenger cars more generally rather than carsharing specifically.

In summary, climate impact outcomes show a wide range of results across studies. The direction and magnitude of change depend jointly on which users adopt, how many private vehicles are actually displaced, how patterns of vehicle use and relocation evolve operationally, and how electricity systems and fuel supply chains are represented. This diversity underlines the need to interpret environmental outcomes in terms of underlying mechanisms rather than headline percentage reductions alone.

2.3.2 Energy use

Patterns in cumulative energy demand broadly mirror those in GHG emissions. Non-LCA studies consistently find lower direct fuel use for users who shed private vehicles or reduce VKT [24, 25]. In European carsharing services, [31] show reductions in household fuel consumption following membership adoption.

LCA studies report similar trends when carsharing fleets are smaller or more efficient than the local private-car fleet [21, 26]. However, as with GHG emissions, several mechanisms can lead to neutral or higher energy use:

- Short, induced trips when some users make additional low-cost, short-distance carsharing trips that replace walking or cycling [23].
- Transit substitution, where shifts from public transport to carsharing can increase total energy use [17, 25].
- Relocation and idle kilometres in free-floating systems, which may require substantial rebalancing and increase the energy intensity of operations [23, 34].
- Charging strategy for BEVs, since coordinated depot charging tends to reduce energy-system impacts, whereas opportunistic or on-street charging can increase marginal fossil-based electricity consumption [6].

Overall, reductions in energy use are reported in many contexts, but not universally. Outcomes depend heavily on the balance between avoided private driving and operational overhead, as well as on local electricity systems for electric fleets.

2.3.3 Air pollutants and photochemical formation

Many studies report reductions in local tailpipe pollutants (NO_x, CO, HC, primary PM) when carsharing fleets are newer, better maintained, or electrified. Migliore et al. [26] found significant decreases in several pollutants in Palermo when shared vehicles replaced older private ones. The review by Arbelaez Vélez [18] similarly noted improvements in combustion-related emissions for a shared hybrid fleet.

However, some studies document stable or increased pollutant emissions in particular contexts. Non-exhaust particles such as tire and brake wear remain present regardless of powertrain and may rise with higher trip turnover. For BEV-based services, upstream emissions from electricity generation become more relevant, especially where marginal electricity supply is fossil intensive [26]. Supplementary LCA results from Nong et al. [28] show a similar pattern, with particulate-matter impacts increasing for shared BEVs due to electricity generation and battery-production processes. Photochemical smog formation potential often declines with electrification, although the magnitude of this effect depends on local driving dynamics, congestion conditions, and the carbon intensity of the electricity mix.

2.3.4 Ozone depletion

Evidence on ozone-depletion impacts in carsharing LCAs is limited, but existing studies indicate that the dominant contributors arise upstream, particularly in vehicle manufacturing, refrigerant production, and energy-supply chains. Reductions in tailpipe emissions therefore have little direct influence on ozone-depletion potential, and shared fleets, especially when electrified, primarily reflect the characteristics of these upstream processes.

Supplementary results from Nong et al. [28] show that shared ICEVs can exhibit higher ozone-depletion burdens than shared BEVs, and that electrified systems perform better when upstream electricity and manufacturing chains have lower emissions of halogenated gases. Broader LCA studies support this trend. Koroma et al. [35] report that BEVs generally exhibit lower ozone-depletion impacts than gasoline vehicles, largely due to reduced upstream fuel-processing emissions, while Ellingsen et al. [14] find that BEV ozone-depletion potential declines further under cleaner electricity mixes and more modern refrigerant practices.

2.3.5 Acidification, eutrophication, and toxicity

Evidence in these impact categories shows a combination of improvements and upstream burden shifts. Supplementary results from Nong et al. [28] indicate that shared ICEVs and shared BEVs have broadly comparable terrestrial ecotoxicity impacts, with BEVs slightly higher due to battery-production emissions and ICEVs higher due to fuel-supply-chain burdens. Terrestrial acidification follows a similar pattern. Shared ICEVs tend to exhibit marginally higher impacts than shared BEVs because of upstream emissions from gasoline production and combustion, whereas battery-related processes dominate the BEV profile.

For freshwater and marine eutrophication, the shared BEV fleet can show higher impacts than the shared ICEV fleet, largely driven by metal extraction, refining, and electricity-generation processes associated with battery systems. These patterns are consistent with broader EV LCAs, which report that electrification reduces combustion-related acidification and toxicity but increases several upstream impacts linked to materials production and electricity supply [14, 15, 33].

2.3.6 Resource and material depletion

Resource depletion results are strongly influenced by the materials required for vehicle and battery production. LCA studies find that BEVs generally entail higher initial resource burdens compared to ICEVs due to battery components [14, 22, 33]. Whether carsharing mitigates or exacerbates these burdens depends largely on the extent to which vehicle and battery production impacts are distributed across realised lifetime mobility service [22,36,37]:

- High LTM can amortise resource use across a larger service output.
- Low LTM, premature battery failure, or high turnover increases depletion impacts [14].
- Recycling infrastructure and EoL practices significantly influence outcomes [38].

As summarised by Wolfram et al. [36], material efficiency, understood as achieving more functional use per unit of embedded impact, is a key determinant of environmental favourability across resource categories. Carsharing can support material efficiency goals when it enables higher LTM per vehicle without accelerating premature retirement or excessive component replacement, but the literature rarely models these **lifetime functional use of vehicle** explicitly.

2.3.7 Infrastructure and land use

Infrastructure and land-use impacts are rarely quantified in LCAs but are discussed in planning and transport studies. Station-based systems require dedicated parking and occasionally additional charger siting, whereas free-floating systems may reduce demand for private parking [19]. In some cities, replacing private cars with shared vehicles decreases parking pressure and enables curb space reallocation [29].

However, the magnitude of these effects varies substantially. Free-floating services can also increase competition for on-street parking or generate localised congestion if they attract short urban trips. Noise and exposure impacts may improve or worsen depending on whether carsharing substitutes for or supplements private car use [27]. Because these effects are highly context dependent and mediated by local policy (for example parking regulation, curb allocation, charging siting), infrastructure impacts remain a developing research area.

Table 2.4, 2.5, and 2.6 synthesise observed environmental effects across existing studies, allowing a comparative view of where carsharing delivers benefits and where trade-offs emerge, and underscoring that outcomes cannot be generalised without careful attention to underlying mechanisms and constraints.

2.4 Determinants and mechanisms explaining environmental outcomes

Section 2.3 summarised the environmental outcomes reported for carsharing across multiple indicator families. This section examines the causal structure behind those outcomes. Across the literature, two primary mechanism families and one key constraint recur: (i) user

Table 2.4 Environmental outcomes reported in carsharing studies: climate and energy indicators.

Indicator family	Frequently reported improvements	Conditions or factors influencing outcomes
Climate impacts	Reductions when private car ownership decreases or when shared fleets achieve sufficient **operational vehicle use**; BEV advantages in low-carbon grids.	Outcomes vary with induced demand, relocation activity, electricity mix, modal shifts, allocation rules, and vehicle lifetime mileage.
Energy use	Lower direct fuel consumption when users shed vehicles or reduce VKT; efficient shared fleets can lower energy demand.	Higher or neutral impacts are possible when carsharing induces short trips, replaces transit, or requires relocation; charging strategy and electricity mix matter for BEVs.

Table 2.5 Environmental outcomes reported in carsharing studies: air pollution and toxicity indicators.

Indicator family	Frequently reported improvements	Conditions or factors influencing outcomes
Air pollutants	Lower tailpipe emissions with newer or electrified fleets; potential local exposure benefits.	Non-exhaust PM remains; upstream emissions from electricity generation; congestion and speed profiles influence outcomes.
Acidification, eutrophication, and toxicity	Potential reductions in combustion-related acidification when shared BEVs replace ICEVs; some parity between shared ICEVs and BEVs in ecotoxicity.	Trade-offs between battery production and fuel supply chains; BEVs may have higher freshwater and marine eutrophication; electricity mix, metal processing, and **lifetime vehicle use patterns** strongly influence outcomes.
Ozone depletion	Potential improvements when **operationally well-used** BEVs replace underused ICEVs or older private vehicles.	Upstream burdens from refrigerants, battery manufacturing, and fossil-based electricity can dominate; spatial redistribution of impacts is common.

Table 2.6 Environmental outcomes reported in carsharing studies: resource use and land-use indicators.

Indicator family	**Frequently reported improvements**	**Conditions or factors influencing outcomes**
Resource depletion	Favourable outcomes when **production impacts are distributed across high realised lifetime mobility service**; benefits increase with reuse and recycling.	Unfavourable when **lifetime vehicle use is low**, turnover high, or recycling limited; battery replacement increases burdens.
Infrastructure and land use	Potential reductions in private parking needs; curb reallocation opportunities.	Localised congestion or parking pressure may increase depending on behaviour and policy; station siting and charging layout are important.

behaviour and adoption, (ii) vehicle and material pathways (material efficiency mechanisms), and (iii) fleet operations and service design as an operational constraint on how those mechanisms can be realised in practice. Their effects unfold within a broader set of contextual and institutional conditions, including the built environment, governance frameworks, pricing structures, and mobility-system integration [18–20, 39].

These determinants jointly influence three proximate drivers of environmental performance: activity (expressed as Person-Kilometres Travelled (PKT) or VKT), intensity (energy or emissions per unit of activity), and system overheads and temporal profiles (idle and relocation kilometres, charging behaviour, and time-of-use electricity). Understanding how mechanisms and constraints interact to shape these drivers provides the conceptual basis for interpreting the diverse environmental outcomes observed in carsharing research.

2.4.1 User behaviour and adoption

Behavioural change is one of the most frequently examined drivers of environmental outcomes in carsharing and constitutes a core causal mechanism. Membership can influence car-ownership decisions, annual driving distance (VKT, Vehicle Miles Travelled (VMT) or PKT), trip length, destination choice, and modal substitution. Numerous survey-based and diary-based studies report that individuals who shed a private vehicle or postpone a planned purchase often reduce their total car travel and, in some cases, increase their use of public transport and active modes [24, 30, 40]. These adjustments are usually interpreted as leading to lower direct fuel use and tailpipe emissions, although full life-cycle implications are less frequently quantified.

A consistent finding across the literature is that the magnitude and direction of behavioural effects depend less on the average member and more on the profile of adopters. Former car owners with above-average annual mileage can generate substantial reductions in both VKT and life-cycle emissions once they shift to carsharing and downsize their household fleet [30]. By contrast, individuals without prior car access or with low baseline mileage may generate new motorised trips or substitute from efficient modes such as walking, cycling, or transit, which can offset the reductions achieved by other groups [23].

Differences between station-based and free-floating services add further nuance. Station-based RT systems are consistently associated with stronger reductions in vehicle ownership, because the need to return a vehicle to its home station discourages habitual or spontaneous car use and reinforces multimodal travel patterns [24,41,42]. Users commonly access stations by walking or public transport, and trips tend to be more purpose driven, such as errands, family visits, or activities involving carrying goods or travelling with companions. These patterns result in relatively high occupancy and limited induced demand [43, 44]. These characteristics help explain why RT systems are particularly effective at reducing ownership and suppressing future vehicle purchases.

FF systems, by contrast, enable more spontaneous and short-distance travel due to their flexible, one-way design. Several studies show that such services can encourage households, especially those with multiple cars, to delay or reconsider vehicle purchases, and in some cases to sell a second car [45, 46]. Positive user experience with shared EVs may also accelerate openness to adopting EVs privately [46]. The relationship with public transport is more context dependent. While free-floating cars can substitute for transit on short trips where access and walking times are perceived as burdensome [47], empirical evidence generally suggests that large-scale replacement of transit is limited once walking distance, vehicle search time, and parking availability are considered [48,49]. Complementarity can also arise in neighbourhoods where transit coverage is sparse, although reliability concerns, particularly uncertainty about return-trip availability, tend to limit full reliance on free-floating vehicles [50].

Socio-demographic factors, residential setting, and baseline travel patterns further shape user responses to both service types [6,51,52]. Urban residents with strong public transport access are more likely to integrate carsharing into multimodal routines and to reduce their private fleet, whereas suburban users without viable alternatives may employ shared vehicles as an additional motorised option [19, 23]. Income, age, and household structure influence both adoption and modal substitution patterns [51, 53].

Behavioural mechanisms also affect occupancy and substitution patterns. Environmental benefits are strongest when shared vehicles replace low-occupancy private-car trips, and weakest when they displace efficient or high-capacity modes such as metro or bus [17, 54]. Trip purpose, time of day, and the integration of carsharing with public transport and active modes are therefore central in determining net outcomes. Overall, behavioural heterogeneity creates asymmetric environmental leverage. A relatively small share of high-mileage ex-owners accounts for most potential system-level benefits, while other segments may contribute modest gains or increase total motorised activity. Yet most studies focus on member samples rather than population-wide adoption scenarios, leaving the scalability of these behavioural effects under large-scale adoption insufficiently understood.

2.4.2 Vehicle and material pathways (material efficiency mechanisms)

Beyond behavioural change, carsharing can affect environmental outcomes through vehicle- and material-related pathways. These pathways are commonly discussed in the general LCA literature [36, 55], yet they are rarely framed explicitly in terms of material efficiency in LCA studies of carsharing. According to Allwood et al. [56] material efficiency is understood as the extent to which vehicles and their constituent materials are used intensively and effectively to deliver transport service, such that the environmental burdens associated with production and EoL processes are distributed over a larger amount of functional use. In transport systems dominated by privately owned vehicles, large stocks of material-intensive assets remain idle for most of their lifetime [36]. From this perspective, carsharing can be interpreted as a system-level material efficiency strategy, aiming to provide similar mobility demand with fewer vehicles by increasing functional use of vehicle stock.

LCA studies of carsharing inherently rely on this logic, as production and EoL impacts must be amortised over the service delivered. In assessments of private vehicles, LTM is commonly approximated as the product of annual driving distance and vehicle age, implicitly reflecting behavioural patterns. In carsharing studies [17, 57], higher annual and LTM is typically assumed on the basis that vehicles are accessed by multiple users, drawing on empirical operator data or structural expectations of shared use. This assumption is profoundly in line with real world situation where shared car normally accumulates higher total LTM. However, in most studies vehicle utilisation pattern and LTM are treated as exogenous parameters rather than as outcomes shaped by user behaviour, fleet structure, or operational conditions. As a result, material efficiency is often embedded implicitly in modelling assumptions rather than examined as a mechanism in its own right.

Several LCA studies show that extended LTM can substantially reduce climate and energy impacts per unit of transport service, particularly when shared vehicles are smaller or more efficient than the average private car [17, 21, 26]. For BEVs, where production-phase emissions (especially from batteries) are relatively high, realised LTM and battery longevity become critical determinants of life-cycle performance [14]. Under favourable conditions, characterised by longer LTM, and effective recycling, shared BEV fleets may outperform both private ICEVs and private BEVs on a per-kilometre basis.

A smaller number of recent studies [22, 58] explicitly acknowledge material efficiency as a key mechanism enabled by carsharing. These studies emphasise that shared vehicles can reach higher LTM and deliver more functional use than privately owned cars, thereby improving the amortisation of production and EoL impacts. Nevertheless, even in these cases, the level of vehicle use and LTM are typically imposed as scenario assumptions rather than derived from observed behaviour or operational constraints.

These benefits are further bounded by durability and maintenance considerations. Intensive shared use may accelerate wear on components such as tyres, brakes, and batteries, increase maintenance frequency [59], or lead to earlier retirement of vehicles that are not designed for high annual mileage [25]. In such cases, the effective amortisation horizon may shrink, limiting the material efficiency gains originally expected from sharing. Moreover, if high utilisation of vehicle in the fleet requires frequent replacement of high-impact components (for example mid-life battery replacements), resource and toxicity burdens can increase [59] even when per-kilometre GHG emissions decline [36, 56, 60].

EoL pathways further modulate material efficiency outcomes. High rates of component reuse, remanufacturing, and material recycling can mitigate resource depletion and toxicity impacts [38], whereas limited recovery infrastructure can leave production-phase burdens largely uncompensated. Some studies explore second-life applications for batteries, such as stationary storage [61, 62], which can alter the allocation of impacts between transport and energy sectors [36]. However, such pathways have not yet been systematically explored in the context of carsharing LCA.

Overall, vehicle- and material-related pathways determine whether increased levels and patterns of vehicle use translate into genuine material efficiency or merely redistribute production and EoL burdens. Yet the majority of existing studies treat vehicle use patterns and LTM as fixed inputs, leaving an important gap between the conceptual promise of material efficiency and the conditions under which it can be realised in practice.

2.4.3 Fleet operations and service design as operational constraints

Operational dimensions do not constitute a causal pathway from mobility to emissions in the same sense as behaviour or material efficiency. Instead, they act as constraints and enabling conditions that determine whether behavioural and material-efficiency mechanisms can be realised in practice. Fleet operations translate behavioural demand into actual vehicle movement and operationally realised vehicle use, as reflected in metrics such as annual vehicle mileage, served kilometres, and empty travel. They determine how efficiently fleets convert user activity into delivered mobility and how much overhead (empty kilometres, staff travel, charging trips) is required to sustain a given level of service.

Key variables include spatial and temporal matching between vehicles and demand, relocation intensity, congestion exposure, and charging logistics for electric fleets. RT systems typically exhibit low relocation needs and relatively predictable station occupancy. Vehicles depart from and return to the same stations, enabling operators to manage supply at the station level and to plan maintenance and charging in a centralised manner [6, 19]. This tends to produce more stable station-level vehicle use patterns over time and clearer accounting of station and parking overheads. In such systems, operational design focuses on station placement, fleet size per station, and reservation rules.

FF services achieve higher spontaneity and temporal responsiveness but face pronounced spatial imbalances. Vehicles tend to accumulate in attractor zones such as central business districts and transit hubs and become scarce in peripheral or uphill areas. Operators respond through active relocation, dynamic pricing, or restrictions on drop-off locations [6, 63]. Each relocation trip adds empty kilometres, staff time, and potentially auxiliary vehicles, increasing both energy use and emissions. Case studies show that overhead driving can substantially reduce net GHG gains in some free-floating systems [17, 23].

Congestion exposure and speed profiles further mediate operational impacts. Stop–go driving in dense urban cores increases fuel use and non-exhaust particulate emissions, whereas smoother traffic conditions or interurban trips improve operational intensity, understood as emissions per kilometre [26]. Service design, including policies on maximum trip length, home-area boundaries, and integration with transit, shapes which kinds of trips are most common.

For electric fleets, operational design interacts with charging logistics. Depot-based charging in station-based or corporate fleets allows operators to coordinate charging with off-peak electricity, manage state-of-charge buffers, and minimise empty kilometres for charging. In contrast, on-street or public charging in free-floating services can require additional repositioning and may rely more heavily on marginal, potentially fossil-based generation during peak periods [6]. Charging power, dwell times, and the spatial distribution of chargers all influence the temporal profile of electricity demand and, therefore, the effective carbon intensity experienced by the fleet.

In summary, fleet operations and service design act as a hinge between behavioural potential and realised material efficiency. They do not generate environmental impacts on their own, but they constrain the range of vehicle use levels and patterns that can be achieved in practice and determine the level of operational overhead that accompanies behavioural change. Existing operational studies highlight these constraints but rarely connect them to life-cycle environmental metrics, especially under large-scale adoption.

2.4.4 Interactions among determinants and constraints

These three determinant families do not operate in isolation. Behaviour determines the composition of demand and substitution patterns. Fleet operations translate that demand into vehicle movement within spatial and temporal constraints. Vehicle and material pathways govern how embedded and operational burdens are amortised. The built environment provides the spatial and institutional context that enables or constrains all three. The environmental performance of carsharing therefore emerges from the joint action of two causal mechanisms (behaviour and material efficiency) operating within the bounds set by operational feasibility and broader contextual conditions.

Conceptually, positive combinations might occur when policies and service design align with favourable behavioural and spatial conditions. Dense urban areas with good public transport, supportive parking policy, high carsharing adoption among former car owners, and well-managed BEV fleets using low-carbon electricity can achieve high levels of vehicle use in carsharing fleet, reduced private car ownership, and efficient operations in tandem. Under such conditions, reductions in GHG emissions, energy use, and local pollutants can coincide with improvements in land-use efficiency.

Conversely, misalignments can turn potential gains into modest or even negative outcomes. Examples include free-floating systems in dispersed, car-oriented built environments that attract mainly low-mileage or carless users, high relocation intensity due to poor spatial matching, BEV fleets operating on carbon-intensive grids with limited charging coordination, or service designs that mainly substitute for public transport rather than private car use. In such cases, increased operational overheads, limited material efficiency gains, and unfavourable substitution patterns can erode or reverse aggregate environmental benefits.

The literature thus supports a determinant-based perspective in which environmental outcomes depend on (i) who adopts and how their travel changes, (ii) how intensively and for how long shared vehicles are used, and (iii) whether operational conditions allow sufficiently high levels of vehicle use to be achieved with limited service overhead. However, these determinants are rarely analysed together in a way that clarifies their individual contributions and combined effects under large-scale adoption.

2.5 Contextual factors shaping determinants

The determinants reviewed in Section 2.4 do not operate in isolation. Their expression depends on broader contextual conditions that structure the environment in which behavioural responses, material-efficiency pathways, and operational feasibility unfold. These contextual factors include pricing and incentives, governance and regulation, urban form and infrastructure, sociodemographic and equity conditions, and industrial policies affecting material flows.

Crucially, these contextual conditions are not mechanisms and are not equivalent to operational feasibility. They do not directly convert mobility activity into emissions, nor are they intrinsic design features of a specific fleet. Instead, they shape the setting in which behavioural mechanisms can emerge, influence whether high levels of vehicle use are operationally feasible, and determine how strongly material-efficiency strategies can be realised in practice.

A recurring theme in the literature is that contextual factors partly determine whether shared mobility systems activate favourable patterns such as reduced car ownership, high annual mileage in shared fleets, or improved EoL recovery, or whether they instead reinforce rebound travel, low levels of vehicle use, premature retirement of vehicles, and weak material recovery [20, 48, 56, 60].

2.5.1 Pricing and incentives

Pricing shapes behavioural mechanisms by influencing mode choice, adoption decisions, and travel frequency. Numerous studies show that membership fees, per kilometre pricing, and bundled packages modify both the probability of joining carsharing and the likelihood of substituting private-car trips with shared vehicles [23, 40, 64]. Low marginal-cost pricing can stimulate additional discretionary trips among carless or occasional car users, whereas distance-based pricing can limit rebound effects by making high car-kilometre use more expensive.

Influence on operational feasibility. Pricing incentives also affect fleet operations and thus operational feasibility. Tariffs, discounts, and penalties can reduce spatial imbalance and operational overhead when they nudge users to return cars to undersupplied areas, which lowers the need for staff-based relocation and deadheading [63]. Conversely, free-minute packages or strong volume discounts can increase peak concurrency and strain fleet capacity, making it more difficult to maintain acceptable availability with a given fleet size.

Influence on material efficiency. The influence of pricing on material efficiency is indirect. Tariffs that make short, low-occupancy trips relatively expensive and reward consolidated or shared trips can encourage higher annual vehicle mileage and support higher effective LTM. By contrast, pricing structures that favour very short, low-occupancy trips or unlimited-use packages for low-mileage users can limit realised annual mileage per vehicle and weaken material-efficiency potential, especially when the fleet attracts predominantly short-trip demand.

Table 2.7 Pricing factors and their influence on determinants

Pricing factor	**Behaviour**	**Operational feasibility**	**Material efficiency**
Per kilometre and per minute fees	Affects adoption, trip frequency, and rebound effects	Shapes demand timing and trip length, with implications for fleet capacity	Indirect influence via annual vehicle mileage and trip composition
Dynamic pricing	Redirects travel demand spatially and temporally	Can reduce relocation needs and improve operationally achievable vehicle use levels	No direct effect; indirect via annual and lifetime vehicle use patterns
Congestion or environmental fees	Encourages multimodal travel and car shedding	Modifies trip distribution and peak loads	Can favour lighter vehicles and higher lifetime mileage per vehicle

2.5.2 Governance and regulation

Governance decisions determine how shared mobility is allowed to operate, which neighbourhoods receive service, and how operators manage fleets [39, 65–67]. Regulatory frameworks affect all three determinants by shaping demand for carsharing, the design space available to operators, and the incentives for durable and circular vehicle designs.

Influence on behaviour. Parking policies, licensing requirements, access to designated carsharing spaces, and restrictions on private parking shape whether households view shared mobility as a credible alternative to owning a private vehicle. Cities that limit private parking or implement low emission zones tend to observe stronger substitution toward shared mobility and lower private vehicle holdings [53, 68].

Influence on operational feasibility. Governance strongly conditions operational feasibility. Vehicle caps, restricted service areas, parking rights, requirements for minimum availability, and charging regulations influence how efficiently fleets can be deployed. Poorly aligned regulations can increase deadheading, reduce the level of vehicle use that can be achieved in operation, and create barriers for BEV charging, for example when public chargers are scarce or access rules are restrictive [6, 19, 69].

Influence on material efficiency. Conceptually, governance is crucial for material efficiency beyond patterns of vehicle use alone. Policies can shape:

- minimum durability standards for shared vehicles,
- requirements for modular and repairable components,
- EoL recycling targets,
- remanufacturing incentives,
- battery second-life and recycling mandates,
- reporting obligations on material flows.

These interventions determine whether shared fleets prolong component life or prematurely retire vehicles due to regulatory, contractual, or corporate constraints. Governance is therefore a key determinant of system-wide material flows and the feasibility of achieving high material efficiency in shared fleets [38, 56].

2.5.3 Urban form and infrastructure

Urban form shapes both the demand for carsharing and the feasibility of efficient operations. Dense, mixed use neighbourhoods with high quality transit create conditions where carsharing can substitute for private vehicles rather than supplement them [19, 42, 67].

Table 2.8 Governance factors and their influence on determinants

Governance factor	**Behaviour**	**Operational feasibility**	**Material efficiency**
Parking regulations	Affects private car ownership decisions and carsharing attractiveness	Determines access to curb space and stations, with implications for deadheading and operational vehicle movement	No direct effect; indirect via demand composition and vehicle use
Fleet caps or permits	Screen eligible service areas and market entry	Constrain fleet sizing, coverage, and the level of vehicle use achievable with a given fleet	Indirect via fleet composition, turnover, and service design
Circular economy rules	Limited direct behavioural impact	Minimal direct impact on daily operations	Strong influence on durability, reuse, remanufacturing, and recycling

Influence on behaviour. Urban residents in dense cores with good transit access are more likely to shed private vehicles and rely on carsharing for occasional trips. Suburban users with low transit access more often employ carsharing to supplement motorised travel rather than to replace car ownership [70]. These behavioural differences can directly influence emissions outcomes and the extent to which carsharing reduces rather than adds motorised kilometres.

Influence on operational feasibility. Urban form strongly conditions operational feasibility by affecting:

- travel distances between consecutive bookings,
- parking search times and circulation,
- relocation needs and feasible relocation strategies,
- which service areas can support high availability with moderate fleet sizes.

Compact and mixed use areas tend to reduce deadheading and allow higher throughput per vehicle, whereas dispersed land use and low densities make it more difficult to maintain acceptable service levels without very low levels of vehicle use per vehicle.

Influence on material efficiency. Although indirect, urban form affects material efficiency by influencing patterns and levels of vehicle use and thus realised LTM. Under sparse land use conditions, even shared fleets may achieve low annual mileage, which weakens the amortisation of embedded emissions. Dense, multimodal environments are more conducive to high throughput per shared vehicle and therefore to higher material efficiency.

Table 2.9 Urban form factors and their influence on determinants

Urban form factor	**Behaviour**	**Operational feasibility**	**Material efficiency**
Density and mixed use	Encourages car shedding and multimodal travel	Reduces relocation and search time, improving vehicle throughput	Supports higher annual mileage per shared vehicle and higher realised LTM
Transit availability	Encourages multimodal substitution and limits rebound	Reduces reliance on shared cars for everyday trips	No direct material effect; indirect via demand composition
Parking supply	Affects mode choice and car ownership decisions	Influences fleet circulation and dwell patterns	No direct influence; indirect via annual vehicle mileage and lifetime use

2.5.4 Equity, access, and sociodemographic patterns

Equity is increasingly recognised as a central dimension of shared mobility systems [67, 71]. Access to carsharing is shaped by income, digital literacy, credit status, neighbourhood safety, immigration background, and broader patterns of spatial disadvantage. These factors determine who participates in shared mobility and therefore which behavioural profiles drive environmental outcomes.

Influence on behaviour. Low income households and recent immigrants often face barriers including credit card requirements, smartphone access, lack of banking credentials, or higher perceived risk [71, 72]. These constraints can exclude users who might otherwise achieve substantial emission reductions through modal substitution or reduced car ownership. Conversely, more affluent users may employ carsharing mainly for convenience, with limited environmental benefit if it does not replace private vehicles or high impact trips.

Influence on operational feasibility. Service coverage is typically concentrated in dense and affluent neighbourhoods, where operators can minimise operational costs and relocation needs [73]. This spatial concentration can reduce access in marginalised areas and increase operational overhead if fleets must be repositioned to meet dispersed demand. Equity oriented coverage requirements may improve access but can make operational feasibility more challenging in low demand or peripheral areas.

Influence on material efficiency. Equity influences material efficiency indirectly by shaping which mobility patterns can access carsharing. Shared fleets achieve stronger material efficiency gains when they attract private-car owners whose vehicles are under-utilised and whose travel patterns can be pooled. Structural access barriers, such as credit requirements, immigration status, digital access, or limited service coverage, can prevent these users from joining. When this happens, adoption may skew toward convenience-oriented or very occasional users whose trips contribute very few kilometres to the shared fleet. This leads to low annual mileage per vehicle, making it difficult to amortise embedded emissions even when vehicles are technically durable.

Table 2.10 Equity factors and their influence on determinants

Equity factor	**Behaviour**	**Operational feasibility**	**Material efficiency**
Income and credit barriers	Screen adoption and limit who can join	Minimal direct operational impact in served areas	Indirect via user mix and annual vehicle mileage
Service in disadvantaged neighbourhoods	Limits behavioural substitution if coverage is low	Raises relocation needs or reduces coverage when service is extended to low-demand areas	Can limit achievable annual mileage per vehicle when demand is sparse
Digital and licensing barriers	Reduce participation among specific groups	No direct effect on daily operations	Indirect through demand concentration and user composition

In sum, the environmental performance of carsharing is not an inherent property of any service model. It is the outcome of intertwined behavioural mechanisms, material efficiency mechanisms, and an operational feasibility constraint, all of which are conditioned by pricing, governance, urban form, and equity contexts. Recognising these dependencies motivates the methodological diversity reviewed in Section 2.6 and the research gaps synthesised in Section 2.7.

2.6 Methods used in the literature

Studies assessing the environmental implications of carsharing rely on three main methodological traditions: (i) empirical transport analyses of behavioural change, (ii) operational and simulation models analysing supply-side dynamics, and (iii) life-cycle and environmental assessments measuring full-system impacts. These approaches interrogate different parts of the causal chain reviewed in Section 2.4 and employ distinct data sources, validation strategies, and assumptions about patterns and levels of vehicle use, fleet composition, and user behaviour. This section reviews these methods and their associated data inputs, with emphasis on the conceptual nuances that are most relevant for interpreting previous findings and for motivating the analytical choices made in this dissertation.

2.6.1 Empirical transport methods (pre- and post-adoption studies)

Empirical transport studies focus primarily on how carsharing adoption alters car ownership, travel activity, and modal substitution. Two broad empirical designs dominate this literature. The first relies on cross-sectional comparisons between members and non-members, or between early adopters and the general population. The second uses longitudinal or retrospective data to compare behaviour before and after joining a carsharing service.

Early work was largely based on member surveys, in which respondents reported their vehicle holdings, annual distance driven, and changes in mode share following adoption [5, 24]. These instruments established the now-familiar findings that many members reduce their car ownership and that some proportion of trips shifts to public transport, walking, or cycling. However, survey-based approaches are vulnerable to recall bias and often lack temporal detail, particularly for short trips or complex multimodal chains.

More recent studies complement or replace surveys with richer travel-activity data, such as household travel diaries, smartphone-based trip logging, and Global Positioning System (GPS) traces linked to carsharing accounts [31, 46, 53]. These data enable finer-grained reconstruction of origin–destination patterns, trip purposes, time-of-day profiles, and multimodal integration. Some studies also link carsharing membership to national or regional travel surveys, allowing comparison with non-members and with broader urban populations.

Transport researchers typically analyse these data using regression models, discrete-choice models, or mixed logit specifications to identify determinants of adoption and usage, including residential density, public transport accessibility, parking supply, household structure, income, and pricing [53, 63, 70]. These models consistently highlight substantial behavioural heterogeneity. The same service can induce pronounced reductions in VKT for some users while increasing car kilometres for others.

Despite this detailed treatment of travel behaviour, the environmental implications of these changes are often only approximated. Many transport studies either do not quantify environmental outcomes at all, or rely on simplified tailpipe emissions factors applied directly to changes in VKT, without considering operational overheads such as relocation or embedded vehicle impacts. As a result, there is a methodological separation between empirical transport studies and LCA studies, even when both address nominally similar questions about environmental impacts of carsharing.

2.6.2 Operations and simulation models (supply, utilisation, relocation)

Operational analyses examine how shared fleets perform under real-world spatial and temporal constraints. They address questions such as how many vehicles are required to meet a given demand, how frequently vehicles must be relocated, what levels of availability users experience, and how system utilisation varies across space and time. Methodologically, this work draws on two main sources: empirical operator datasets and simulation models.

When accessible, operator data provide a detailed record of system functioning. Booking and reservation logs, vehicle availability snapshots, GPS trajectories, odometer readings, and maintenance or relocation records allow researchers to reconstruct patterns of idle time, vehicle movement, and service availability [74]. These reconstructions are used to identify spatial imbalance, quantify the magnitude of relocation operations, and estimate utilisation rates at the vehicle or station level. However, such datasets are typically proprietary, limited to one or a few cities, and collected under specific operational policies, which constrains their generalisability.

Simulation-based studies, in turn, use synthetic or calibrated demand and emulate how vehicles are assigned to trips under alternative operational rules. Agent-based Models (ABMs), optimisation formulations, and discrete-event simulations are employed to estimate required fleet sizes, expected waiting times, relocation needs, and service reliability [7, 75–77]. For electric carsharing, these models are extended to include battery state of charge, charger location, power levels, and charging queues, linking feasibility and performance to energy constraints [10, 12, 78, 79]. In these frameworks, relocation strategies, home-area definitions, and station-layout choices become explicit design variables.

Operational studies therefore provide a detailed description of the supply side. They show how demand is transformed into vehicle movement, how much empty-kilometre overhead is required to maintain service, and how **operational vehicle use varies across space and**

time as a function of demand patterns and infrastructure. Yet, as with empirical transport studies, most operational models include environmental aspects only in a rudimentary fashion. When emissions or energy use are reported, they are often derived by applying average or speed-dependent emissions factors to simulated VKT, without explicitly representing embedded vehicle impacts or interacting with full LCA inventories. This limits the extent to which operational and LCA findings can be compared or combined, and it leaves open the question of how operational feasibility constrains environmental performance under large-scale adoption.

2.6.3 Life-cycle assessment approaches

Environmental assessments of carsharing predominantly rely on LCA concepts, but with substantial methodological diversity that shapes how results are interpreted and compared. Four distinctions recur across the literature and are particularly relevant for understanding how previous studies conceptualise carsharing systems and represent patterns and levels of vehicle use, operational overhead, and system boundaries.

Product vs. service-system framing. A central distinction concerns whether carsharing is modelled as a product system, where the vehicle is the unit of analysis, or as a mobility service, where transport output is the functional unit.

- Product-oriented studies allocate environmental burdens to a vehicle and express results per kilometre of vehicle lifetime mileage or per unit of manufacturing output. Examples include [80], which compare carsharing vehicles with private cars by allocating production impacts over assumed lifetime mileage.

- Service-oriented studies allocate impacts to the transport service delivered and use functional units such as person-kilometre, trip tasks, or mobility bundles (for example [17, 26, 32, 57]). This framing aligns more closely with the fact that carsharing modifies patterns of vehicle use and redistributes vehicle kilometres among users.

Both framings are valid but emphasise different questions. Product-oriented approaches highlight material efficiency and amortisation of embedded impacts, whereas service-system approaches better capture substitutions across modes and service configurations.

Static vs. dynamic utilisation assumptions. A key methodological distinction concerns how vehicle utilisation is represented.

Static utilisation is common in LCA-oriented studies. Annual mileage, lifetime mileage, or utilisation rates are given as exogenous inputs, often derived from surveys, operator reports, or assumptions reflecting typical operations (for example [17, 21, 22, 26]). This approach is consistent with attributional LCA practice because it supports controlled comparisons across technologies and service types.

By contrast, dynamic utilisation arises primarily in the operations and system-design literature, where utilisation is an emergent property of spatial and temporal supply and demand interactions. Studies such as [7, 10, 53, 77] simulate or observe vehicle movement, relocation, idle periods, station occupancy, charging operations, and fleet size constraints. These models do not estimate environmental impacts directly, but they illustrate how realised throughput and idle time depend on service configuration, demand concentration, and operational strategy.

Static and dynamic approaches therefore serve complementary purposes. Static utilisation supports clearly defined scenario comparisons in LCA frameworks, while dynamic modelling highlights how realised vehicle use may vary under specific behavioural or operational conditions. This distinction helps explain the wide range of utilisation values reported in the literature and underscores the importance of clarifying utilisation assumptions when interpreting environmental results.

Attributional, consequential, and prospective perspectives. Carsharing LCAs differ in whether they represent average conditions, system-wide changes, or future scenarios.

- Attributional LCAs estimate environmental intensity under observed or assumed conditions, using average energy, technology, and vehicle use profiles. Most carsharing LCAs fall into this category (for example [17, 26, 57]).
- Consequential LCAs consider marginal or system-wide changes such as changes in vehicle manufacturing, induced demand, avoided private car purchases, or energy-system shifts [81]. These remain less common but appear in studies evaluating the broader impact of shared mobility options [82].
- Prospective LCAs incorporate future technology trajectories, projected electricity mixes, or anticipated operational models to evaluate scenarios such as full fleet electrification or large-scale adoption of shared vehicles. This type of study remains rare in shared mobility research.

These perspectives answer different questions. Attributional LCAs assess current practice, consequential LCAs explore systemic effects, and prospective LCAs address future contexts.

Boundary and allocation rules. Boundary-setting choices differ substantially across studies and contribute to variation in reported results.

- Allocation of production impacts varies. Studies allocate embedded vehicle impacts per kilometre [21, 57, 80], per user [17, 22], or per city context [25].
- Operational overheads such as relocation kilometres, maintenance trips, staff travel, or charging repositioning are sometimes included explicitly [34] but are omitted in others.
- Infrastructure and charging may be excluded, partially included (for example charger production only), or fully integrated (for example grid expansion, station siting), depending on study goals.
- Electricity and energy-system modelling ranges from average grid intensities to time-of-use or marginal emissions factors [22], with implications for BEV-heavy fleets.

These boundary decisions reflect the aims and data constraints of each study rather than methodological errors. However, they help explain divergent findings across GHG, energy, and resource categories, and they highlight the difficulty of directly comparing results without careful attention to assumptions about vehicle use, adoption composition, and operational feasibility.

Viewed as a whole, these methodological distinctions clarify how LCA-based studies of carsharing conceptualise the system under analysis, represent vehicle use, and allocate burdens. They also illuminate why results differ across contexts and why integrating behavioural, operational, and environmental evidence remains analytically challenging.

2.6.4 Data sources and integration

The methods reviewed above depend on a broad range of data sources that differ in coverage, resolution, and accessibility. Broadly, the literature mobilises four types of empirical data, namely travel activity, operator records, urban form, and energy-system data, alongside process-based environmental inventories.

Travel activity and origin–destination data are drawn from household travel surveys, regional or national mobility surveys, travel diaries, and increasingly from smartphone- or GPS-based trip logging. These sources provide information on trip rates, purposes, modes, and origin–destination patterns, sometimes complemented by panel structures that allow before–after comparisons for carsharing adopters [23, 31, 42]. In a smaller number of studies, passive data sources such as call detail records or app-based traces are used to characterise background demand patterns or compare members with non-members. These datasets are rich in behavioural detail but often lack information on vehicle technology, operational overheads, or the precise timing of activities at the sub-minute scale relevant for operations.

Operator data offer a complementary, supply-side perspective. Booking logs, vehicle availability records, GPS trajectories, odometer readings, relocation logs, charging or refuelling events, and maintenance records allow detailed reconstruction of vehicle use and idle periods [74]. For electric fleets, charging logs and state-of-charge histories provide information on charging locations, energy delivered, and dwell times [10, 12]. These datasets are well suited to characterising patterns of vehicle use, relocation, and operational constraints, but they are typically proprietary, geographically limited, and rarely linked to socio-demographic or attitudinal information about users.

Urban and built-environment data, including land-use and zoning maps, parking inventories, curb-use regulations, road and transit networks (for example OpenStreetMap (OSM) and General Transit Feed Specification (GTFS)) [83], and congestion indicators, are used to contextualise both behaviour and operations. They help explain adoption patterns, spatial imbalance, and the feasibility of specific operational models, such as free-floating in dense cores versus station based in lower-density areas. However, such data are unevenly available across cities and are often compiled from disparate sources, creating challenges for comparative work.

Energy-system and emissions data play a central role in both non-LCA emissions studies and LCA-based assessments. Speed- and technology-dependent emissions factors from tools such as HBEFA, MOVES, COPERT, or Greenhouse gases, Regulated Emissions, and Energy use in Technologies (GREET) are frequently used to convert VKT into pollutant and GHG emissions. For electric fleets, time-varying electricity carbon intensity, marginal versus average emission factors, and temperature-dependent vehicle efficiency all influence results. In parallel, LCA studies depend on process-based inventories such as ecoinvent or national life-cycle databases, complemented by industry reports and manufacturer disclosures for battery chemistries, recycling yields, and vehicle component masses [22, 84]. These inventories are detailed but typically represent average or generic processes rather than city-specific conditions.

Integrating these data sources within a single analytical framework remains challenging. Behavioural datasets rarely include operational detail; operator datasets rarely include socio-demographics; and LCA inventories seldom reflect the temporal or spatial variability of local energy systems and urban contexts. Timing also differs. Travel surveys are often annual or multi-year; operator logs may be continuous over months; and grid-intensity profiles vary hourly or seasonally. These misalignments, coupled with differing system boundaries and allocation rules, contribute to the methodological fragmentation highlighted in the previous subsections and motivate a staged, mechanism-based approach rather than a single integrated model.

2.7 The necessity for this research

This chapter reviewed the carsharing literature across four interrelated domains: service typologies, reported environmental outcomes, the determinants and mechanisms proposed to explain those outcomes, and the analytical methods used to study them. The literature provides substantial evidence that carsharing can contribute to environmental objectives under certain conditions. At the same time, it reveals persistent inconsistencies in how environmental outcomes are measured, explained, and extrapolated beyond small-scale or early-stage deployments. These inconsistencies complicate efforts to assess when, for whom, and under which conditions carsharing delivers robust environmental benefits at the urban scale.

Across behavioural, operational, and environmental strands of the literature, two recurring challenges are apparent. First, environmental outcomes are often reported without a clear distinction between the mechanisms that generate them and the assumptions under which they are evaluated. Second, different bodies of work emphasise different determinants, such as behavioural change, material efficiency, fleet operations, or service design, but rarely situate these determinants within a shared analytical structure. As a result, policy-relevant questions about large-scale deployment are frequently addressed using simplified or idealised assumptions regarding adoption, vehicle use, or service feasibility, even though the same literature documents substantial heterogeneity in behaviour and strong spatial and temporal constraints on shared mobility systems.

Behavioural mechanisms and scalability. Behavioural studies consistently show that carsharing adoption influences car ownership, annual driving distance, modal substitution, and trip patterns. However, the magnitude and direction of these effects vary across user groups, neighbourhood contexts, and service models. Much of the available empirical evidence is derived from early adopters or limited deployments, which constrains its applicability to city-wide adoption scenarios. In addition, behavioural studies often focus on average or representative responses, which is appropriate for characterising typical effects but insufficient for understanding how heterogeneous responses aggregate as adoption expands across a diverse population.

Only a limited share of behavioural studies translate observed changes in travel behaviour into life-cycle environmental outcomes. This omission is consequential because heterogeneity in baseline travel demand and modal access implies heterogeneity in environmental impacts. As a result, it remains unclear which user groups offer substantial environmental leverage under carsharing and which may generate rebound effects when gaining access to shared vehicles. This gap motivates the focus of Chapter 3, which examines how empirically documented behavioural responses scale to system-level environmental outcomes under different adoption structures and spatial contexts, without assuming a single representative adopter.

Operational constraints and feasible service delivery. Operational research provides detailed insight into the spatial and temporal dynamics of carsharing systems, including vehicle availability, spatial imbalance, relocation activity, charging logistics, and peak demand conditions. These elements do not constitute behavioural or environmental mechanisms in themselves. Rather, they define the conditions under which shared vehicles can reach trips and deliver mobility services in practice.

Most operational models are designed to support cost control, service reliability, or fleet management objectives. Environmental performance is rarely evaluated explicitly, and life-cycle impacts are seldom integrated into operational decision-making. Moreover, operational studies typically analyse existing systems or marginal changes in fleet size, rather than large-scale adoption scenarios in which service demand and fleet requirements change substantially. As a result, the literature offers limited guidance on how operational feasibility constrains environmental performance when carsharing is expanded beyond its current scale. This motivates the treatment of operational feasibility as a service-delivery constraint in Chapter 5, where realised vehicle use and trip coverage are derived from explicit spatial and temporal rules rather than imposed as assumptions.

Environmental assessment and material efficiency through vehicle use. LCA studies quantify emissions associated with vehicle production, energy use, maintenance, and EoL processes. However, many rely on static or idealised assumptions regarding annual distance, lifetime vehicle use, or fleet size. These assumptions are often inconsistent with the behavioural diversity and operational constraints documented elsewhere in the literature. Because the environmental intensity of mobility depends strongly on how embedded vehicle impacts are distributed across delivered service, such simplifications can substantially affect estimated outcomes.

Only a limited number of studies explicitly connect patterns of vehicle use over the lifetime to the behavioural and operational processes that generate them. As a result, material efficiency is frequently treated as a modelling input rather than as a determinant shaped by demand structure and vehicle consolidation. This limits the interpretability and policy relevance of environmental assessments, particularly when comparing private and shared mobility systems. Chapter 4 responds to this gap by analysing material efficiency through empirical lifetime mileage relationships, grounding life-cycle outcomes in observed patterns of vehicle use rather than assumed averages.

Fragmentation and implications for analytical design. The reviewed literature offers valuable insights into individual aspects of carsharing systems, but it does not yet provide a coherent, mechanism-oriented explanation of environmental outcomes under large-scale adoption. Behavioural studies rarely account for operational constraints. Operational models seldom link service feasibility to life-cycle impacts. Environmental assessments often abstract from both behavioural heterogeneity and service- delivery limits. This fragmentation creates a gap between empirical evidence and the type of structured, determinant-specific analysis required to inform robust policy and planning decisions as carsharing moves from niche applications to broader deployment.

2.7.1 Implications for the dissertation: rationale for a determinant-based structure

The gaps identified in this chapter do not merely motivate the choice of topics for the empirical chapters. They point to a structural limitation in the existing evidence base. Behavioural responses, material efficiency through lifetime functional use of vehicles, and operational feasibility are all recognised as important, yet they are rarely analysed in a way that allows their respective contributions to environmental outcomes to be distinguished clearly.

A first implication is that behavioural responses cannot be treated as homogeneous or uniformly beneficial when assessing large-scale adoption. Evidence from early adopters does not reveal how environmental performance evolves as carsharing expands to user groups with different travel needs, baseline access, and spatial contexts. The dissertation therefore treats behavioural change as a distinct determinant, not because behaviour operates independently of other factors, but because its population-level consequences must be understood before being interpreted alongside material efficiency strategy or operational constraints.

A second implication is that material efficiency, as expressed through lifetime functional use of vehicles, is environmentally decisive but conceptually ambiguous when treated as a fixed parameter and inherent property of LCA model. Existing environmental assessments adopt a wide range of assumed vehicle-use levels, making comparison across studies difficult and obscuring the role of vehicle consolidation. By analysing material efficiency separately in Chapter 4, the dissertation clarifies how heterogeneity in annual driving demand and total lifetime functional use of vehicle (i.e., LTM) shapes life-cycle outcomes under controlled access conditions.

A third implication is that operational feasibility conditions whether favourable behavioural and material efficiency conditions can be realised in practice. High vehicle use and full trip coverage are common assumptions in environmental analyses, yet operational research shows that these outcomes depend on spatial layout, temporal demand patterns, and fleet availability. Treating operational feasibility as a separate determinant in Chapter 5 makes it possible to evaluate how service-delivery constraints bound environmental performance without conflating feasibility with behavioural change or material efficiency.

This determinant-based analytical structure is a methodological choice rather than a claim that these determinants operate independently in reality. By examining behavioural responses, material efficiency, and operational feasibility under controlled and transparent assumptions, the dissertation establishes a basis for synthesis in the concluding chapter, where their interactions and implications for large-scale deployment are interpreted explicitly. The following chapters implement this structure and collectively address the central objective of the dissertation, namely to identify the behavioural, material efficiency, and operational conditions under which carsharing can deliver robust environmental benefits rather than outcomes that rely on idealised or implicit assumptions.

CHAPTER 3 BEHAVIOURAL RESPONSES AND SYSTEM-LEVEL ENVIRONMENTAL OUTCOMES

Chapter note.

This chapter builds on a peer-reviewed article presented at the 102nd Annual Meeting of the Transportation Research Board:

Nong, Y. R., Ciari, F., Majeau-Bettez, G., Patouillard, L., and Trépanier, M. (2023, January). *Prospective Environmental Impact of Carsharing: A Snapshot of Large-Scale Use of Carsharing.* Washington, D.C.

The TRB paper was an early version of this work and reported preliminary results based on a single adoption level of 40%. It presented an initial exploration of how individuals with different baseline mobility habits adjust their travel patterns after joining carsharing.

For inclusion in this dissertation, the chapter has been substantially expanded. The scope now covers progressive adoption from zero to one hundred percent within each eligible user group, uses a fully developed life-cycle assessment framework, and integrates a more comprehensive interpretation of behavioural mechanisms. The framing, contextualisation, discussion, and conclusion sections have been rewritten to align the analysis with the determinant-based structure of the dissertation and to clarify the policy relevance of the findings. The methodological structure remains consistent with the original study, but the analysis presented here is significantly more complete in both scale and narrative coherence.

3.1 Context and scope

The International Energy Agency [85] projects continued growth in global mobility demand per capita alongside rising car ownership rates. These trends pose significant challenges for the decarbonisation of urban transport systems. Carsharing has therefore been widely discussed as a potential strategy to reduce vehicle kilometres travelled, lower emissions, and accelerate the diffusion of low-emission vehicle technologies. Empirical studies report reductions in private-car use and car ownership following carsharing adoption, as well as increases in walking, cycling, and public transport use [31, 39, 42, 46, 86]. The comparatively rapid fleet turnover of shared systems may further facilitate early electrification [25].

Despite these promising mechanisms, estimates of the environmental impacts of carsharing vary widely across studies. LCAs report greenhouse gas reductions ranging from a few percent to nearly fifty percent relative to private-car use, depending on assumptions regarding behavioural change, vehicle technology, and system boundaries [17, 24, 31, 57, 80, 87]. A key source of this variability lies in how behavioural responses are represented and interpreted at scale. Many studies rely on average behavioural adjustments derived from member surveys or pilot programs [17, 25], and apply these to characterise typical user impacts. This approach has been instrumental in establishing the potential environmental relevance of carsharing at the individual level. However, it provides limited insight into how impacts evolve as adoption expands across heterogeneous urban populations. In particular, it offers little guidance on how system-level outcomes depend on adopter composition, adoption order, or spatial context.

This chapter builds on the behavioural and LCA framework established in the literature, but addresses a different question. Rather than asking whether carsharing reduces emissions for a representative user, it examines how life-cycle impacts evolve as adoption increases progressively within distinct adopter groups. Adoption is treated as a continuous policy variable rather than a binary outcome, allowing system-level outcomes to be traced as participation expands from early adopters to broader segments of the population. Access to carsharing supply is assumed to be unconstrained in order to isolate aggregation effects arising from behavioural responses.

To this end, literature-based behavioural adjustments are applied to a synthetic population representing the Greater Montréal Area, capturing heterogeneity in daily travel demand, modal use, and residential location. Behavioural change is not modelled endogenously. Instead, fixed elasticities drawn from empirical studies are applied in a controlled manner to two groups commonly identified as potential carsharing adopters: individuals without access to a private car and individuals with occasional access. This design allows the analysis to focus on how aggregation structure and spatial distribution influence system-level outcomes, without introducing additional assumptions about adoption mechanisms.

The objective of this chapter is not to forecast future emissions with precision, but to clarify how well-documented behavioural responses translate into life-cycle impacts as carsharing expands beyond early adopters. The analysis identifies conditions under which emission reductions accrue steadily, as well as situations in which additional adoption yields diminishing or counterproductive effects. Results are evaluated under a mixed fleet reflecting Montréal's current vehicle composition and Québec's low-carbon electricity mix, with sensitivity analyses exploring alternative adoption orders, full electrification, and variation in assumed LTM.

By combining heterogeneous daily travel patterns with mode-specific life-cycle emission intensities, this chapter provides a metropolitan-scale perspective on the environmental implications of scaling carsharing. Its contribution lies not in proposing new behavioural elasticities, but in clarifying how adoption structure and spatial context condition the translation of individual-level effects into system-level outcomes, and in making explicit the assumptions required when carsharing is considered as a large-scale policy intervention.

3.2 Materials and methods

3.2.1 Synthetic population and spatial resolution

This study uses an activity-based synthetic travel-demand dataset representing the urban population of the Greater Montréal Area (Montréal's Census Metropolitan Area) (GMA). The population was generated within MATSim's activity-based simulation framework [88] and is based on the dataset developed by Manout and Ciari [89]. It represents the complete daily activity schedules and travel patterns of approximately 3.0 million individuals for a typical weekday, including all motorised and non-motorised modes.

Each individual is associated with a home location, allowing travel behaviour to be linked to spatial units within the metropolitan area. This spatial resolution is essential for examining how carsharing impacts vary across urban and suburban contexts as adoption scales. No downscaling or additional calibration was applied. All analyses rely on the full synthetic population.

3.2.2 Identification of potential carsharing adopters

Empirical studies consistently show that carsharing adoption is strongly associated with limited access to private vehicles. Carless households exhibit the highest propensity to join carsharing services, while households with intermittent access show moderate adoption rates. In contrast, households with unrestricted access to private vehicles are consistently found to be unlikely adopters [39, 42, 53, 90].

Based on this evidence, the analysis focuses on two potential adopter groups:

- *carless users*, who have no access to a household vehicle;
- *occasional car users*, who have intermittent or shared access to a household car.

Individuals with continuous access to a private vehicle are treated as principal car users and are assumed unlikely to adopt carsharing at scale. This group remains unchanged across all scenarios.

3.2.3 Operationalisation within the synthetic population

The MATSim synthetic population distinguishes three levels of car availability at the individual level: *never*, *sometimes*, and *always* available. These attributes are used directly to operationalise the adopter groups defined above. Individuals classified as *never available* are assigned to the carless user group, while those classified as *sometimes available* are assigned to the occasional car user group.

Table 3.1 summarises the distribution of the synthetic Montréal population across the three car availability groups. The focus of the analysis is restricted to carless and occasional car users, as these groups are consistently identified in the literature as the most plausible carsharing adopters.

Table 3.1 Distribution of the synthetic Montréal population by car availability.

Car availability group	**Count**	**Share**
Never available (carless users)	462,491	15.4%
Sometimes available (occasional users)	1,078,032	35.6%
Always available (principal car users)	1,465,442	48.9%

To ensure that behavioural adjustments are applied only where meaningful, individuals whose daily car-related distance is below 1 km are excluded from the eligible population, as such short distances are typically walkable or served by public transport. In addition, only individuals holding a valid driving licence are considered eligible adopters.

After applying these criteria, the eligible population consists of:

- 10,008 carless users;
- 605,625 occasional car users.

3.2.4 Spatial structure and residential density classification

To examine how the environmental impacts of carsharing evolve as adoption expands across space, the synthetic population is linked to residential census tracts. Each individual is assigned to a census tract based on the location of their home activity, allowing travel behaviour to be analysed in relation to neighbourhood-level characteristics.

Residential density is calculated for each census tract as the ratio of the number of synthetic residents to the land area of the tract. This measure provides a simple and transparent proxy for urban form, capturing differences between dense central areas and lower-density suburban environments within the metropolitan region.

Census tracts are then grouped into five residential density classes using a quantile-based classification. The classes are defined such that each contains approximately one-fifth of the synthetic population, ordered from lowest density (*Q1*) to highest density (*Q5*). This approach avoids the use of arbitrary density thresholds and ensures that comparisons across classes are not driven by uneven population sizes. The resulting density classes therefore represent relative positions along the metropolitan density gradient rather than absolute definitions of urban or suburban areas.

Figure 3.1 illustrates the resulting spatial distribution of residential density classes across the metropolitan region.

These density classes provide the spatial framework within which adoption scenarios are constructed. They allow adoption to be interpreted not only in terms of the share of the population adopting carsharing, but also in terms of the urban contexts in which adoption occurs. How these classes are used to define adoption sequences is described in the following subsection.

3.2.5 Scenario development and adoption scaling

Carsharing adoption is modelled as a progressive process, increasing from 0 to 100 percent of each eligible group. Adoption is treated as a continuous policy variable rather than a

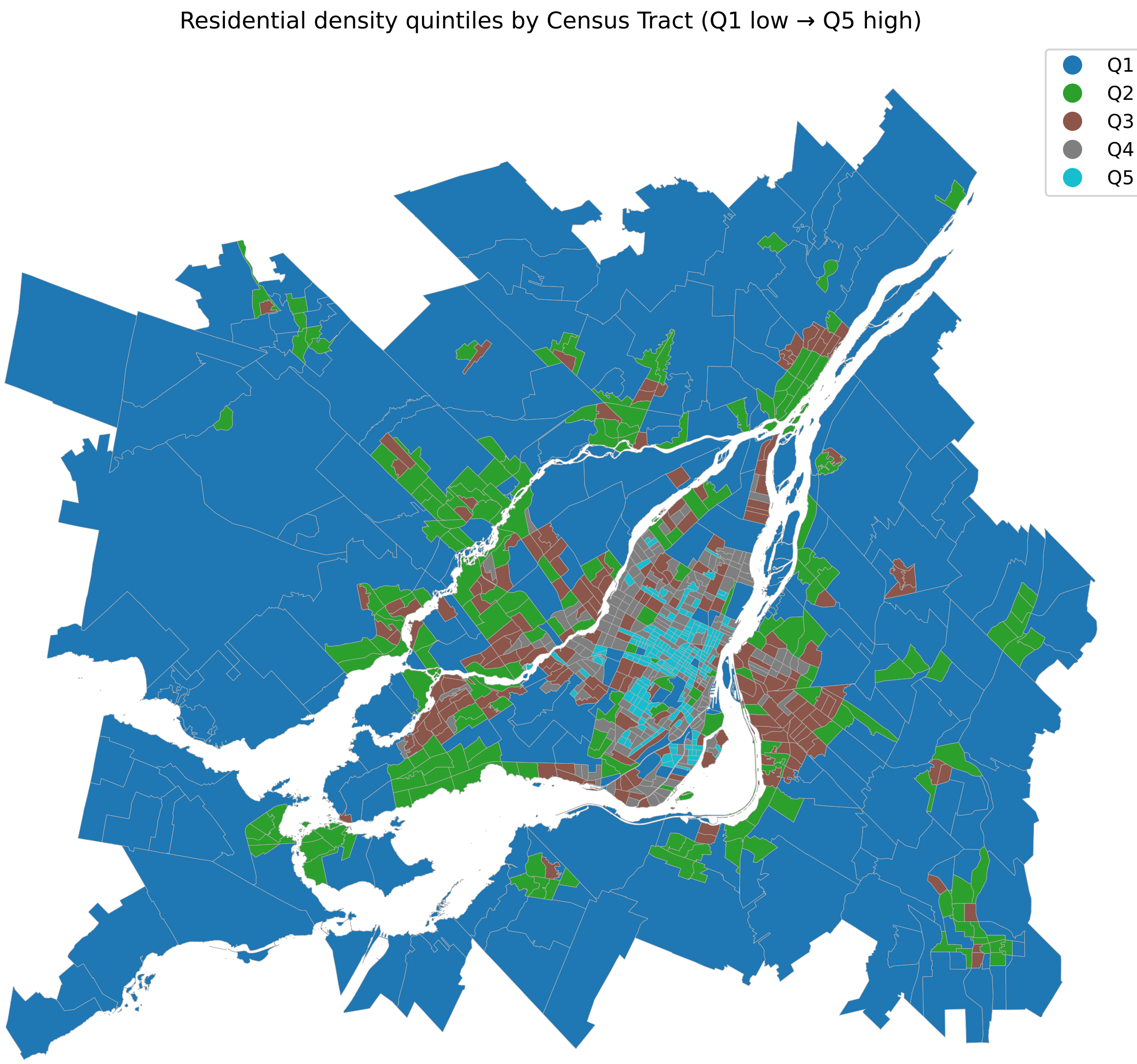

Figure 3.1 Residential density quintiles by census tract in the Greater Montréal Area. Census tracts are grouped into five classes (Q1–Q5) based on synthetic population density, from lowest (Q1) to highest (Q5).

binary outcome. This allows the analysis to examine how environmental impacts evolve as carsharing expands beyond early adopters, rather than focusing on a single assumed uptake level.

Adoption scaling affects only the *composition of adopters*. Behavioural adjustments, fleet characteristics, and life-cycle emission intensities are held constant across all adoption levels. This design isolates the role of adoption structure in shaping aggregate environmental outcomes.

Adopters are selected sequentially based on two dimensions:

- total daily travel demand;
- residential location, classified using census-tract-based density categories.

In the main analysis, adopters with lower total travel demand living in higher-density areas are prioritised. This ordering reflects the spatial concentration of existing carsharing services and the higher feasibility of shared mobility in dense neighbourhoods. Sensitivity analyses explore alternative adoption orders, including high-demand-first and randomised selection, to assess the robustness of system-level outcomes under identical behavioural assumptions.

3.2.6 Changes in mobility patterns of carsharing adopters

Carsharing adoption is represented through literature-based behavioural adjustments applied to individuals selected as adopters at each adoption level. The direction and magnitude of these adjustments depend on prior access to a private vehicle. Individuals who are not selected as adopters retain their baseline mobility patterns.

Reference values. The *Medium* scenario uses central behavioural adjustments reported in the North American carsharing literature, drawing on before–after and comparative evidence from Cervero et al. [42], Cooper et al. [91], and Martin and Shaheen [92]. The use of literature-based behavioural adjustments is a common approach in environmental assessments of carsharing, where city-specific before–after datasets are rarely available. Existing studies have similarly relied on empirically observed behavioural changes from member surveys or pilot programs and applied them as exogenous inputs to evaluate environmental outcomes [17, 24, 25, 31].

To date, no comparable before–after behavioural change study has been conducted for Montréal. As such, the behavioural adjustments adopted here should not be interpreted as precise representations of local responses. Instead, they provide a transparent and documented reference case for examining how well-established behavioural mechanisms may translate into environmental impacts in the Montréal context.

Behavioural bounds. Rather than introducing additional behavioural modelling assumptions, uncertainty in the transferability of these literature-based effect sizes is represented through behavioural bounds. The *Low* and *High* scenarios are defined as a uniform $\pm 25\%$ scaling around the reference values. These bounds are not intended to represent alternative behavioural mechanisms or to predict local behaviour. Their purpose is to test how sensitive system-level environmental outcomes are to plausible variation in the magnitude of behavioural change, given the absence of Montréal-specific empirical evidence.

The resulting parameter values used in the three behavioural scenarios are summarised in Table 3.2. Figure 3.2 and 3.3 illustrate the corresponding change in total daily travel distance for carsharing adopters.

3.2.7 Fleet representation and vehicle size assumptions

Private vehicle characteristics are based on the 2022 vehicle registry of the Société de l'assurance automobile du Québec (SAAQ), which reports approximately 1.89 million passenger vehicles in circulation in the GMA [93]. Vehicles are classified by drivetrain and by curb-mass-based size categories derived directly from the Québec fleet. These size classes therefore reflect North American vehicle characteristics, rather than European segmentation schemes.

The registered private fleet is dominated by petrol vehicles, with electric vehicles representing only a small share. Small and mid-size vehicles together account for more than 90 percent of all registered passenger cars (Table 3.3), while large vehicles constitute a minority and therefore play a limited role in aggregate metropolitan-scale life-cycle impacts.

Carsharing vehicles are represented using Communauto's 2022 operational fleet. This fleet consists exclusively of small and mid-size vehicles across petrol and battery-electric drivetrains (Table 3.3). The representation reflects the observed fleet composition at the time of analysis, rather than a projected or optimised future configuration.

Vehicle model information for the Communauto fleet is confidential and therefore not reported. To avoid confounding life-cycle comparisons with unobserved differences in vehicle specifications, vehicle mass and battery mass are parameterised at the size-class level and held identical across private and carsharing fleets. Battery mass values are anchored to representative electric vehicle models: Fiat 500e (42 kWh) and Renault Zoe (52 kWh) for small vehicles (midpoint 320 kg), Tesla Model 3 Long Range (77 kWh) for mid-size vehicles, and Tesla Model S (100 kWh) for large vehicles [94].

Table 3.2 Behavioural bounds applied to literature-based reference values. The *Medium* scenario reproduces reported percentage changes. The *Low* and *High* scenarios represent a uniform ±25% variation in effect magnitude relative to the reference values.

Adopter group	**Behavioural effect (%)**	**Low**	**Medium**	**High**	**Source**
Carless users	Shift from car-passenger to carsharing	14.3	19.0	23.8	[42]
	Change in public transport use	−25	0	+25	[92]
	Change in cycling	+1.5	+2.0	+2.5	[92]
	Change in walking	+5.3	+7.0	+8.8	[92]
Occasional car users	Reduction in private-car driving	−18.8	−25.0	−31.3	[91]
	Shift from car driving to carsharing	4.1	5.4	6.8	[42]
	Change in public transport use	−25	0	+25	[92]
	Change in cycling	+1.5	+2.0	+2.5	[92]
	Change in walking	+5.3	+7.0	+8.8	[92]

Table 3.3 Fleet composition and mass parameterization by vehicle size class for the private passenger-vehicle fleet and the Communauto carsharing fleet.

Size class	**Share (%)**	**Petrol (%)**	**Diesel (%)**	**EV (%)**	**Vehicle mass (kg)**	**Battery mass (kg)**
Private passenger-vehicle fleet						
Small	52	98.9	0.6	0.5	1,285	320
Mid-size	39	95.5	0.5	4.0	1,690	480
Large	9	87.5	7.7	4.8	2,258	550
Communauto carsharing fleet						
Small	60	95	0	5	1,285	320
Mid-size	40	95	0	5	1,690	480
Large	0	–	–	–	–	–

Representative fuel and energy consumption parameters are defined by vehicle size class and applied consistently to both fleets (Table 3.4). These values correspond to typical combined (city and highway) averages for passenger vehicles in Canada, based on Natural Resources Canada fuel-consumption guides and EnerGuide ratings [95].

In the mixed-fleet configuration, battery-electric vehicles are represented in all size classes in proportion to the observed 2022 fleet composition (Table 3.3). Although EVs remain a minority of the registered private fleet, their share is non-zero across small, mid-size, and large vehicles, and the Communauto fleet similarly includes EVs within both small and mid-size classes. This parameterization preserves consistency with the empirical registry and operator fleet data while allowing life-cycle intensities to reflect the observed drivetrain mix by size class.

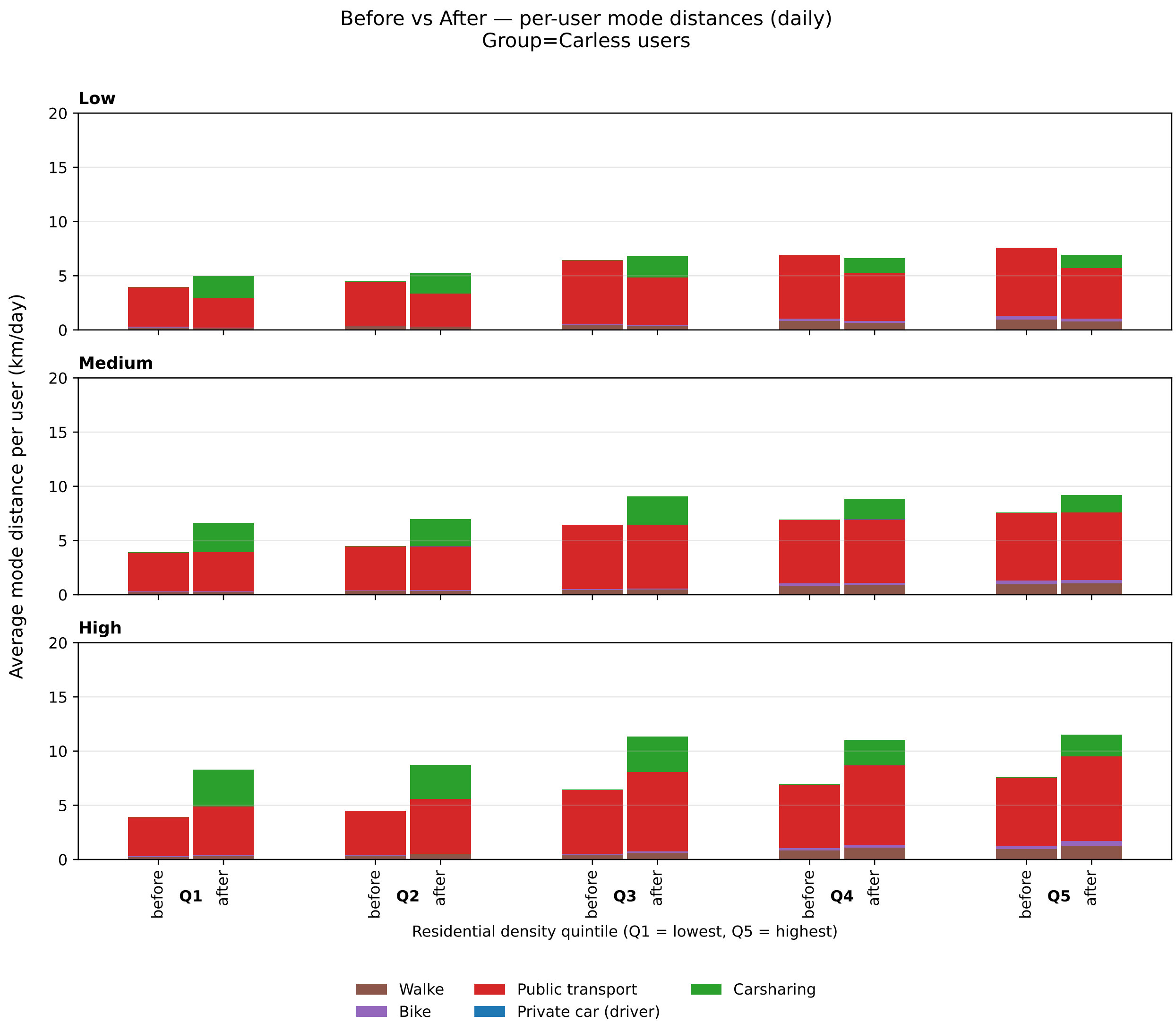

Figure 3.2 Before and after total travel distance for carsharing adopters across carless user groups.

3.2.8 Life-cycle assessment

LCA framework is used to quantify carbon fooprints associated with motorised travel across carsharing adoption levels. LCA is appropriate in this context because it captures vehicle production, energy supply, and EoL processes in addition to use-phase emissions, allowing behavioural change and fleet electrification to be evaluated consistently within a single accounting framework.

The system boundary is city-wide and includes private cars, carsharing vehicles, public transport, and active modes. All vehicle pathways follow a cradle-to-grave boundary, while fuels

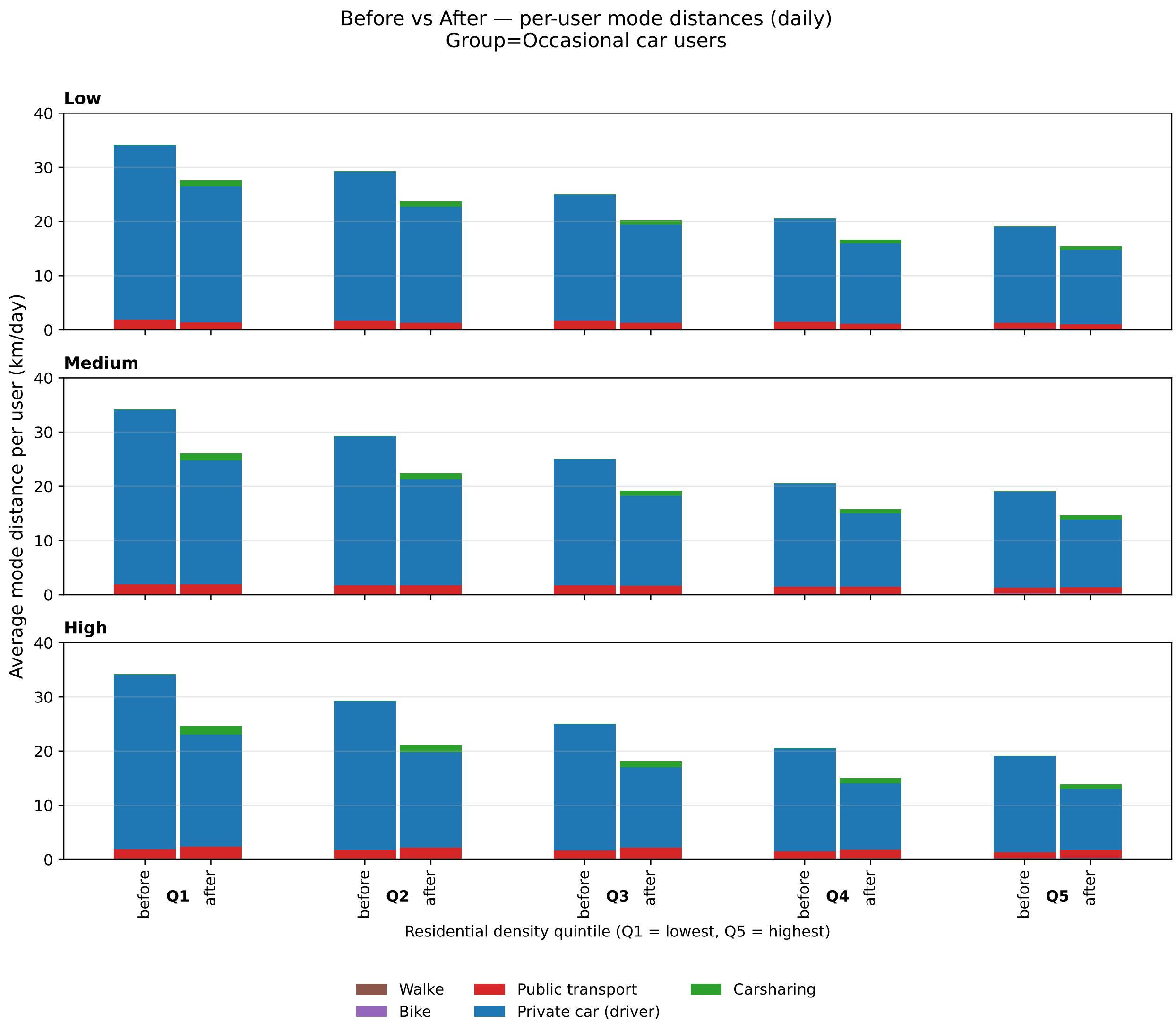

Figure 3.3 Before and after total travel distance for carsharing adopters across occasional car user groups.

and electricity follow a well-to-wheel boundary. Electricity impacts reflect Québec's low-carbon generation mix (approximately 98% renewable). Detailed system boundaries, inventory choices, and background processes are documented in Appendix A.

Life-cycle inventory

The life-cycle inventory (LCI) was assembled using OpenLCA 2.6.0 with the ecoinvent 3.8 cut-off database. Private cars are represented using three drivetrains (petrol, diesel, battery electric) and three size classes (small, mid-size, large), reflecting the observed vehicle registry in Montréal. Carsharing vehicles are represented using small and mid-size vehicles only,

Table 3.4 Representative fuel and energy consumption parameters by vehicle size class, applied consistently to both private and carsharing fleets.

Size class	**Petrol (L/100 km)**	**Diesel (L/100 km)**	**EV (kWh/100 km)**	**EV battery capacity (kWh)**
Small	7.2	5.8	15	47
Mid-size	8.6	7.0	18	77
Large	11.0	9.0	22	100

consistent with the current Communauto operational fleet.

LTM is a key scaling parameter linking vehicle production and EoL impacts to mobility demand. For public transport and active modes, LTM values embedded in ecoinvent transport service processes are used directly. For private and carsharing vehicles, LTM is derived endogenously from observed travel behaviour.

Specifically, LTM is calculated from the average daily driving distance of principal car users and occasional car users. Individuals with less than 5 km of daily car driving are excluded to avoid zero-inflation from structurally inactive driving days. The resulting average daily distance is scaled to an annual value using a correction factor of 1.228 to align survey-day travel with reported annual driving statistics [96], multiplied by 365 days per year, and finally multiplied by the average vehicle lifetime of 8.67 years observed in Montréal. This yields a private-vehicle LTM of 110,490 km.

Carsharing vehicles are assumed to achieve twice this LTM (220,980 km), reflecting higher functional use per vehicle in shared fleets [32]. This assumption is applied uniformly and serves as a material efficiency mechanism rather than a behavioural outcome.

Battery lifetime is assumed to coincide with vehicle lifetime. Traction batteries are retired together with the vehicle, and no battery replacement during the service life is modelled. Battery production and EoL impacts are therefore allocated across the same LTM as the vehicle itself. This is a conservative and transparent modelling choice given the uncertainty surrounding battery replacement rates, second-life applications, and reuse pathways at scale.

Vehicle occupancy is assumed to be one for passenger cars. For public transport modes, including buses and trains, occupancy levels follow the default assumptions provided in the ecoinvent database. This ensures consistency with the underlying life-cycle inventories and avoids introducing additional behavioural assumptions.

Life-cycle impact assessment

Climate change potential (kg CO_2-eq) is used as the primary impact indicator and is calculated using the ReCiPe Midpoint (H) method. Other impact categories are computed but available only in the Supporting Information in Appendix A.

To link LCA results with travel activity, each mode is assigned an emission intensity expressed in kg CO_2-eq per person-kilometre. For private cars, intensities are computed as fleet-weighted averages across vehicle size and drivetrain, using Montréal's observed fleet composition. For carsharing, intensities reflect the current Communauto fleet mix in the mixed-fleet configuration.

In sensitivity analyses exploring full electrification, all-electric fleet intensities are computed as size-weighted averages using battery-electric vehicle parameters only.

Public transport is represented as an equal split between diesel bus and electrified metro. Cycling and walking intensities follow ecoinvent defaults. Distance travelled as a car passenger is not assigned a separate emission intensity; instead, it is used to infer carsharing driving distance for carless users following adoption.

Fleet-weighted mode-specific intensities used in the scenario analysis are shown in Figure 3.4, while detailed size- and drivetrain-specific intensities, background processes, and electricity and fuel assumptions are reported in Appendix A.

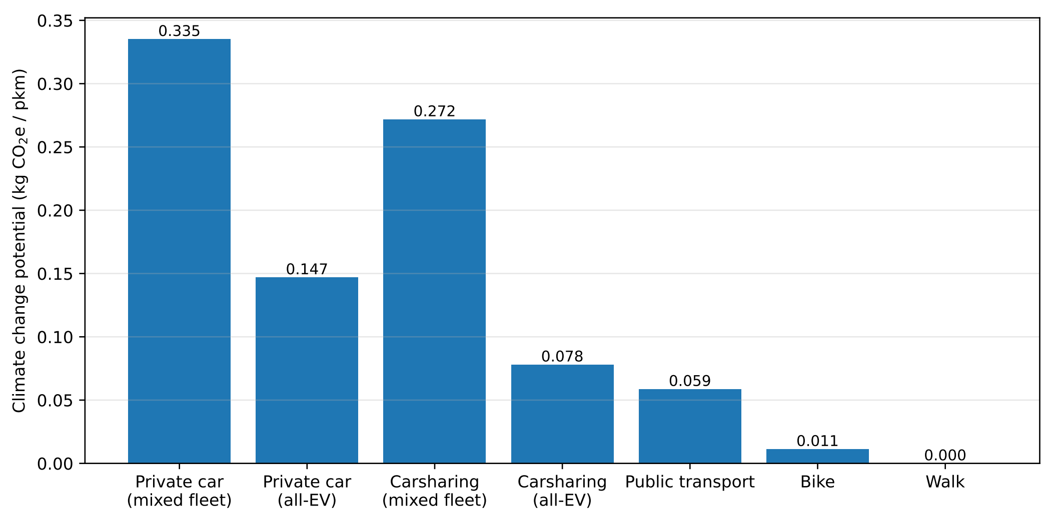

Figure 3.4 Life-cycle emission intensities used in the scenario analysis (fleet-weighted values).

3.2.9 Life-cycle emission calculation

For each individual i, daily travel distances by mode are combined with mode-specific life-cycle emission intensities. Emission intensities account for vehicle production, energy use, maintenance, and EoL treatment. For each mode m, the emission intensity I_m represents cradle-to-grave greenhouse gas emissions per person-kilometre.

Individual-level life-cycle emissions are calculated as:

$$E_i = \sum_m d_{i,m} \cdot I_m, \tag{3.1}$$

where $d_{i,m}$ denotes the distance travelled by individual i using mode m.

City-wide emissions are obtained by aggregation across all individuals:

$$E_{\text{city}} = \sum_{i=1}^{N} E_i. \tag{3.2}$$

These calculations are applied consistently to the baseline case and to a range of carsharing adoption scenarios. Behavioural adjustments are applied exogenously using estimates from empirical studies, allowing the analysis to examine how documented behavioural responses translate into life-cycle impacts as carsharing adoption expands across population groups and space.

3.3 Results

3.3.1 Individual carsharing user's impacts

This subsection reports average per-user life-cycle emissions before and after carsharing adoption for the two adopter groups, evaluated at full adoption under the mixed fleet configuration. Results are shown separately by residential density quintile and behavioural bound (Low, Medium, High).

For carless users, average per-user emissions increase after adoption across all density quintiles and behavioural scenarios (Figure 3.5). The magnitude of the increase varies with residential density and behavioural bounds, but the direction of change is consistent. Higher-density quintiles exhibit lower absolute emissions both before and after adoption, reflecting shorter baseline travel distances. The spread between low, medium, and high behavioural scenarios is modest relative to differences across density classes.

For occasional car users, average per-user emissions decrease after adoption in all density

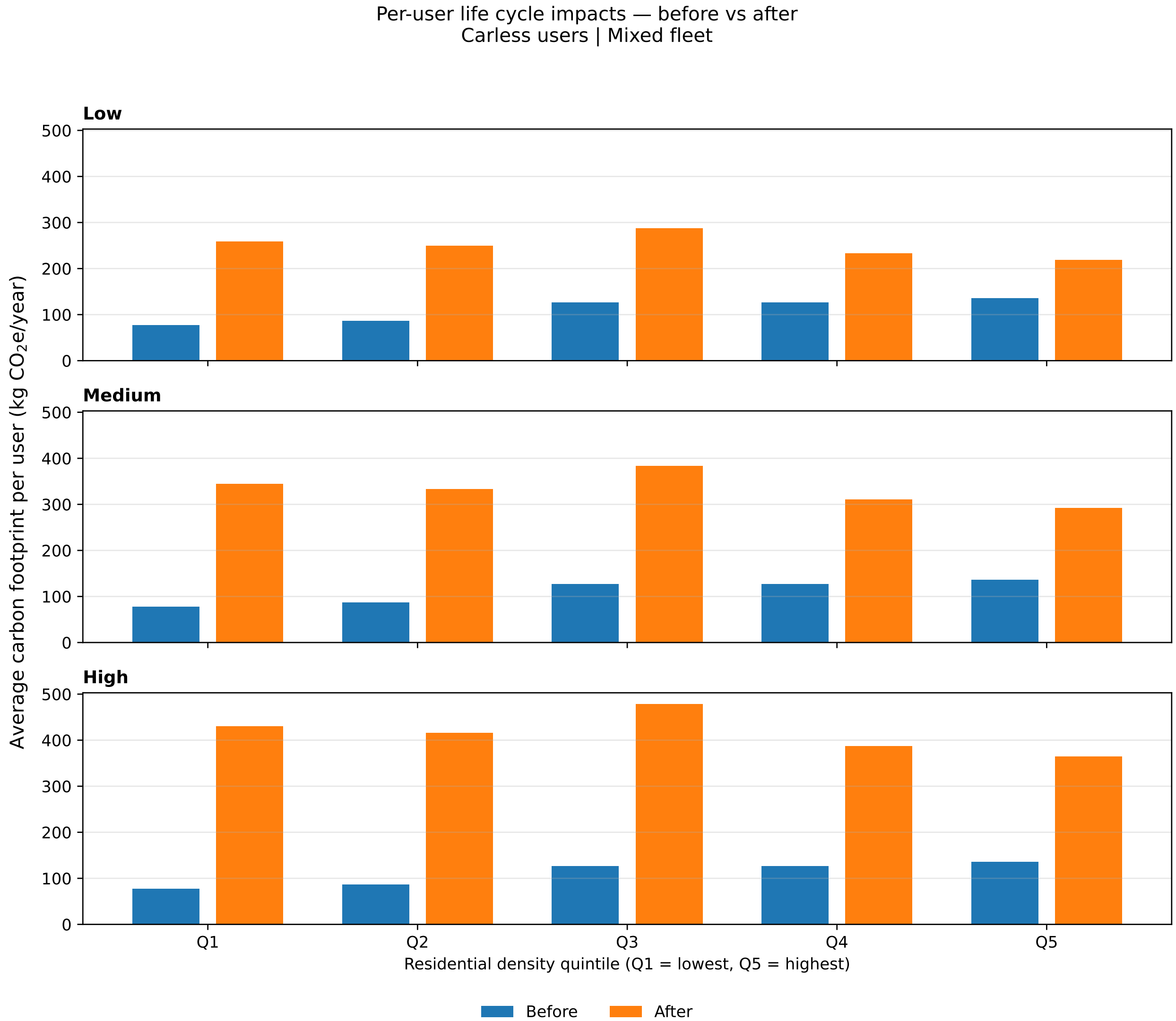

Figure 3.5 Average per-user life-cycle emissions before and after adoption for carless users, by residential density quintile and behavioural bound (mixed fleet).

quintiles (Figure 3.6). Emission reductions are larger in higher-density areas and increase in magnitude from the low to the high behavioural bound. Baseline emissions are substantially higher than for carless users, and the absolute change associated with adoption is correspondingly larger.

Across both groups, residential density strongly structures per-user life-cycle impacts, while behavioural bounds primarily affect the magnitude rather than the direction of change. These individual-level results form the basis for the aggregated system-level analysis presented in the following subsection.

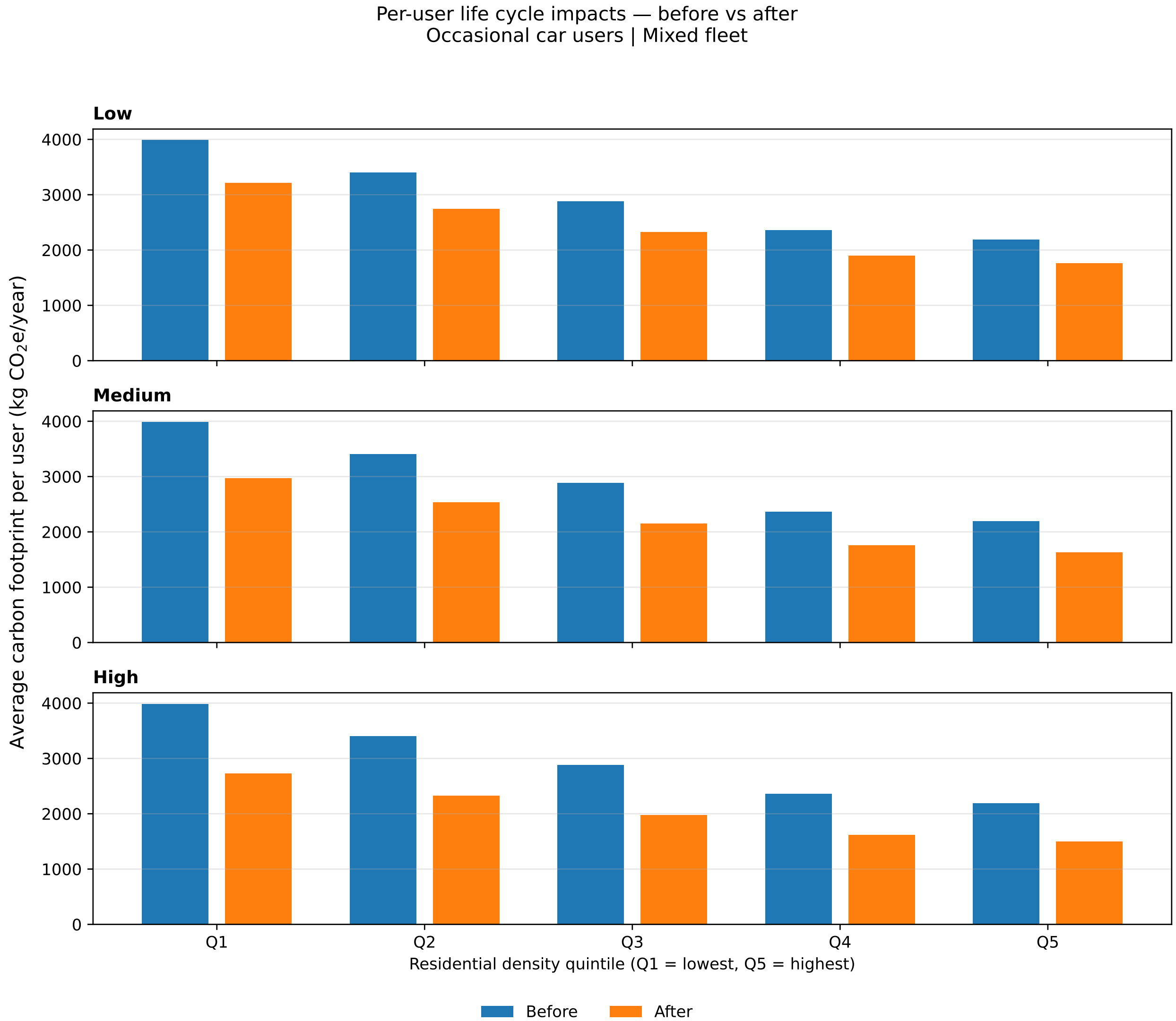

Figure 3.6 Average per-user life-cycle emissions before and after adoption for occasional car users, by residential density quintile and behavioural bound (mixed fleet).

3.3.2 System-level life-cycle emissions under progressive adoption

System-level impacts are assessed by aggregating life-cycle emissions across all individuals within each eligible group as carsharing adoption increases from zero to full uptake. At each adoption level, total emissions are computed as the sum of emissions from carsharing adopters under adjusted mobility patterns and non-adopters retaining their baseline behaviour. Adoption is expressed as a relative share of the eligible population, ranging from 0 (no adoption) to 1 (full adoption).

Figure 3.7 presents the corresponding results for carless users. Because adoption introduces

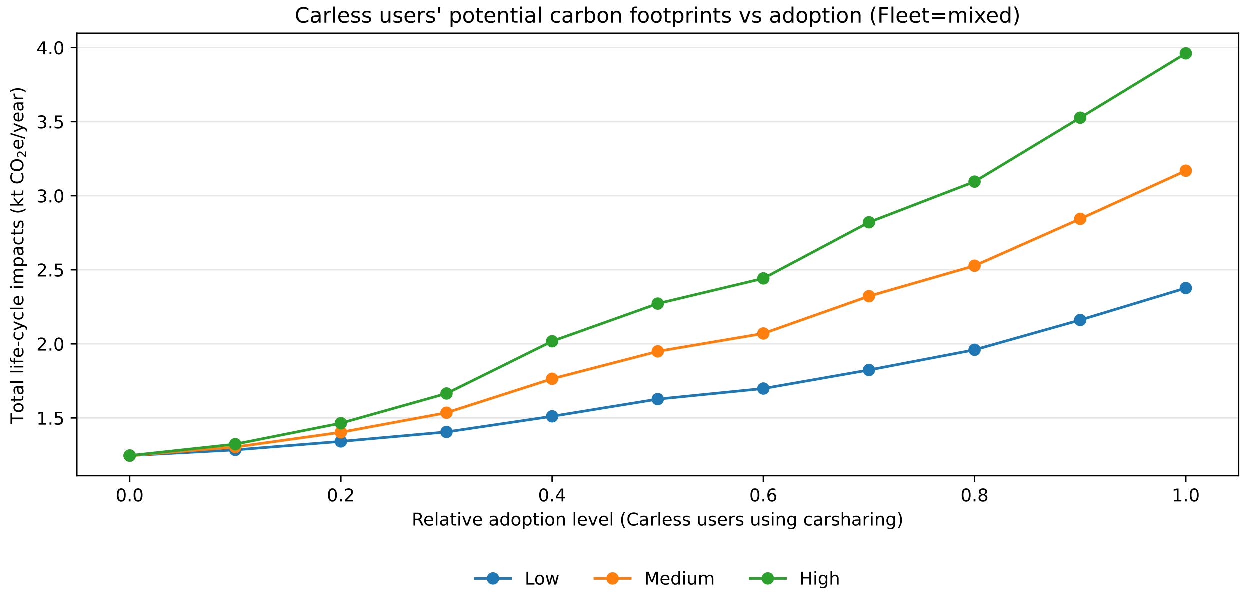

Figure 3.7 Total life-cycle emissions of carless users as a function of carsharing adoption level under a mixed fleet. Adoption is expressed as the relative share of the eligible population (0 = no adoption, 1 = full adoption). Total emissions include both carsharing adopters and non-adopters at each adoption level.

direct access to driving for this group, total emissions increase with adoption level under all behavioural bounds. As with occasional users, emissions at zero adoption are identical across scenarios, and divergence between behavioural bounds grows with increasing adoption.

Figure 3.8 shows total annual life-cycle emissions for occasional car users under a mixed fleet. At zero adoption, total emissions are identical across behavioural scenarios, as no individual has yet adopted carsharing. As adoption increases, total emissions change monotonically with adoption level, reflecting the cumulative effect of behavioural adjustments applied to a growing share of the population. Differences between the low, medium, and high level behavioural bounds become increasingly visible as adoption approaches full uptake.

Together, these figures describe how aggregate life-cycle emissions evolve as carsharing scales from a niche service to full adoption within each eligible group, under identical fleet assumptions and behavioural mechanisms.

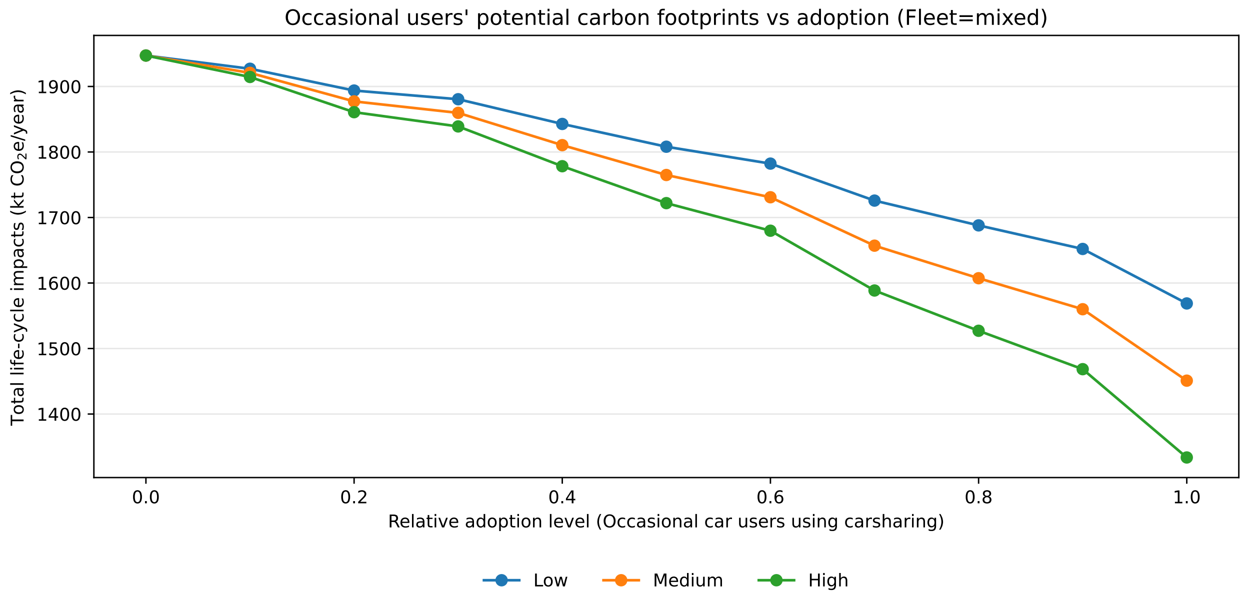

Figure 3.8 Total life-cycle emissions of occasional car users as a function of carsharing adoption level under a mixed fleet. Adoption is expressed as the relative share of the eligible population (0 = no adoption, 1 = full adoption). Total emissions include both carsharing adopters and non-adopters at each adoption level.

3.4 Sensitivity analysis

3.4.1 Fleet electrification benchmark

This sensitivity analysis examines whether fleet electrification alters the direction of behavioural impacts associated with carsharing adoption when life-cycle emissions are considered. The analysis compares baseline travel behaviour with carsharing adoption under a fully electric fleet benchmark, applied uniformly to all adopters. Behavioural adjustments remain identical to those used in the mixed-fleet case.

Figure 3.9 and 3.10 report average life-cycle emissions per adopter before and after carsharing adoption for both adopter groups. For carless users, adoption under a fully electric fleet continues to increase average life-cycle emissions, although the magnitude of the increase is substantially reduced relative to the mixed-fleet case. For occasional car users, adoption continues to reduce average emissions, with electrification amplifying the reduction.

These results indicate that fleet electrification affects the magnitude of environmental impacts but does not change their direction. In particular, the increase in emissions observed for carless users persists despite near-zero use-phase emissions. This reflects the contribution of non-use life-cycle processes, such as vehicle production and EoL, which are not scaled by driving activity and therefore remain significant.

3.4.2 Carsharing adoption order and system-level outcomes

This sensitivity analysis examines how system-level life-cycle emissions respond to alternative assumptions about the *order in which eligible individuals adopt carsharing.* All scenarios rely on identical behavioural adjustments and fleet characteristics. Only the sequence in which adopters are selected differs across cases.

Three adoption orders are evaluated for each adopter group. In the first case, individuals with *lower total daily travel demand* adopt first. In the second case, individuals with *higher total daily travel demand* adopt first. In the third case, adopters are selected randomly from the eligible population. Adoption increases progressively from zero to full uptake in all cases.

Figures 3.11 and 3.12 report the resulting system-level emissions for carless users and occasional car users, respectively.

For **carless users**, adoption order has a clear influence on aggregate outcomes. When individuals with lower total travel demand adopt first, system-level emissions remain lower across the adoption range compared to both random adoption and the high-demand-first strategy. Prioritising carless users with higher total travel demand leads to higher system-level emissions throughout the scaling process.

For **occasional car users**, the pattern is reversed. When individuals with higher total travel demand adopt first, system-level emissions are lower and closely follow the nearly linear trend observed under random adoption. In contrast, prioritising lower-demand occasional users results in consistently higher system-level emissions over the adoption range.

Across both adopter groups, random adoption produces a smooth and approximately linear evolution of system-level emissions. Results are virtually identical across different random seeds, indicating that random selection averages behavioural effects across the eligible population at each adoption level.

In summary, these findings show that non-linear system-level responses is the result of the correlation between adoption order and user characteristics, rather than from behavioural assumptions or fleet parameters. Random adoption effectively averages behavioural effects across the eligible population at each adoption level, thereby reproducing a smooth and stable scaling pattern. This sensitivity analysis therefore highlights adoption order as a structural assumption that shapes aggregate outcomes, even when all other elements of the analysis are held constant.

3.5 Interpretation of results

This study examined how the environmental impacts of carsharing depend on adopter composition, adoption order, and spatial context when behavioural responses are specified exogenously and access to vehicle supply is assumed to be unconstrained. Behavioural adjustments are drawn from the existing literature and applied consistently across the population, without modelling adoption decisions or behavioural change mechanisms. The analysis therefore focuses on how documented individual-level responses aggregate to system-level life-cycle outcomes under different adoption structures. By moving beyond a single representative user, the chapter clarifies why reported environmental impacts of carsharing vary widely across studies and cities even when similar behavioural assumptions are used.

A central finding is that adopter composition strongly shapes system-level outcomes. For individuals with occasional access to a private car, carsharing adoption leads to consistent reductions in life-cycle emissions as adoption expands. These reductions arise because behavioural adjustments substitute private-car driving with shared mobility that has lower life-cycle emission intensities. In contrast, for individuals without prior access to a private vehicle, adoption increases life-cycle emissions across the adoption range. In this case, carsharing introduces additional motorised travel that was previously absent or limited, and this increase dominates aggregate outcomes even when shared vehicles exhibit lower emissions per kilometre.

The contrasting responses across user groups are consistent with findings reported by Amatuni et al. [17], who also identify divergent environmental outcomes depending on baseline car access and travel behaviour. They differ from results reported by Arbeláez Vélez and Plepys [54], who find emission reductions for carless users. This discrepancy can be explained by two factors. First, their analysis assumes behavioural changes that favour substitution away from motorised travel even among users without prior car access. Second, their assessment focuses primarily on use-phase emissions. In contrast, the present study applies life-cycle accounting and behavioural adjustments grounded in before–after evidence from North American contexts, which explicitly include increases in motorised travel for carless adopters. When production and other non-use phases are included, additional driving carries a measurable environmental cost even when vehicles are shared or electrified.

Drivetrain technology affects the magnitude of impacts but not their direction. Electrification substantially lowers life-cycle emission intensities for both adopter groups. For occasional car users, this amplifies the reductions associated with behavioural substitution. For carless users, it reduces the size of the increase but does not reverse it. This reflects a life-cycle constraint. Even when use-phase emissions are very low, emissions associated with vehicle production, maintenance, and EoL treatment remain significant. Additional motorised travel therefore continues to have environmental consequences under a life-cycle perspective. Electrification complements behavioural substitution but does not replace it.

Sensitivity analyses on adoption order further show that system-level outcomes depend not only on who adopts, but also on the sequence in which adoption occurs. For carless users, prioritising individuals with lower total travel demand results in lower aggregate impacts than prioritising high-demand individuals, while random adoption produces an approximately linear response. For occasional car users, prioritising high-demand individuals yields lower system-level emissions than prioritising low-demand users, reflecting the larger potential for substituting private-car driving among high-mileage drivers. These patterns indicate that non-linear aggregate responses emerge from correlations between user characteristics and adoption order, even when behavioural assumptions and vehicle characteristics are unchanged.

These results clarify the additional assumptions required to move from individual-level assessment to system-level interpretation. Average per-user effects are appropriate for characterising typical outcomes, but system-level impacts depend on how heterogeneous individual responses are distributed across the population and over the adoption process. Cities with similar average per-user effects may therefore experience different aggregate outcomes depending on population structure, spatial context, and adoption dynamics.

From a policy perspective, the findings indicate that carsharing is not a uniform climate mitigation instrument. Occasional drivers represent a clear opportunity for emission reductions, as their adoption reliably substitutes higher-intensity private-car travel. Carless users remain important for accessibility, equity, and system viability, but their large-scale adoption does not generate comparable climate benefits and may increase life-cycle emissions if introduced without strong multimodal integration. Policies that prioritise membership growth without considering adopter composition and spatial context risk overstating environmental benefits.

3.6 Limitations

Several limitations should be acknowledged. First, behavioural adjustments are drawn from North American empirical studies and are not calibrated specifically to Montréal. While this approach is consistent with much of the existing literature, it introduces uncertainty in the local magnitude of behavioural responses. Behavioural bounds are therefore used to explore plausible variation, but they do not replace Montréal-specific before–after evidence.

Second, the synthetic population represents a typical weekday and does not capture weekend, seasonal, or longer-term behavioural variation. Third, operational constraints such as vehicle availability, relocation, pricing, and waiting times are intentionally excluded in order to isolate aggregation effects arising from behavioural responses. These factors may further constrain operationally realised vehicle use in practice and are not reflected in the reported impacts.

Fourth, adoption order is represented using stylised rules based on total travel demand and residential density. This approach is suitable for examining how aggregation structure affects system-level outcomes, but it does not model behavioural diffusion or adoption decisions. In practice, adoption is influenced by social networks, pricing, marketing, and institutional factors that are not represented here. Future work could integrate explicit adoption and diffusion models to refine how adoption sequences unfold over time.

Additionally, adopter groups are analysed separately rather than combined into a single city-wide adoption scenario. This avoids introducing assumptions about cross-group adoption shares, but it also means that total impacts for Montréal as a whole are not estimated directly. Instead, the analysis highlights how aggregate outcomes depend on the relative size of each adopter group, which varies across cities.

Finally, while a full LCA framework is applied, the analysis does not seek to disentangle behavioural effects from life-cycle parameters such as vehicle production intensity or assumed LTM. At the system level, these elements are intrinsically linked. The results should therefore be interpreted as showing how documented behavioural responses translate into life-cycle impacts under fixed material and technology assumptions.

3.7 Summary and implications

This study assessed how the environmental impacts of carsharing evolve as adoption expands across a heterogeneous urban population, using empirically grounded behavioural adjustments and a LCA framework. Adoption was treated as a structured and progressive process rather than a binary intervention, making explicit how user heterogeneity, adoption order, and spatial context shape system-level outcomes.

The results show that environmental performance depends fundamentally on who adopts carsharing and how adoption unfolds across the population. Adoption by individuals with occasional access to a private car consistently reduces life-cycle emissions, while adoption by individuals without prior car access increases emissions due to additional motorised travel. These patterns persist across adoption levels and under alternative adoption orders and electrification assumptions. Electrification reduces the magnitude of impacts but does not reverse trends driven by behavioural change when life-cycle effects are considered.

The main contribution of this study is to clarify how system-level outcomes depend on aggregation structure when individual behavioural responses are specified exogenously. When adoption is random or implicitly average-based, aggregate impacts scale smoothly and approximately linearly. When adoption is structured by user characteristics and spatial context, system-level outcomes diverge substantially even under identical behavioural and technological assumptions. Adoption structure therefore conditions how individual-level effects translate into system-level environmental performance.

For research, these findings highlight the importance of explicitly stating aggregation assumptions when extending individual-level environmental assessments to population-scale conclusions. For policy, they indicate that carsharing should not be evaluated solely on the basis of membership growth. Environmental benefits depend on which users are reached and how adoption aligns with existing travel patterns and urban form.

Overall, this chapter provides a transparent assessment of behavioural scaling under controlled conditions. By linking documented behavioural responses to life-cycle impacts at the metropolitan scale, it clarifies why carsharing outcomes differ across contexts and prepares the ground for subsequent analyses of material efficiency and operational feasibility.

Supplementary data

Further details and complementary analyses related to the results can be found in Appendix A.

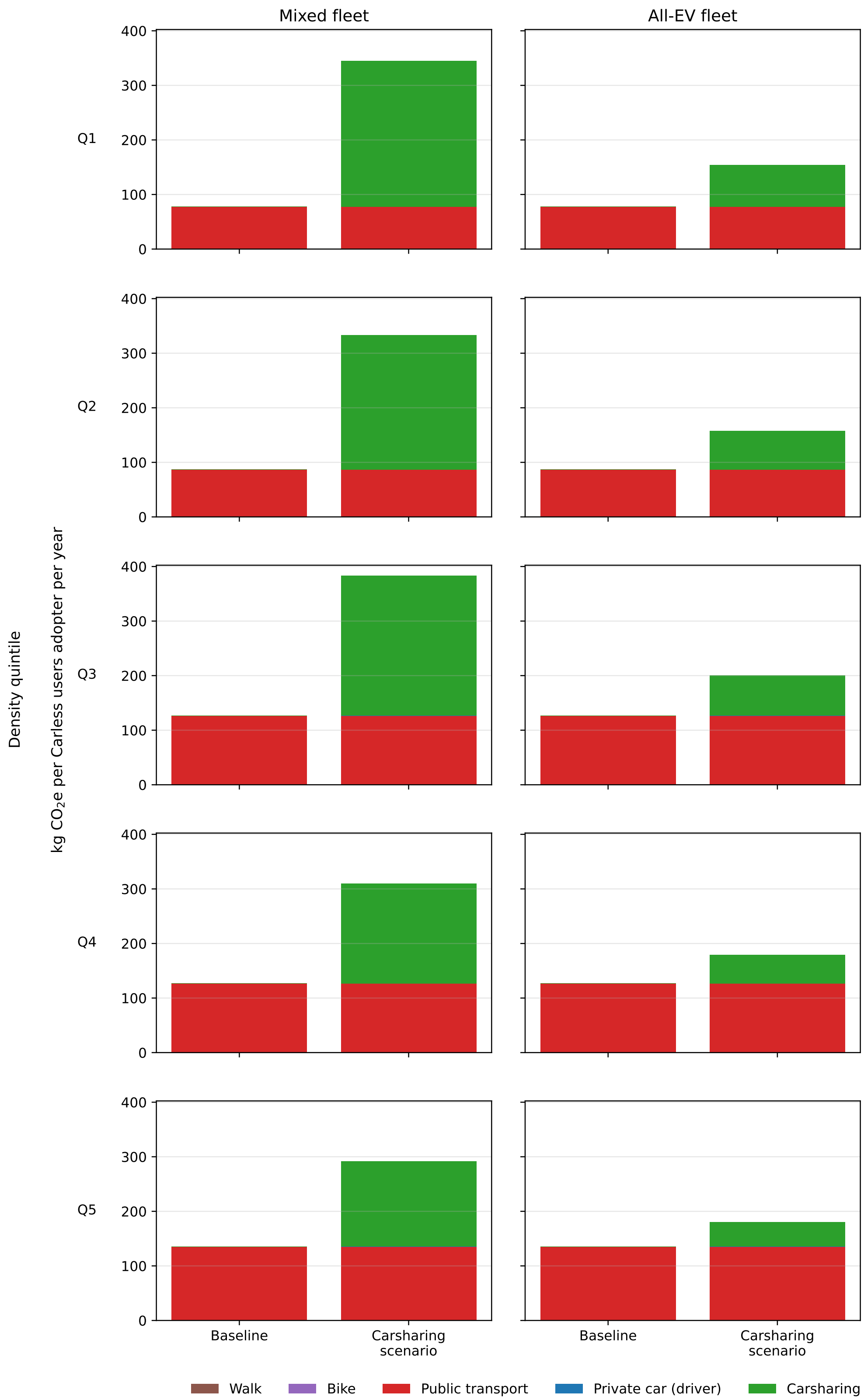

Figure 3.9 Carless users: Average life-cycle emissions per adopter before and after carsharing under the full electric benchmark.

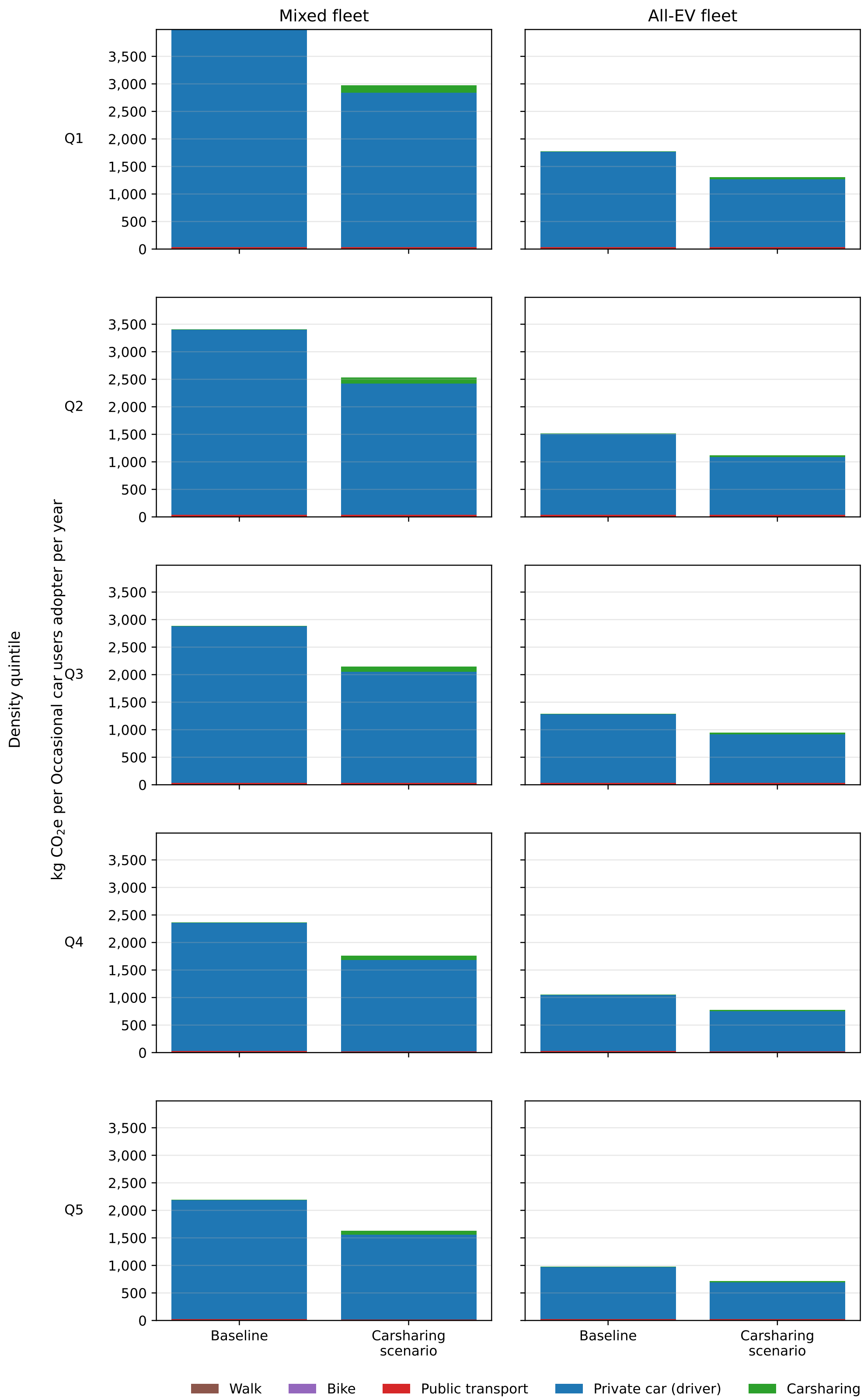

Figure 3.10 Occasional car users: Average life-cycle emissions per adopter before and after carsharing under the full electric benchmark.

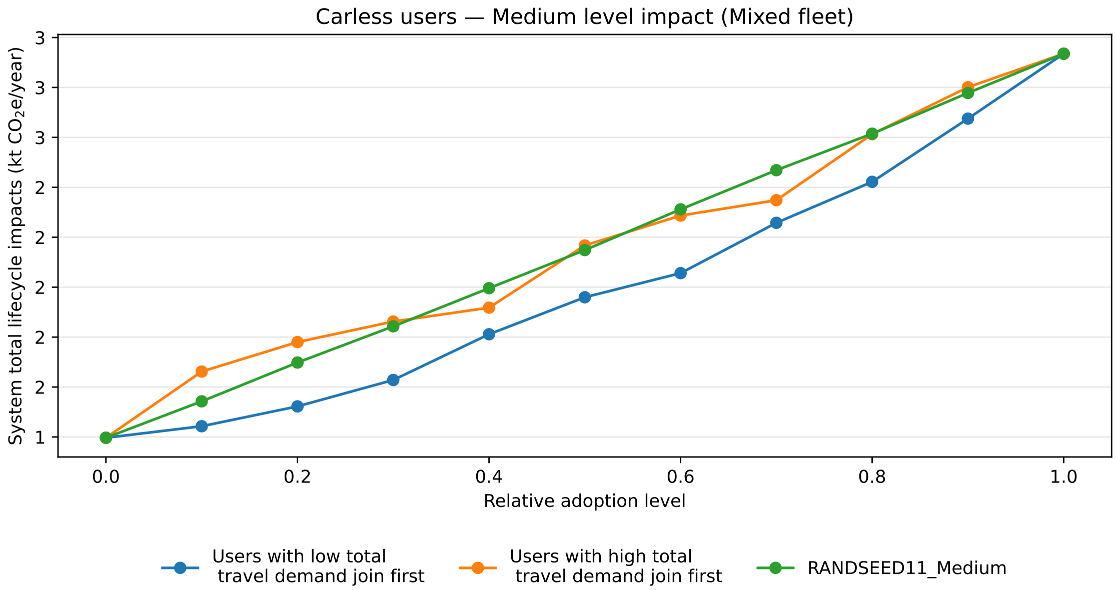

Figure 3.11 System-level life-cycle emissions for carless users under alternative adoption orders in the Medium behavioural scenario (mixed fleet). Results are shown for adoption sequences prioritising lower total travel demand, higher total travel demand, and random selection.

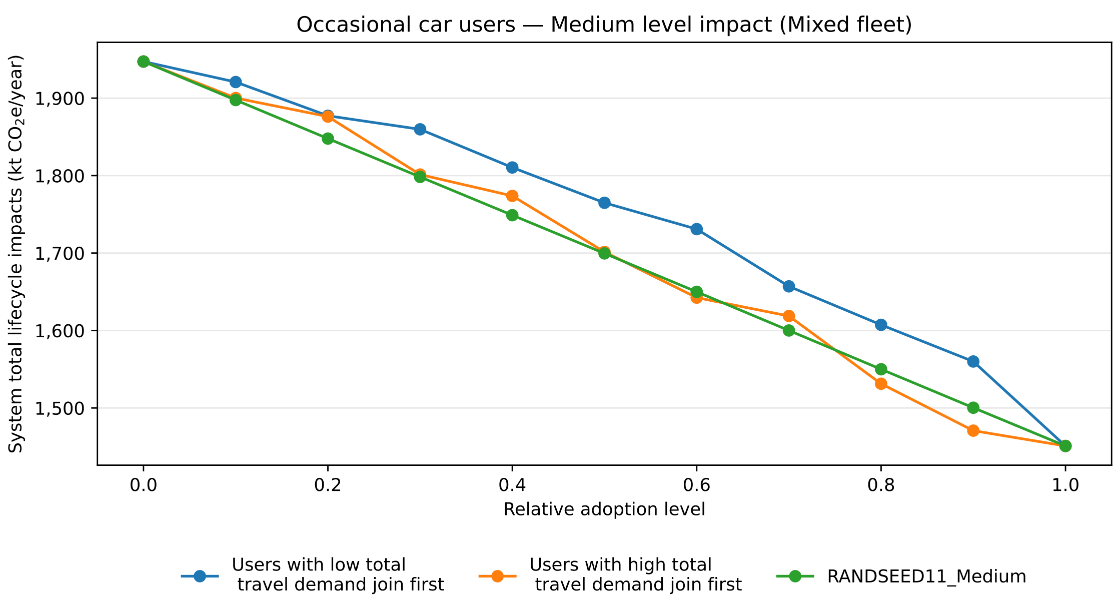

Figure 3.12 System-level life-cycle emissions for occasional car users under alternative adoption orders in the Medium behavioural scenario (mixed fleet). Results are shown for adoption sequences prioritising lower total travel demand, higher total travel demand, and random selection.

CHAPTER 4 MATERIAL EFFICIENCY STRATEGY AND LIFE-CYCLE IMPACTS

Chapter note.

This chapter is based on part of the peer-reviewed article:

Nong, Y. R., Ciari, F., Majeau-Bettez, G., Patouillard, L. (2025). "Material efficiency for transport decarbonization: A case study of carsharing in Montreal." *Transportation Research Part D: Transport and Environment*, 133, 104509. https://doi.org/10.1016/j.trd.2025.105037

The chapter integrates elements of the article within the broader dissertation framework. Minor editorial adaptations were made to ensure consistency with the dissertation structure.

4.1 Context and scope

Car production relies heavily on non-renewable materials such as steel, aluminum, and rare earth metals, and the manufacturing process generates substantial GHG emissions, contributing to the vehicle's overall environmental footprint even before use. LCA studies highlight that production and disposal emissions often represent a large portion of a vehicle's carbon footprint, particularly for EVs where manufacturing impacts are more prominent [15, 33]. These findings highlight the need for strategies that reduce material-related emissions across the vehicle life cycle.

One such strategy is improving material efficiency, which is best understood as a strategy that aims to provide the same or greater level of service with fewer material inputs [56]. In transport, this can be enhanced by optimizing vehicle design, promoting reuse, or enabling more intensive use of a smaller number of vehicles through shared mobility [36]. Among these strategies, shared use has been identified as a promising pathway, as it allows the fixed environmental costs of production and disposal to be distributed over a greater amount of transport service [14, 15, 33]. This service is often referred to as functional use, commonly measured by the LTM a vehicle accumulates over its service life. Shared mobility systems, such as carsharing, offer a practical example of this mechanism. For instance, although each car in the fleet requires the same material input as a privately owned car, the system as a whole needs fewer vehicles to satisfy the travel demand of users. By being used more intensively, these vehicles accumulate greater LTM. As a result, the embedded production and EoL emissions are distributed over more person-kilometre, reducing the carbon footprint per unit of service and reflecting a more efficient use of material resources without increasing total travel demand or vehicle stock.

This study aims to quantify the climate impacts and benefits that arise from one key mechanism associated with carsharing: an improved material efficiency achieved through the more intensive use of shared vehicles over time to provide same transport demand.

We implement this mechanism by examining the relationship between a vehicle's annual driving distance and its total LTM, which together determine how effectively a car is used over its service life and its resulting carbon footprint.

Using LCA, we first estimate carbon footprint of carsharing at the user level, expressed as carbon footprint per person-kilometre. These per-user results are then scaled to the city-wide level by modeling a continuum of hypothetical adoption scenarios while holding travel demand of each individual constant. These scenarios progressively shift eligible users to shared vehicle use in an ascending order of annual driving distance, allowing us to quantify how carbon impacts evolve as adoption expands within the car user population.

To support this analysis, we use empirical data from Quebec's vehicle retirement records to estimate LTM as a function of annual driving distance, a synthetic population representing mobility demand in Montreal, and operational data from Communauto to model shared vehicle usage.

The central research question guiding this study is: How does carsharing influence carbon footprint through greater material efficiency, and how do these efficiency gains vary across user types and levels of adoption at the city-wide scale?

This study contributes to the literature by combining a material efficiency strategy with bottom-up, user-level modeling to estimate the climate impacts and benefits of carsharing. While it does not model behavioural changes, which are often a major focus of shared mobility research, it complements such studies by isolating a quantifiable mechanism with a direct monotonic relationship: the more intensive use of vehicle through shared mobility lowers the non-operational related impacts per person-kilometre. By focusing on this foundational effect and holding travel demand of each individual constant, the study provides a conservative baseline for understanding carsharing's environmental potential, offering insights for planning and scaling even in the absence of broader behavioural shifts.

4.2 Literature review

4.2.1 Material efficiency strategies in transportation

Material efficiency refers to optimizing resource use throughout a product's lifecycle, aiming to reduce raw material extraction, production inputs, and waste, while maintaining functionality and value [55]. This includes strategies such as lightweighting, recycling, reuse, demand reduction, and product life extension, all designed to minimize resource consumption and energy use while maximizing utility. In the transportation sector, these approaches have gained prominence for their potential to reduce environmental impacts.

At the vehicle level, lightweighting reduces both material input and operational energy use [87, 97, 98], while recycling and reuse help limit demand for virgin materials and reduce EoL waste [99]. Remanufacturing, for example, reusing carbon fiber-reinforced polymer frames [38], has also emerged as a promising strategy to close material loops and improve resource recovery.

At the system level, shared mobility services such as carpooling, public transit, and carsharing increase vehicle occupancy and utilisation, allowing fewer vehicles to meet the same mobility demand [36, 40]. Unlike private cars, which often sit idle for most of the day [100], shared vehicles serve multiple users and deliver more person-kilometres per unit of material input. In terms of material efficiency perspective, this intensification of use improves how effectively each vehicle delivers transport service over its lifespan and significantly reduces vehicle lifecycle emissions. Shared mobility systems like carsharing may also postpone or eliminate the need for private vehicle purchases [40, 69, 101]. This ultimately contributes to slower vehicle stock growth and lowering the upstream environmental burden of vehicle production, without implying a reduction in total travel demand.

Carsharing can therefore be interpreted as a system-level strategy for material efficiency, where more intensive vehicle use helps distribute fixed production impacts across more kilometres of service. While conceptually aligned with material efficiency principles, this mechanism remains underrepresented in carsharing assessments, which tend to emphasize behavioural or modal effects such as changes in car ownership, mode choice, and travel demand [6, 18, 19, 46]. To further understand the environmental significance of this mechanism, it is necessary to examine how production and EoL stages shape a vehicle's total carbon footprint.

4.2.2 Life cycle assessment of vehicle production and end-of-life

LCA is a standard method for evaluating the environmental impacts associated with all stages of a vehicle's service life, including raw material extraction, manufacturing, use, and EoL treatment. A consistent finding across many LCA studies is that there is a significant contribution of the production and disposal phases to a vehicle's total GHG emissions. This is especially true for EVs, where production-related emissions can outweigh those from the use phase, particularly in regions with clean electricity [15].

The vehicle manufacturing process involves energy-intensive activities such as mining, smelting, and fabrication of materials like steel, aluminum, and rare-earth elements. For EVs, battery production, especially lithium-ion cells, is a major contributor to the carbon footprint. As a result, the emissions associated with producing an EV are often substantially higher than those for an ICEV [16, 33]. Studies suggest that emissions from BEV production and battery systems can be nearly equivalent to the tailpipe emissions of ICEVs [16, 33].

Although less prominent than the production phase, the EoL stage also contributes to environmental impacts, particularly through energy used in dismantling, challenges in recycling, and residual material losses. Disposal emissions remain relatively fixed per vehicle, regardless of its lifetime usage. Therefore, vehicles that are retired early or driven minimally result in a higher per-kilometre carbon footprint, reflecting poor material efficiency [102]. LCA studies show that extending LTM of vehicle can mitigate these fixed emissions per kilometre [58]. However, many studies still rely on uniform or idealized assumptions that may not reflect real-world usage patterns. This limits the accuracy and relevance of LCA findings for shared mobility systems.

Additionally, few studies incorporate user-specific variation into LCA models. Yet carbon outcomes depend not only on vehicle characteristics, but also on how vehicles are actually used. Applying user-specific data, such as annual driving distance linked to observed retirement mileage, can help reveal how material efficiency varies across the population [102] and scales under different carsharing adoption scenarios.

In summary, LCA studies make it clear that addressing only the use-phase emissions of vehicles is insufficient for achieving deep decarbonization in transport. Significant reductions can be achieved by improving material efficiency, which requires focusing on upstream production impacts and downstream EoL processes [36, 37, 103]. The next section reviews how the environmental benefits have been framed in the carsharing literature and where material efficiency considerations remain missing or underdeveloped.

4.2.3 Evidence from carsharing studies

Recent review studies [6, 18, 19] emphasize that carsharing's environmental benefits arise from both behavioural and systemic changes. Environmental assessments of carsharing consistently demonstrate that it can reduce environmental impacts, particularly GHG emissions at both user and system levels. However, the magnitude of these reductions varies widely across studies, depending on local context, system design, and assumptions about user behaviour.

Arbelaez Velez [18] and Liao and Correia [6] highlight that demand-side dynamics—especially changes in usage behaviour, access pattern, and user characteristics—are central to understanding carsharing's environmental impacts. Carsharing can prompt users to give up private cars [**?**, 21, 30, 104], reduce their total driving distances [22, 31, 92], shift to more sustainable modes [17, 21, 22, 54, 104]. In many cases, these effects occur in combination, reinforcing each other [25]. These behavioural shifts remain the dominant lens through which carsharing's climate impacts and benefits are assessed.

Some studies also touched on vehicle-level material efficiency with implications on environmental outcomes of carsharing such as extended LTM [17, 57] and lightweight vehicle design combined with high occupancy [87].

Likewise, socio-demographic selection in carsharing adoption has been observed since the

2000s [52], and more recent research confirms that many carsharing users still share common traits [6, 51], raising questions about how results generalize as adoption expands to different groups of users. These observations suggest that, in addition to behavioural and system-level changes, carsharing outcomes may also be shaped by factors beyond behavioural changes and the heterogeneity of the users who adopt the service.

4.2.4 Research gap

Despite these insights, existing assessments of carsharing continue to frame climate impacts and benefits primarily through vehicle shedding, mode shift, and reduced travel demand. Other contributing mechanisms remain underexamined. In particular, material efficiency strategy in carsharing's climate impacts and benefits is not treated as a distinct factor and quantified with empirical data, although some studies have incorporated LTM extensions in their models [17, 57]. Similarly, user heterogeneity is often overlooked, with most evaluations assuming a uniform annual driving distance across private car owners rather than accounting for variation in actual use [17, 54, 84, 104], even though variation in annual driving distances can strongly shape outcomes [102]. Without accounting for such variability, existing studies risk overestimating environmental benefits and miss opportunities to identify which users contribute most to material efficiency gains.

This study addresses these gaps by modeling the effect of material efficiencies on carbon footprints of carsharing, at both the user and city-wide levels. By linking annual driving distance to lifetime vehicle mileage and life cycle emissions, we quantify how carsharing alters carbon outcomes across different user groups and adoption scenarios. This bottom-up, usage-based approach complements behavioural studies by highlighting a parallel mechanism with important implications for sustainable transport planning.

4.3 Study area

The Montreal GMA, with a population of around 4 million residents, serves as the focal point of this research. The GMA is divided into eight regions, with Downtown Montreal functioning as its economic hub. This area is notable for its higher population and job densities, particularly in the central neighborhoods. In contrast, regions outside the island of Montreal primarily feature lower-density suburbs. The GMA offers an array of transportation options, including four metro lines, five commuter rail lines (exo), one light rail transit (REM), and an extensive bus network. Despite the extensive public transit infrastructure, car remains the dominant mode of commuting. A survey conducted by Sioui et al. [44] of 1,311 households revealed that 48 % of typical Montreal households own at least one car, while 17.3 % own more than two cars. Similarly, Lachapelle et al. [105] found that 64 % of GMA commuters, including dwellers living in North and South Shore, travel to work by car.

4.4 Materials and methods

4.4.1 Life cycle assessment

In this study, we used `Carculator`, a Python-based LCA library, to implement our LCA model. Carculator is an open-source tool that allows for user-specific model adjustments and sensitivity analyses, incorporating stochastic uncertainty [15,16,106]. The LCI database used is `ecoinvent 3.8 cut-off`. This system model allocates environmental burdens to the first user of a material or product and excludes credits for downstream recycling or reuse. This approach is commonly used in attributional LCA to reflect immediate impacts of product use.

Goal and scope

The goal of the LCA is to quantify the climate benefits of one key mechanism associated with carsharing: *improved material efficiency through more intensive use of shared mobility infrastructure to provide the same transport demand.*

The system boundary includes vehicle production, use, energy supply, and EoL) phases. Only the production and EoL stages are directly relevant to material efficiency, as they capture embedded emissions amortized over a vehicle's lifetime mileage (LTM). Use-phase emissions are included to contextualize operational emissions and ensure completeness, but they are not central to the material efficiency outcomes targeted in this study.

Vehicle cycle The vehicle cycle refers to the material flows of the physical vehicle from production to end-of-life. It includes:

- **Vehicle production:** emissions and resource use from manufacturing major components (e.g., glider, powertrain, battery), including steel, aluminium, and plastics.
- **Vehicle EoL:** emissions from dismantling, recycling, and disposal. Efficient material recovery processes can reduce environmental impact.

Energy cycle The energy cycle encompasses energy provision and use during vehicle operation, emphasizing energy efficiency rather than material efficiency:

- **Energy supply:** emissions from extracting, producing, and distributing fuels or electricity.

- **Vehicle operation:** emissions from driving, including fuel combustion for ICEVs or electricity consumption for BEVs, as well as ongoing maintenance (e.g., oil changes, part replacements).

This delineation aligns with the LCA process diagram shown in Figure 4.1, illustrating interactions between the vehicle and energy cycles.

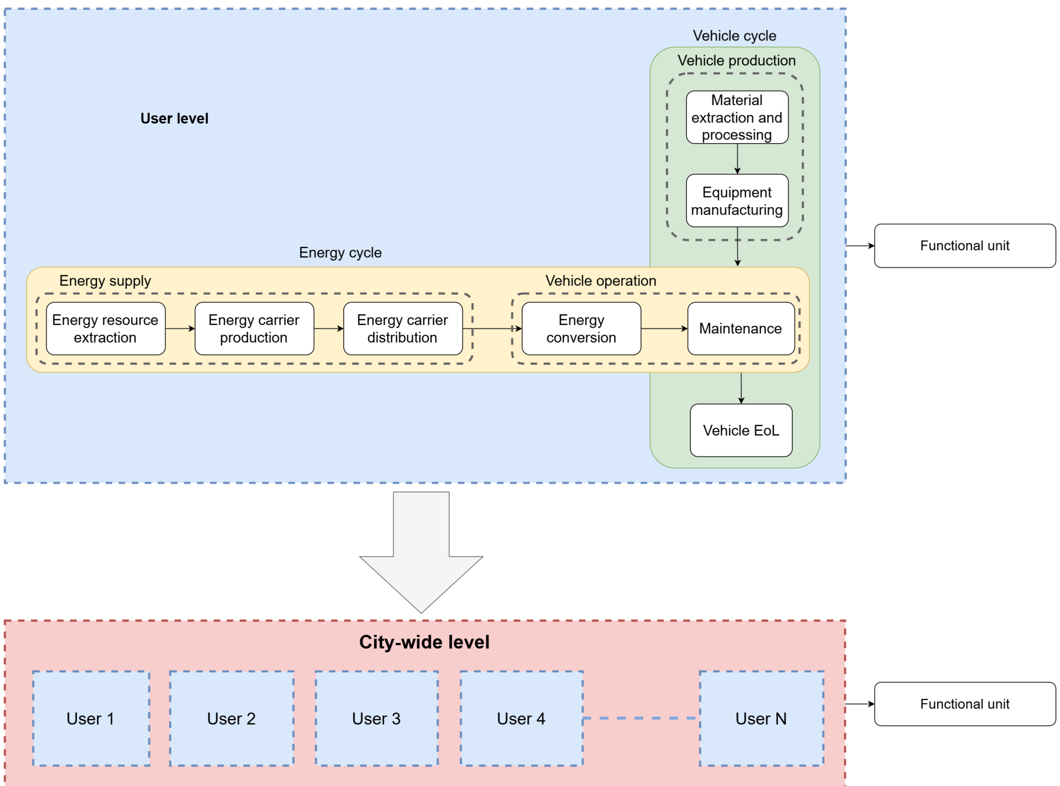

Figure 4.1 LCA process tree representing system boundaries and analytical framework used to evaluate environmental impacts of carsharing at the user and city-wide levels.

Excluded processes The following processes were excluded due to data limitations or because they fall outside the scope of material efficiency:

- environmental impacts of road construction and parking infrastructure,

- impacts related to carsharing operations, such as vehicle relocation and operator activities.

Functional unit

- **User-level carbon footprint:** 1 person-kilometre (pkm) of transport provided using either a private car or a carsharing vehicle.
- **City-wide carbon footprint:** total annual carbon footprint ($ktCO_2$-eq/year) associated with meeting the fixed personal mobility demand of Montréal's car-using population in 2024.

Geographical and temporal scope The analysis focuses on Montréal, Canada, incorporating regional travel behaviour, carsharing penetration, and electricity supply characteristics. The temporal scope corresponds to the year 2024.

Fleet composition assumptions To isolate the effect of LTM on carbon footprint, the same representative small-sized vehicle is assumed in both private and carsharing scenarios. This ensures that carbon footprint differences arise solely from LTM and not from vehicle type or technology.

While current carsharing fleets often favor smaller vehicles, it is unclear whether this trend would persist under large-scale adoption. To avoid speculative assumptions and maintain consistency, we apply the same representative vehicle across both scenarios.

- **BEV:** representing full electrification.
- **ICEV-p:** gasoline-powered, the most common fuel type in Montréal. Diesel ICEVs were excluded due to low market share and similar carbon profiles [16].

Calculation of carbon footprint

This section outlines carbon footprint (CF) equations at both the user level and the city-wide level.

User-level carbon footprint For an individual i using a private vehicle with technology j, the carbon footprint is:

$$\mathrm{CF}_{i,j}^{\mathrm{priv}} = \frac{\mathrm{CF}_{\mathrm{prod},j} + \mathrm{CF}_{\mathrm{EoL},j}}{\mathrm{LTM}_i} + \mathrm{CF}_{\mathrm{use},j} + \mathrm{CF}_{\mathrm{energy},j}. \tag{4.1}$$

Where:

- $\mathrm{CF}_{\mathrm{prod},j}$: production emissions (including battery for BEVs),
- $\mathrm{CF}_{\mathrm{EoL},j}$: end-of-life emissions,
- $\mathrm{CF}_{\mathrm{use},j}$: driving emissions,
- $\mathrm{CF}_{\mathrm{energy},j}$: upstream energy supply emissions,
- LTM_i: lifetime mileage of the vehicle used by individual i.

For carsharing, the CF uses the *fleet-average* LTM:

$$\mathrm{CF}_{i,j}^{\mathrm{cs}} = \frac{\mathrm{CF}_{\mathrm{prod},j} + \mathrm{CF}_{\mathrm{EoL},j}}{\overline{\mathrm{LTM}}_{\mathrm{fleet}}} + \mathrm{CF}_{\mathrm{use},j} + \mathrm{CF}_{\mathrm{energy},j}. \tag{4.2}$$

Note that $\overline{\mathrm{LTM}}_{\mathrm{fleet}}$ does not depend on the behaviour of individual users.

City-wide carbon footprint At the city level, the carbon footprint is aggregated across all car users. For adoption rate R and technology j:

$$\mathrm{CF}_j^{\mathrm{city}}(R) = \sum_{i=1}^{N} \mathrm{CF}_{i,j}(R) \cdot d_i, \tag{4.3}$$

where:

- d_i = annual driving distance of individual i,
- N = total number of individuals.

Life cycle inventory of vehicles

Vehicle LCI values are derived from [15] and adapted for this study by modifying vehicle specifications, battery properties, lifetime mileage, driving cycles, and electricity mix.

Vehicle specifications Vehicle mass strongly influences embedded emissions and energy consumption. Table 4.1 summarises the specifications used. Curb mass values were obtained from Québec vehicle retirement records. The BEV battery capacity (63 kWh) corresponds to a 2022 Nissan Leaf.

Vehicle and battery lifetime mileage Each vehicle is assigned a unique LTM (see Section 4.4.4). For BEVs, we assume the battery and vehicle share the same LTM and retire simultaneously.

Table 4.1 Vehicle specifications for a representative average-sized passenger car

Vehicle type	**Curb mass (kg)**	**TTW energy (kWh/km)**	**TTW fuel (L/km)**	**Battery mass (kg)**	**Battery capacity (kWh)**
BEV	1 788	0.162	–	364	63
ICEV-p	1 458	–	0.059	–	–

Battery energy properties We assume Nickel-Manganese-Cobalt (8-1-1) (NMC811) battery chemistry, widely used in Canada. Battery mass is determined using an energy density of 0.209 kWh/kg [107]. The resulting production intensity (102 kg CO_2-eq/kWh) aligns with estimates by [108].

Driving cycle The Worldwide Harmonized Light Vehicles Test Cycle (WLTC) is used as the driving cycle, representing a blend of urban, suburban, and highway conditions typical of Montréal's driving patterns.

Electricity mix The electricity mix reflects Québec's grid: hydro (94%), wind (5%), biomass/geothermal (0.7%), petroleum (0.2%), natural gas (0.1%), and solar (<0.1%) [109].

Life Cycle Impact Assessment

Life Cycle Impact Assessment (LCIA) were assessed using the ReCiPe 2008 Hierarchist method (v1.13). Among its 18 midpoint indicators, we focus on the **climate change** midpoint, expressed in CO_2-eq using 100-year GWP factors from IPCC AR4 [110].

Complete LCA results are provided in Appendix B.

4.4.2 Annual driving distance

Annual driving distances are derived from a synthetic population representing 100% of residents in the study area. The synthetic population was constructed from the 2018 Origin–Destination (OD) survey and census data. It reproduces the spatial and demographic structure of the metropolitan region and reflects weekday travel behaviour as captured by the OD survey. Each individual is assigned a weekday-only activity plan, and car distances are calculated as Euclidean distances between consecutive activity locations connected by car mode.

A key limitation is that the dataset represents only a single weekday, excluding weekend and inter-daily variability. However, this is a common constraint in transport modelling [111]. To approximate annual driving behaviour, we compare our weekday-based estimates to observed annual statistics for Québec [96], which report an average of 12,740 km/year, or approximately 34.85 km/day. In our synthetic data, the average daily car distance among users is 25.52 km, with values ranging from 0.02 km to 548.32 km per person per day. This average represents a 26.77% underestimation relative to observed data. To align the synthetic results with real-world travel patterns, we apply a scaling ratio of 1.3656 to car distances.

This scaling enables construction of an annualized driving distance distribution that preserves spatial and demographic detail while maintaining consistency with empirical travel behaviour. Among the synthetic population, 1,530,502 individuals (50.92%) are identified as car users. The resulting distribution of annual driving distances after scaling is shown in Figure 4.2, illustrating the variability in car use across the population.

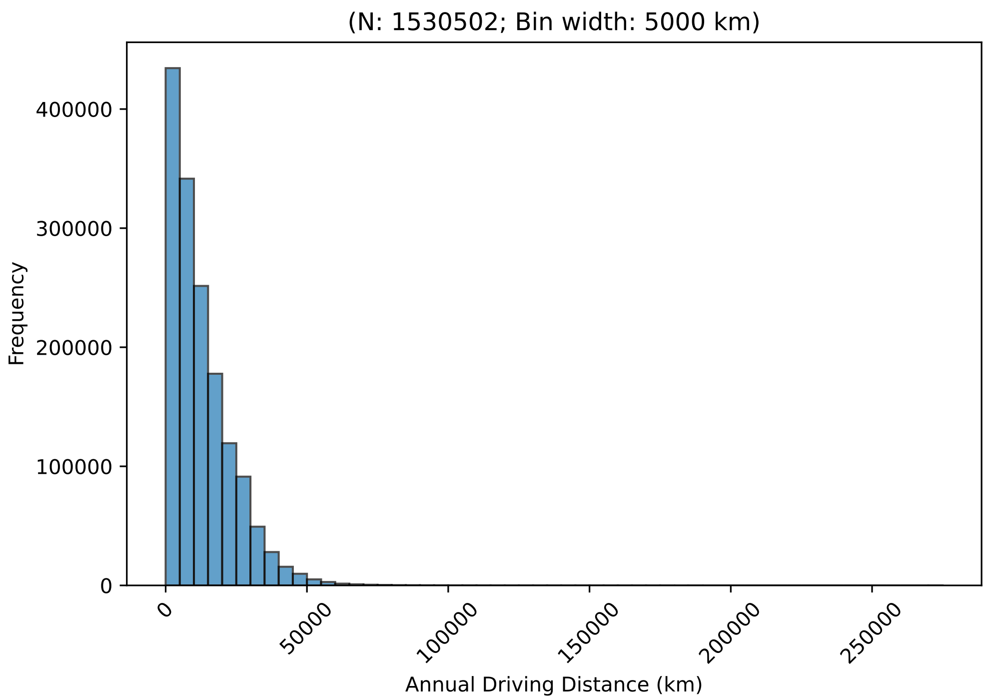

Figure 4.2 Distribution of annual driving distances among car users in the synthetic population after scaling.

4.4.3 Vehicle longevity function

In this study, LTM is estimated using a vehicle longevity function derived from Québec vehicle retirement data. We first describe the data source and processing, then present the longevity equation and its application to private cars (LTM_i) and carsharing vehicles ($\overline{\mathrm{LTM}}_{\mathrm{fleet}}$).

Data description

The analysis uses an empirical dataset on retired vehicles in Québec, comprising 11,005 records collected between 2011 and 2022. The dataset was provided by the SAAQ and represents a 0.5% random sample of all deregistered vehicles in the province. It includes a broad spectrum of vehicle categories, such as light-duty, medium-duty, and heavy-duty vehicles. These are further classified by usage type, including private automobiles, commercial automobiles, taxis, motorcycles, scooters, camping vehicles, service vehicles, and agricultural vehicles.

Key attributes include odometer reading at EoL (used as the vehicle's LTM), production and retirement years, curb mass, fuel type, and vehicle model. To focus on light-duty vehicles relevant to material efficiency, we validated the curb mass distribution, confirming good representation of both light cars and light trucks (the dominant categories in the current Québec fleet).

Data processing

We retained three key variables: LTM, vehicle calendar age, and annual driving distance. After removing entries with missing data (e.g., registration year, retirement year, odometer reading), the dataset was reduced to 10,130 vehicles. Calendar age was computed as the difference between registration and retirement years, and annual driving distance was derived by dividing LTM by age, assuming constant use over the vehicle's life.

To align with the scope of this study, we filtered for gasoline and electric private, commercial, and taxi vehicles, resulting in 9,606 records. We then removed outliers beyond ± 2 standard deviations in both calendar age and annual distance, yielding a final sample of 8,639 vehicles for LTM analysis.

4.4.4 Data analysis

Analysis of Québec vehicle retirement data indicates that vehicles are retired for multiple reasons, including accumulated wear, age, and economic depreciation, which together generate a non-linear relationship between annual driving mileage and LTM. To capture this pattern, we applied polynomial curve fitting to the scatter of annual mileage versus LTM. This approach smooths noise while representing the central trend in the data. Figure 4.3 shows the resulting relationship, where LTM increases with annual mileage but at a diminishing rate. Alternative curve fitting methods were also tested; corresponding results are provided in Appendix B.

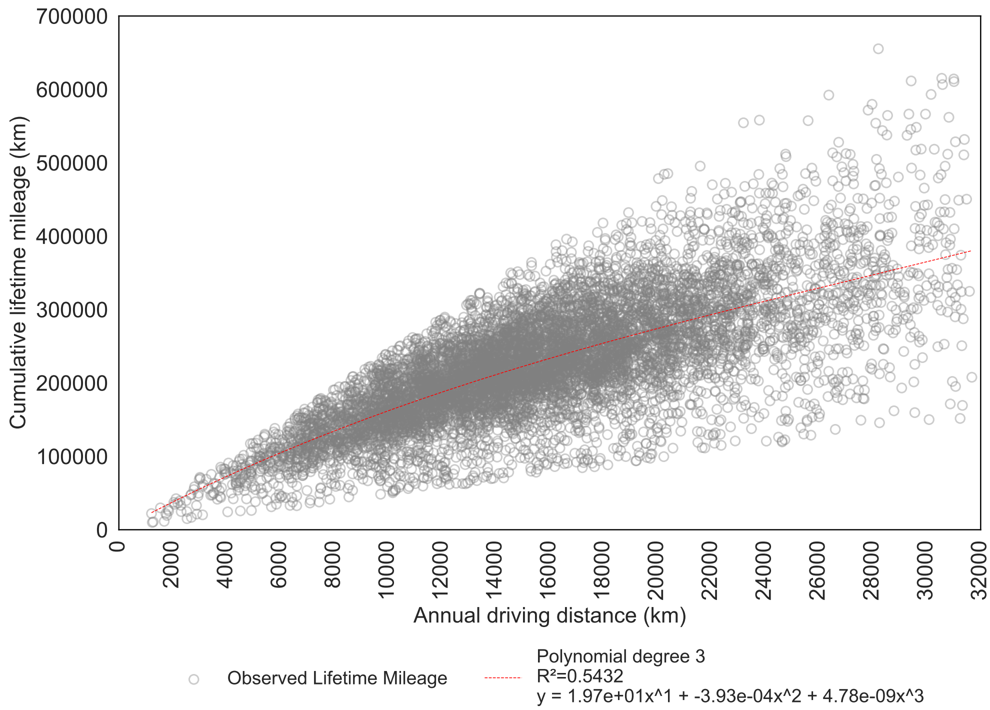

Figure 4.3 Relationship between lifetime mileage and annual driving distance for retired vehicles in Québec.

The longevity function used to predict the LTM of private and shared vehicles is:

$$\mathrm{LTM}_{\mathrm{mode},i} = 1.97 \times 10^{1}\, x - 3.93 \times 10^{-4}\, x^{2} + 4.78 \times 10^{-9}\, x^{3}, \tag{4.4}$$

where $\mathrm{LTM}_{\mathrm{mode},i}$ is the total distance (in km) that a vehicle can be driven over its service life in mode mode $\in$ {private car, carsharing} for user i, and x is the annual driving distance (km/year).

Estimation of private cars' lifetime mileage

To estimate LTM_i for each private car in Montréal, we apply Eq. 4.4, using the annual driving distance of individual i as the input x. This yields user-specific LTM values, allowing heterogeneity in vehicle longevity across the population. Summary statistics and distributions of the resulting LTMs are reported in Supporting Information 1.

Estimation of carsharing lifetime mileage

Assumptions about carsharing vehicles' LTM vary widely in the literature. Some studies assume it is similar to that of private cars [80], while others estimate up to double the mileage due to more intensive use and improved maintenance efficiencies [32, 112]. Other work suggests that shared vehicles may have lower LTMs because of rapid fleet turnover [113].

In this study, we estimate the LTM of carsharing vehicles using operational data from Communauto in Montréal (2008–2021), which shows an average annual driving distance of 21,273 km. This value is inserted into the longevity function (Eq. 4.4) to obtain a representative LTM for shared vehicles. Unlike private cars, where LTM is modelled at the individual level, carsharing LTM is treated as a fleet-level average, since shared vehicles accumulate mileage across many users. A single representative LTM is therefore applied to all carsharing vehicles:

$$\overline{\mathrm{LTM}}_{\mathrm{fleet}} = 287{,}246 \text{ km}. \tag{4.5}$$

Here, $\overline{\mathrm{LTM}}_{\mathrm{fleet}}$ is the total distance that a shared car can be driven over its service life.

4.4.5 Hypothetical carsharing scenarios

To assess the potential environmental impact of carsharing, we develop hypothetical adoption scenarios that allocate users to shared vehicle use.

While real-world carsharing adoption depends on multiple factors (e.g., service availability, convenience, attitudes, and income), we adopt a simplified annual-distance-based allocation to examine how shifts in user assignment affect carbon emissions. This choice is guided by data availability: annual driving distance is the only behavioural variable in the dataset that can be used systematically for this purpose. The proposed framework would remain valid if a more detailed discrete choice model were available.

Annual driving distance thus serves as the sole criterion for carsharing adoption. Users are ranked from lowest to highest mileage, under the assumption that those driving less annually are more likely to adopt carsharing, whereas those exceeding the average yearly mileage of a carsharing vehicle remain private car users.

To ensure scenario robustness, users with annual driving distances below 1,000 km/year are excluded. This threshold reflects two considerations:

- **Behavioural outliers:** individuals driving less than 1,000 km/year likely represent atypical patterns (e.g., collectors, very infrequent drivers, or individuals with abundant alternative modes).

- **Analytical integrity:** preliminary analysis revealed that including ultra-low-mileage users introduces noise and skews the distribution of driving behaviour, disproportionately influencing model sensitivity and adoption thresholds.

Based on the scaled annual distance distribution, approximately 80% of users drive fewer than 21,273 km/year and are considered eligible for carsharing. The remaining 20% exceed this threshold and are assumed to continue using private vehicles. For total carbon footprint calculations, the carbon footprints of these higher-distance users are always attributed to the private car category.

4.5 Methodology's limitations

This study adopts a simplified modelling framework that relies on several assumptions. These limitations should be considered when interpreting the results. Accordingly, the estimates should be viewed as indicative outcomes under clearly defined assumptions, rather than as precise predictions.

First, the LCA relies on the `ecoinvent` database, which is not fully tailored to the Montréal context. Regional variations in vehicle production processes and material composition are only partially captured, introducing uncertainty into the results.

Second, we assume identical vehicle size and technology in both private and carsharing scenarios. Although carsharing fleets currently tend to use smaller vehicles, it is unclear whether this pattern would persist under large-scale adoption. To avoid speculative assumptions and isolate the effect of more intensive use, we adopt a conservative baseline that holds vehicle characteristics constant across scenarios (see Section 4.4.1).

Third, annual driving distance is estimated solely from weekday travel and thus underrepresents weekend trips. As a result, individual-level annual distances are approximate, despite being rescaled to match aggregate statistics.

Fourth, carsharing adoption is modelled exclusively as a function of annual driving distance, with lower-distance users assumed to adopt carsharing first. While this approach avoids the need for detailed behavioural parameters, it simplifies the complex decision-making processes underlying carsharing uptake and does not capture factors such as accessibility, income, or attitudinal heterogeneity.

4.6 Results

4.6.1 Carbon footprint across user categories

Figure 4.4 reveals a clear pattern: users with lower annual driving distances contribute most to carbon reductions when switching to carsharing. For those driving under 5,000 km per year, life-cycle emissions decrease by up to 89% for BEVs and 63% for ICEV-p vehicles. Even users in the 5,000–10,000 km range see substantial reductions between 53% and 19%, respectively, highlighting that low-mileage drivers typically underutilize the embedded resources of their private vehicles.

In the 10,000–15,000 km range, which aligns with the average observed driving distance (see Section 4.4.2), reductions remain meaningful at 30% (BEVs) and 8% (ICEV-p), though they are less pronounced due to more balanced vehicle use. Above 15,000 km per year, the carbon footprint advantage of carsharing diminishes.

For any user driving beyond 25,000 km annually, switching can result in an *increased* carbon footprint, as such individuals already make efficient use of the embedded resources in their private vehicles. Carsharing operators typically retire vehicles earlier, based on lower age and mileage thresholds, than some high-mileage private users would. As a result, if these individuals switched to carsharing, they might require more than one shared vehicle over the same time span to meet their high annual travel demand. This could lead to higher overall production and end-of-life emissions, offsetting the benefits of shared mobility.

4.6.2 Carbon footprint for city-wide car users

Figure 4.5 presents the total annual carbon footprint for the car-using population under varying levels of hypothetical carsharing adoption. According to our assumptions (see Section 4.4.5), 80% of users are eligible for carsharing based on their annual driving distances. Adoption scenarios therefore represent a progressive shift within this subgroup. The remaining 20%, who are ineligible for carsharing, continue using private cars in all scenarios, and their emissions are always counted under private cars.

As the share of eligible users adopting carsharing increases, we observe a steady decline in total carbon footprint, especially between 10% and 60% adoption rates. This trend reflects the cumulative effect of shifting users who drive less than 15,000 km/year—identified in Section 4.6.1 as having the greatest per-user reduction potential—from private cars into the carsharing system. By moving from underutilized private cars to more intensively used shared vehicles, carsharing facilitates material efficiency gains that translate into lower annual

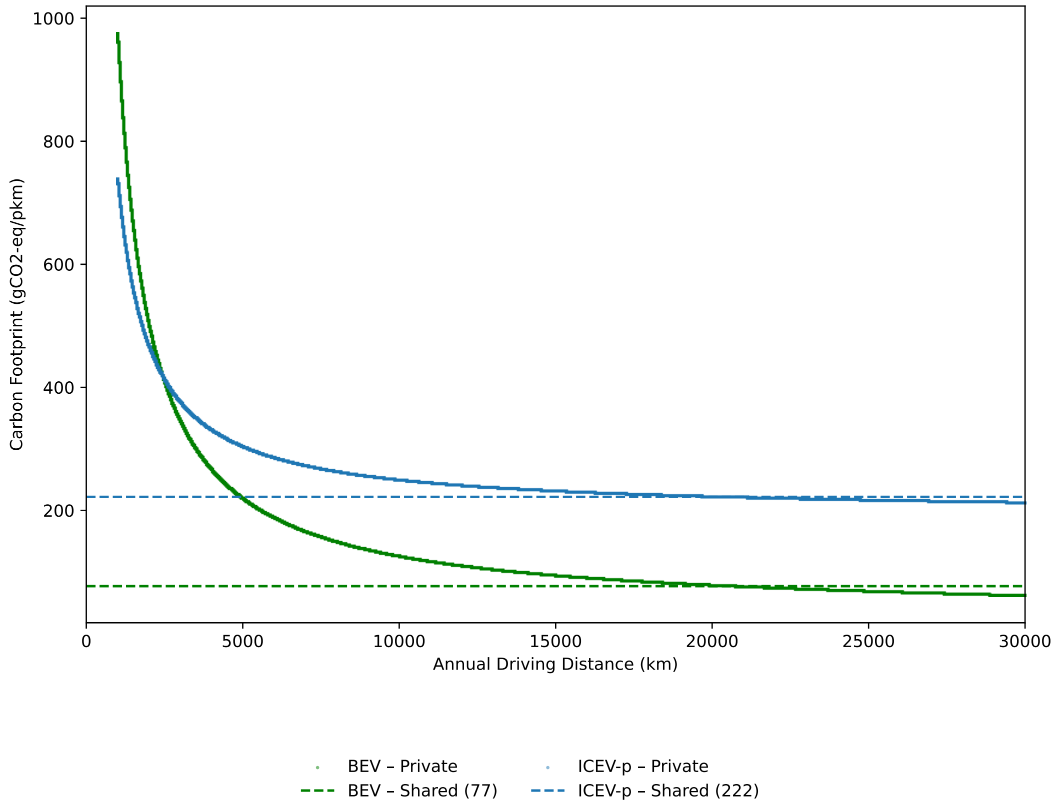

Figure 4.4 Relative change in life-cycle carbon footprint when switching from private car to carsharing, by annual driving distance category and powertrain.

carbon footprints.

When comparing vehicle technologies, the key difference lies in which life-cycle phases dominate the carbon footprint. For BEVs, most emissions arise from vehicle production and end-of-life. Carsharing helps reduce the annual impact of these fixed emissions by enabling more intensive use of vehicle resources (i.e., maximizingLTM per vehicle unit). In contrast, ICEV-p emissions are primarily driven by fuel combustion and scale with distance travelled. Carsharing still yields reductions for ICEV-p users, particularly those with low annual driving distances, but the marginal benefits decline as higher-mileage users are included.

Importantly, even when high-mileage users operate their private vehicles efficiently in material terms, their total carbon footprint remains high due to the scale of travel demand. This underscores that material efficiency alone is not sufficient to ensure environmental benefit at high usage levels. The climate value of carsharing is strongest when it enables the demand of underutilized private vehicles to be served more efficiently, and not when it encourages or accommodates additional driving.

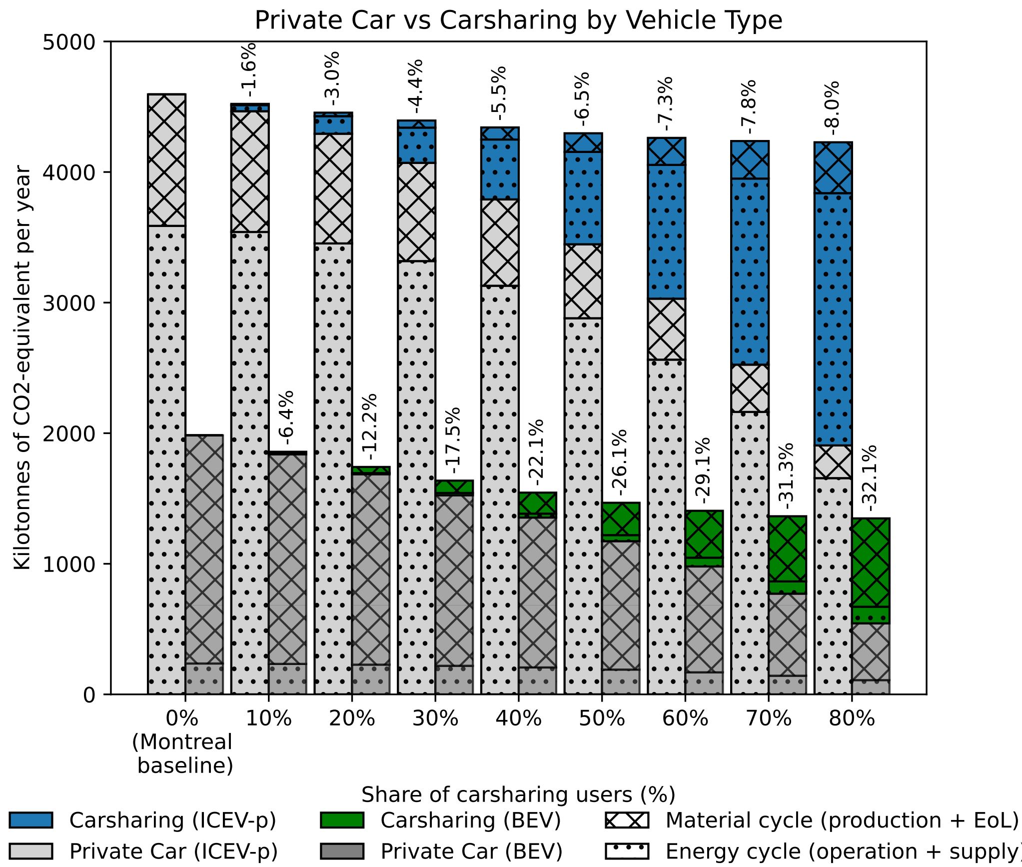

Figure 4.5 Total annual carbon footprint for the car-using population under different hypothetical carsharing adoption rates, by powertrain.

4.7 Interpretation of results

4.7.1 User-specific climate impacts

Most prior studies report average reductions in GHG emissions (e.g., [17, 25, 31, 54]). However, to the best of the authors' knowledge, previous work has not distinguished between different types of users in terms of annual driving distance. Our study introduces a user-level perspective, revealing that the carbon impacts and benefits of carsharing are not evenly distributed across the population.

The results show that users with low to moderate annual driving distances, who tend to underuse their private vehicles, offer the highest potential for carbon reductions when they switch to shared mobility. These users form a clear and high-impact target group for carsharing policies.

In contrast, high-mileage users are typically not suitable candidates. Under the effect of material efficiency, they already achieve relatively low carbon footprints per person-kilometre by using their vehicles intensively over their lifetime mileage. Transitioning these individuals to shared systems does not improve environmental performance and may, in fact, be counterproductive. High-mileage users can consume fleet capacity, reduce vehicle availability for other users, and place additional strain on shared systems, without yielding meaningful carbon reductions. Empirical evidence also shows that this group is largely absent from carsharing programs [51, 53, 114], likely due to structural constraints such as long commutes or lack of access to reliable public transit.

Between these two groups is a middle segment—users with moderate to high mileage—whose suitability for carsharing is less clear. Whether they should be targeted depends on the specific goals and constraints of a given city or program. In compact urban areas with strong public transit, these users may be viable candidates. In more car-dependent settings, however, their inclusion may dilute the environmental efficiency of shared systems. The decision to include or exclude them should reflect local policy priorities such as emission reduction targets, available fleet capacity, budget constraints, and the broader mobility context.

This three-tiered distinction, namely clearly suitable, clearly unsuitable, and context-dependent users, provides a sharper basis for carsharing policy design than promoting shared mobility universally. Doing so helps ensure that public investment or operational focus is directed where it can yield the greatest environmental return.

These three user groups also intersect with the choice of vehicle technology. While EVs reduce operational emissions, their production is materially intensive, particularly due to battery manufacturing and associated mineral extraction [115]. Carsharing mitigates these pressures by enabling more intensive use of each EV over its service life. Low-mileage users, whose annual mileage does not offset the production impacts of a private EV, incur lower life-cycle emissions by accessing shared EVs rather than owning private ones. Conversely, allocating private EVs to such users can, in some cases, generate higher life-cycle emissions than an ICEV.

This underscores that the environmental benefits of EVs depend not only on the technology itself but also on how intensively the vehicles are used. Taken together, these findings highlight the importance of aligning both carsharing and EV deployment with user characteristics. Blanket EV promotion policies that treat all users equally risk allocating material-intensive technologies to use cases that do not justify them. Policies should prioritize low-mileage users for carsharing, especially with access to shared EVs, while avoiding strategies that channel scarce material resources into underutilized private vehicles. By targeting the right users with the right technologies, cities can maximize carbon reductions and material efficiency while ensuring that shared fleets remain effective and resilient.

4.7.2 Potential role of operational emissions

While use-phase emissions are included in the analysis under the assumption of equivalent fleet composition, the present framework does not capture potential real-world differences in energy efficiency that could alter operational impacts. In addition, processes such as vehicle relocation, cleaning, and maintenance remain outside the scope. Previous assessment by Vasconcelos et al. [34] suggests that these activities generally account for a modest share of life-cycle impacts, but their significance depends strongly on management practices.

Inefficient relocation or high servicing frequency could erode some of the gains from higher utilisation, particularly in electric fleets where additional energy demand for operations is higher. Vasconcelos et al. [34] emphasize, operational logistics can materially influence both environmental and cost outcomes. Future extensions that couple user-level carbon accounting with operator-level service models could clarify how material efficiency interacts with real-world logistics.

4.7.3 LCA model limitation

This LCA takes an attributional perspective: it strives to quantify the share of impacts that can be associated directly or indirectly with the entire private and shared vehicle fleet usage. This perspective was deemed more appropriate since, in this study, we strove to keep many variables and causal links constant across all scenarios (especially user behaviour) to better highlight the role material efficiency of the shared and private fleets. In future studies, it would be of interest to jointly capture the effect of material efficiency with a broader range of causal mechanisms, including changes in user behaviour, rebound effects, market-mediated mechanisms, etc. Such a study, with extensive causal links, may complement the attributional perspective with a consequential analysis: for example, quantifying the environmental impacts of incentives to marginally increase the reach of shared mobility. As Jones et al. [81] note, attributional and consequential approaches are best viewed as complementary: attributional results establish a necessary reference point, while consequential models extend the analysis to dynamic consequences of transitions. For this study's aim of clarifying the baseline contribution of material efficiency, the attributional approach therefore remains the more reasonable choice.

4.7.4 Generalizability of findings

Although based on Montréal travel behaviour, the methodological framework is transferable. Because the analysis isolates material efficiency—a mechanism that applies broadly across contexts—the same approach can be replicated in other cities using local data on travel behaviour patterns and fleet characteristics.

What will differ are the magnitudes of reduction and the adoption thresholds at which diminishing returns occur, since these depend on local travel demand and fleet use intensity. The central insight—that material efficiency benefits vary strongly across user segments—is generalizable, although the precise contribution of medium-mileage users may depend on local conditions and policy objectives.

4.8 Summary and implications

This study purposely isolates material efficiency as a distinct mechanism and holds travel demand of each individual constant to provide a novel perspective on carsharing's environmental impacts and benefits. In doing so, the assessment represents only a partial view of carsharing's climate potential. By using bottom-up approach, this study highlights that the magnitude of carbon footprint reductions from carsharing is unevenly distributed across the population, with some user groups switching to carsharing being potentially counterproductive. For policy makers, this means designing incentives and EV deployment strategies that prioritize low-mileage households rather than promoting carsharing universally. For cities, it suggests planning around realistic adoption thresholds and aligning fleet capacity with user mix, while also leveraging shared EV fleets to advance electrification goals more efficiently than through private ownership. For operators, it highlights the need to tailor membership models toward low- and mid-mileage users, whose travel patterns align with both profitability and environmental efficiency. By matching technologies and business models to user characteristics, stakeholders can maximize carbon reductions, conserve scarce material resources, and build resilient shared mobility systems. The study has some limitations. The most notable are assuming equal vehicle size for private and shared vehicles, not modeling behavioural or infrastructure constraints, and perhaps most importantly using an estimate of annual driving distance that could be improved with better data. Additionally, while adoption scenarios are structured by ranking in an ascending order of annual mileage, actual carsharing uptake depends on factors such as financial incentives, accessibility, and user locations and preferences. Distance- based modeling is a useful starting point, but future work should refine this approach using more comprehensive adoption models. In essence, this study complements behaviour-focused studies for assessing the climate potential of sustainable carsharing systems. Other effects such as mode shift, reduced car ownership, or induced travel demand undoubtedly play an important role, but they are difficult to measure, context-dependent and therefore hard to generalize. By contrast, the material efficiency effect analyzed here can be quantified objectively, offering a stable foundation for evaluating carsharing's environmental potential. Future work should extend this material efficiency framework by integrating spatial variation in user and fleet distribution, together with temporal variation in travel demand to capture how geographic context and usage dynamics influence the environmental performance of carsharing systems.

Supplementary data

Supplementary data to the original article can be found online at:
`https://doi.org/10.1016/j.trd.2025.105037`. Further details and complementary analyses related to the results can be found in Appendix B.

CHAPTER 5 OPERATIONAL FEASIBILITY AND SHARED-FLEET PERFORMANCE

Chapter note.

This chapter forms the third analytical component of the dissertation and extends the preceding user-level analyses to a system-level perspective. Chapters 3 and 4 examined how behavioural change and material efficiency influence the environmental performance of carsharing from the viewpoint of individual users: who benefits most from sharing, how lifetime mileage varies across drivers, and how carsharing participation reshapes travel demand.

While these analyses established the potential for shared mobility to reduce emissions at the user level, they did not address the operational feasibility of delivering such benefits at scale. In particular, they did not consider how shared vehicles must be allocated across time and space, how many vehicles are required to satisfy demand, or how operationally realised vehicle use is the direct outcome of fleet assignment and service constraints.

The present chapter bridges this gap by introducing a spatial and temporal fleet assignment and scaling framework that explicitly models how shared vehicles serve trips in a large urban network. It builds directly on the material efficiency insights developed in Chapter 4, where lifetime mileage and vehicle use patterns were examined under idealised access conditions, and extends them by incorporating explicit spatial and temporal feasibility constraints. Unlike Chapters 3 and 4, which are based on peer-reviewed articles, this chapter is developed specifically for the dissertation as an integrative, exploratory analysis.

5.1 Context and scope

Numerous empirical and simulation studies have shown that participation in carsharing schemes can lower household car holdings and travel-related carbon footprints [6,18,19,39,40]. With the ongoing electrification of shared fleets, these systems are also viewed as important components of low-carbon urban mobility transitions.

Yet, the environmental benefits of carsharing depend not only on vehicle technology but also on how the system is configured and operated, particularly on fleet management [34]. A fleet that is too small may leave many trips unserved, causing users to revert to private vehicles, while an oversized fleet increases production and idle-capacity emissions. Fleet size therefore acts as a central lever linking service sufficiency, operational efficiency, and environmental performance.

Fleet sizing has been extensively studied in the operational and transportation literature. Analytical, simulation, and optimisation models have explored how the number of vehicles affects service coverage, waiting time, relocation demand, and operator cost [8,9,11,20,75–77]. These studies treat fleet size mainly as an economic or operational decision variable and optimise cost, operational vehicle use, or profit.

Parallel to these efforts, a growing number of studies have examined the environmental impacts of carsharing through LCA. These typically demonstrate reductions in user-level emissions when shared vehicles replace the usage of private ownership [17,22,25,31,84]. However, most LCAs either neglect the fleet size dimension altogether or adopt static assumptions such as fixed fleet sizes, average annual distances, and uniform vehicle use assumptions. In such cases, vehicle use is imposed as an exogenous input, decoupled from the operational dynamics that actually govern system emissions. Many studies also restrict their scope to the use phase [54,101,104], neglecting production and EoL impacts that become critical when fleet size or turnover changes. As a result, the environmental role of fleet size management remains insufficiently understood beyond its operational significance.

The preceding chapters of this dissertation address two of the mechanisms that shape carsharing environmental performance. Chapter 3 examined how behavioural change and user heterogeneity influence carbon footprints when carsharing is adopted at scale. Chapter 4 focused on material efficiency by quantifying how different vehicle use patterns relevant to lifetime allocation vary across user groups, under the simplifying assumption that vehicles are always accessible when needed. These chapters clarified who benefits most from sharing and how vehicle use patterns affect carbon intensity, but they did not examine whether the levels of vehicle use required for material efficiency are operationally achievable once spatial and temporal constraints are taken into account.

This chapter therefore introduces the third component of the dissertation analytical framework. It focuses on operational feasibility and shared-fleet performance. Instead of ordering users by mileage or privileging particular adopter types, it represents trips as a mixed, emergent demand field and uses a fleet assignment process that respects only space, time, and vehicle availability. Operational vehicle use thus arises from trip density and spatial structure at the fleet level rather than from user-level adoption sequences. By coupling this assignment with life-cycle emission accounting, the chapter investigates how fleet size, demand composition, accessibility constraints, and dispatch capabilities jointly determine LTM, functional use per vehicle, and system-wide carbon footprints.

5.1.1 Problem statement

Material efficiency has emerged as a promising strategy for transport decarbonisation [28, 36, 60, 103]. By using vehicles more intensively over their lifetime, the carbon burden of manufacturing can be amortised across a larger amount of service output. Earlier user-level work [28] showed that these material efficiency benefits depend strongly on who shares and how much they drive when vehicles are assumed to be universally accessible. However, realising such benefits at the system level requires appropriate fleet scaling. Operationally realised vehicle use is jointly shaped by user behaviour and by the supply of shared vehicles relative to demand. Fleet supply determines how many trips can be feasibly served, how scheduling unfolds over the day, and how much mobility service can be delivered per unit of embodied material.

The central problem addressed in this chapter is therefore how fleet size functions as a material efficiency lever in an electric carsharing system, once spatial and temporal feasibility constraints are taken into account, and how system-wide carbon footprints evolve as supply or demand is varied.

5.1.2 Research aim and contribution

This chapter examines how fleet size functions as a material efficiency lever in an electric carsharing system, and how system-wide life-cycle carbon footprints evolve as supply or demand is scaled under realistic spatial and temporal constraints. By coupling a spatial and temporal fleet assignment model with life-cycle emission accounting, the analysis quantifies how average kilometres per car, total fleet production, and service feasibility co-change when the shared vehicle supply is adjusted. The central question guiding this chapter is therefore:

> How does fleet size influence life-cycle carbon footprints and service feasibility in shared electric mobility when vehicle trip matching is constrained by time and space?

The chapter contributes in three main ways:

1. **Conceptual contribution:** It reframes fleet size, traditionally treated as an operational or cost parameter, as a material efficiency variable that links service sufficiency, operationally realised vehicle use, and life-cycle emissions. This perspective clarifies why scaling decisions can produce environmental gains or losses even when all vehicles are electric, and how these gains depend on spatial and temporal feasibility of vehicle reuse rather than on user mileage profiles alone.

2. **Methodological contribution:** It develops a spatial and temporal fleet simulation framework designed as a practical diagnostic tool for operators and policymakers. The framework links fleet size to operational vehicle use and environmental outcomes in a transparent and interpretable way. By producing baseline scaling curves, such as fleet size versus served demand and fleet size versus total emissions, it provides immediate insight into how supply decisions translate into material efficiency gains, trade-offs, or diminishing returns, under a car-based scaling logic.

3. **Policy contribution:** It generates actionable indicators that support planning and regulatory decisions. These include break-even fleet sizes, points of diminishing environmental returns, thresholds of operational vehicle use required for material efficiency benefits, and sensitivity to access rules and dispatch capabilities. The chapter illustrates how strategic fleet sizing can help cities and operators balance climate objectives with service performance, and complements the behavioural and user-level material efficiency insights developed in Chapters 3 and 4 with a system-level operational perspective.

Overall, this chapter extends the user-level analysis presented earlier in the dissertation by shifting from who benefits most from carsharing to how a mixed set of shared trips can be served by a finite fleet under spatial and temporal constraints, and what this implies for material efficient decarbonisation of urban mobility.

5.2 Literature review

This section reviews the research strands that are specific to the operational analysis conducted in this chapter. Earlier chapters already synthesised behavioural, material efficiency, and general life-cycle evidence. Here, the focus is restricted to operational determinants that directly shape feasible fleet-level vehicle use in shared electric fleets.

5.2.1 Fleet size and operational performance

Fleet sizing has been widely studied in operations research, particularly for one-way and free-floating carsharing. Early analytical and queueing models characterised the minimum number of vehicles required to satisfy spatially distributed demand under service-level constraints [7]. More recent work relies on simulation or agent-based methods to capture relocation needs, temporal demand variability, and spatial imbalance [6,8,11,75,76,116]. Across these models, fleet size is treated as a decision variable that trades off availability, waiting time, and operator cost.

Electrification introduces additional constraints. Battery range, charging downtime, and charging-station location influence feasible trip chaining in shared EV fleets [10,12,20]. These factors make EV fleet sizing more sensitive to spatial structure than internal-combustion fleets and can increase the importance of dense service areas where trips are short and closely spaced.

5.2.2 Operational dynamics relevant to environmental performance

While most fleet-sizing studies optimise cost or service reliability, a smaller number connect operational dynamics to environmental outcomes. Lausselet et al. [22] and Vasconcelos et al. [34] show that vehicle use levels strongly influence the life-cycle footprint of shared EVs, but they do not systematically explore how vehicle use changes when fleet size is varied over a wide range. Other studies incorporate deadheading or relocation requirements [9, 117], illustrating how empty travel can erode the environmental benefit of electrification when relocation intensity is high.

To date, only one contribution integrates spatial–temporal feasibility, vehicle reuse, and life-cycle cost accounting in a unified framework [34]. Yet even this work does not investigate how operationally feasible vehicle use responds to changes in fleet size, nor how those levels of vehicle use translate into life-cycle environmental impacts. This motivates the simplified but transparent approach developed in this chapter.

5.2.3 Static versus dynamic environmental models

Most LCAs of carsharing rely on static assumptions for LTM, annual distance, occupancy, and fleet size [17, 32, 84]. Vehicle use is treated as an exogenous parameter rather than as a result of system configuration. Such simplifications facilitate comparison between shared and private vehicles but do not capture how operational scaling affects environmental outcomes.

Yet real carsharing systems evolve with demand, geography, and service design [6]. Operationally realised vehicle use, fleet turnover, and LTM are interdependent. Higher levels of realised vehicle use increase the functional output per vehicle, reducing production emissions per kilometre, whereas insufficient supply leads to unmet trips, shifting users back to private vehicles with higher per-kilometre emissions.

Existing LCA studies therefore provide important insights but remain static approximations that do not reflect how vehicle use emerges from operational conditions. A dynamic, operation-aware environmental assessment is needed to capture how changes in service configuration influence environmental outcomes.

5.2.4 Connecting fleet size to material efficiency

Fleet size serves as a system-level proxy for material efficiency. A smaller fleet spreads production emissions across more delivered mobility service, as average vehicle use at the fleet level increases. Mathematically, if total material input M_{fleet} is approximately proportional to the number of vehicles N_{fleet}, and total service output S_{system} depends on mean annual kilometres $\overline{x}$ and occupancy, then material efficiency scales with the level of vehicle use realised by the fleet:

However, if the fleet becomes too small, unserved trips shift to private cars with higher per-kilometre emissions, reducing overall system efficiency. Fleet downsizing therefore exhibits a non-linear trade-off between reduced production burdens and loss of shared service. Identifying the threshold beyond which further downsizing ceases to deliver climate benefits is essential for environmentally sustainable fleet planning.

In short, these strands of literature show that fleet size is a key operational lever, that fleet-level vehicle use strongly shapes life-cycle footprints, and that most environmental assessments treat vehicle use as a static input rather than as the outcome of spatial and temporal feasibility. Chapter 4 identified the levels of vehicle use that would be required for material-efficient shared EVs under ideal access conditions. What remains unclear in the existing literature is whether such levels of vehicle use can actually materialise in a free-floating shared fleet operating under realistic spatial and temporal demand patterns. Addressing this question motivates the operational analysis developed in this chapter.

5.3 Materials and Methods

5.3.1 Analytical objective and scope

This chapter evaluates how operational feasibility constrains the environmental performance of shared electric mobility systems. Starting from an observed set of private-car trips, an operational assignment model determines which trips can be served by a shared fleet under explicit spatial, temporal, and energy constraints. The resulting service patterns and vehicle utilisation levels are then translated into life-cycle carbon footprint intensities per passenger-kilometer using a LCA (LCA) framework.

Three operational assumption families are examined:

1. shared EVs accessed by walking under a fixed access limit,
2. shared EVs accessed by walking with age-dependent walking speed,
3. autonomous EVs dispatched to trip origins within a maximum response time.

Across all scenarios, travel demand is held fixed and corresponds to the observed trips. Differences in environmental outcomes therefore arise solely from operational constraints and fleet availability rather than behavioural change.

5.3.2 Observed trips and model inputs

This subsection defines the empirical demand that serves as input to the operational model.

Trips are indexed by $i \in \{1, \dots, N\}$ and represent realised private-car travel demand. Each trip i is characterised by:

- a trip origin $\mathbf{o}_i = (x_i^o, y_i^o)$ and destination $\mathbf{d}_i = (x_i^d, y_i^d)$, expressed in meters,
- a start time t_i^o and end time t_i^d, expressed in seconds,
- a passenger-carrying distance ℓ_i, expressed in kilometers.

Passenger-carrying distance ℓ_i represents delivered transport service and is the sole quantity used to compute passenger-kilometers. No assumptions about route choice or network paths are introduced beyond spatial proximity at the access and dispatch scale.

For the age-adjusted walking-access scenario only, each trip is additionally associated with an age-group label a_i, which is used to assign a walking speed under a predefined mapping.

5.3.3 Operational assumptions and parameter values

This subsection introduces the parameters required to translate observed trips into operational feasibility conditions.

Walking-access scenarios are defined by a maximum access time T_{acc} (s). This time threshold is converted into a maximum access distance using a walking speed v^{walk} (m/s). In the fixed-access scenario, v^{walk} is constant, whereas in the age-adjusted scenario it depends on the age-group label a_i.

The autonomous dispatch scenario is characterised by an average cruising speed v^{AV} (m/s) and a maximum allowable dispatch time T_{disp} (s).

Electric-vehicle operation is represented using a simplified energy model defined by battery capacity B (kWh), energy consumption rate c (kWh/km), a minimum allowable state-of-charge fraction $\underline{s}$, a charging trigger threshold s_{trig}, and a charger power P_{ch} (kW). Charging is modelled explicitly as a time penalty during which the vehicle is unavailable for new trips.

All numerical values associated with these parameters are reported in Section **??**.

5.3.4 Operational assignment model

This subsection describes how trips are matched to vehicles under the assumed operational constraints.

Trips are processed in increasing order of start time. For each trip, the model determines whether at least one vehicle can feasibly serve the trip and, if so, which vehicle is selected.

Vehicle state representation

At any point in time, vehicles are indexed by j and characterised by three state variables:

- spatial location $\mathbf{x}_j$ (m),
- next-available time τ_j (s),
- available battery energy E_j (kWh).

A vehicle j is temporally available for trip i if its next-available time does not exceed the trip start time:

$$\tau_j \leq t_i^o, \tag{5.1}$$

where t_i^o is the start time of trip i.

Spatial proximity

Spatial feasibility is evaluated using the Euclidean distance between a vehicle and the trip origin:

$$d_{ij} = \|\mathbf{x}_j - \mathbf{o}_i\|_2, \tag{5.2}$$

where d_{ij} (m) denotes the distance between vehicle j and the origin of trip i.

Access and dispatch feasibility

In walking-access scenarios, trip i can be served by vehicle j if the access distance does not exceed the maximum walking distance:

$$d_{ij} \leq v^{\text{walk}} T_{\text{acc}}, \tag{5.3}$$

where v^{walk} is the walking speed assigned to the trip. In the age-adjusted scenario, walking speed depends on age group:

$$v^{\text{walk}} = v^{\text{walk}}(a_i). \tag{5.4}$$

In the autonomous dispatch scenario, vehicles travel empty to the trip origin. The dispatch time required for vehicle j to reach trip i is:

$$t_{ij}^{\text{disp}} = \frac{d_{ij}}{v^{\text{AV}}}, \tag{5.5}$$

and dispatch is feasible if:

$$t_{ij}^{\text{disp}} \leq T_{\text{disp}}. \tag{5.6}$$

The corresponding empty travel distance (deadheading) associated with this dispatch is:

$$\delta_{ij} = \frac{d_{ij}}{1000}, \tag{5.7}$$

expressed in kilometers.

Energy feasibility

This subsection introduces the energy constraints that apply across all scenarios.

Let ρ_{ij} denote the empty travel distance required to reach the trip origin, expressed in kilometers. In the autonomous dispatch scenario, $\rho_{ij} = \delta_{ij}$ (Eq. (5.7)); in walking-access scenarios, ρ_{ij} represents the same origin-proximity distance expressed in kilometers. The total driven distance required to serve trip i with vehicle j is:

$$s_{ij} = \rho_{ij} + \ell_i, \tag{5.8}$$

where ℓ_i (km) is the passenger-carrying trip distance.

The corresponding energy requirement is:

$$\Delta E_{ij} = c\, s_{ij}, \tag{5.9}$$

where c (kWh/km) is the vehicle energy consumption rate.

A vehicle is energy-feasible if the remaining energy after serving the trip remains above the minimum allowable state of charge:

$$E_j - \Delta E_{ij} \geq \underline{s}B, \tag{5.10}$$

where $\underline{s}B$ (kWh) denotes the minimum usable energy.

Assignment and state updates

For each trip i, the candidate set consists of all vehicles that satisfy temporal (Eq. (5.1)), spatial (Eqs. (5.3)–(5.6)), and energy feasibility (Eq. (5.10)). If the candidate set is non-empty, trip i is served and assigned to one vehicle, denoted J_i.

In walking-access scenarios, the selected vehicle minimises d_{ij}. In the autonomous dispatch scenario, the selected vehicle minimises t_{ij}^{disp}.

After assignment, vehicle states are updated as follows:

$$\mathbf{x}_{J_i} \leftarrow \mathbf{d}_i, \tag{5.11}$$

$$\tau_{J_i} \leftarrow \begin{cases} t_i^d, & \text{walking access,} \\ t_i^o + t_{iJ_i}^{\mathrm{disp}} + (t_i^d - t_i^o), & \text{autonomous dispatch,} \end{cases} \tag{5.12}$$

$$E_{J_i} \leftarrow E_{J_i} - \Delta E_{iJ_i}. \tag{5.13}$$

Charging representation and vehicle unavailability

This subsection clarifies how charging is represented operationally and how it affects vehicle availability.

Charging is represented using a simplified but time-explicit rule. If the post-trip state-of-charge fraction satisfies:

$$\frac{E_{J_i}}{B} \le s_{\text{trig}}, \tag{5.14}$$

the vehicle is assumed to initiate a recharge.

Recharging is *not* instantaneous: the vehicle is unavailable for new trips during charging. The charging time is computed from the energy required to return to full charge and the charger power:

$$\Delta t^{\text{ch}} = \frac{B - E_{J_i}}{P_{\text{ch}}} \times 3600, \tag{5.15}$$

where Δt^{ch} is expressed in seconds, $B - E_{J_i}$ is the energy deficit in kWh, and P_{ch} is in kW.

The charging time is added to the vehicle's next-available time, and battery energy is reset to full capacity:

$$\tau_{J_i} \leftarrow \tau_{J_i} + \Delta t^{\text{ch}}, \qquad E_{J_i} \leftarrow B. \tag{5.16}$$

This logic applies identically in all scenarios, including the autonomous dispatch case: while a vehicle is charging, it cannot be dispatched nor accessed.

5.3.5 Fleet-size experiment

This subsection explains how the study evaluates feasibility and environmental outcomes across fleet sizes.

Reference case: constructive discovery with spawning

A reference "100% supply" case is first constructed to identify the minimum fleet required to serve all trips that are feasible under the selected scenario constraints. The assignment is run once in chronological order while allowing the system to introduce additional vehicles when needed. Specifically, if a trip has no feasible candidate vehicle under the rules in Section 5.3.4, a new vehicle is introduced ("spawned") and assigned to that trip. The resulting set of vehicles defines the *fleet universe* and its size is denoted F_0.

This reference case ensures that any loss of service in subsequent experiments is attributable to fleet reduction rather than an arbitrary initial fleet definition.

Scaled-down fleets: restriction without spawning

Fleet reduction is then represented by progressively restricting the available fleet to subsets

$$\mathcal{F}_r \subseteq \{1, \ldots, F_0\}, \tag{5.17}$$

with $|\mathcal{F}_r|$ decreasing across rounds r. For each reduced fleet, the chronological assignment is re-run using the same feasibility and decision rules, but *without* allowing spawning. Trips that cannot be assigned under the reduced supply remain private.

This procedure produces a consistent "supply curve" linking fleet size to (i) the share of feasible trips served, (ii) dispatch burden (AV case), and (iii) the levels of operational vehicle use required of the remaining vehicles.

5.3.6 Service outputs

This subsection defines the operational outputs passed to the LCA stage.

Let z_{ir} equal 1 if trip i is served by carsharing in round r, and 0 otherwise. Delivered shared passenger service is:

$$S_r = \sum_{i=1}^{N} z_{ir}\, \ell_i, \tag{5.18}$$

where S_r is expressed in passenger-kilometers (pkm).

Private passenger service is:

$$P_r = \sum_{i=1}^{N} \ell_i - S_r. \tag{5.19}$$

In the autonomous dispatch scenario, total deadheading distance is:

$$H_r = \sum_{i=1}^{N} z_{ir}\, \delta_{iJ_i}, \tag{5.20}$$

where H_r is expressed in vehicle-kilometers (km). For walking-access scenarios, H_r is defined as zero.

5.3.7 Link to LCA

This subsection converts operational outputs into life-cycle intensities per passenger-kilometer by linking service, utilisation, LTM, and inventory parameters.

From daily service to annual vehicle kilometres

Let T denote the duration of the analysed period in days and F_r the number of vehicles made available in round r. The average annual driven distance per vehicle is:

$$k_r = \frac{V_r}{F_r} \cdot \frac{365}{T}, \tag{5.21}$$

where k_r is in km/year and V_r is the total vehicle-kilometers driven during the analysed period.

When deadheading is excluded from the driven-kilometer basis, $V_r = S_r$. When deadheading is included, $V_r = S_r + H_r$. This distinction is retained throughout the LCA to isolate the contribution of empty travel.

LTM from Chapter 4

To allocate vehicle production and EoL impacts per driven kilometer, the model requires an estimate of LTM implied by the vehicle utilisation level in each fleet-size round. Let k_r denote the annualised driven distance per vehicle in round r (km/year), computed in Eq. (5.21). LTM in round r is then obtained using the LTM relationship (Eq. 4.4) in Chapter 4, expressed as a cubic function of annual distance:

$$K_r = f(k_r), \tag{5.22}$$

with

$$f(x) = 1.97 \times 10^{1}\, x - 3.93 \times 10^{-4}\, x^2 + 4.78 \times 10^{-9}\, x^3, \tag{5.23}$$

where x is annual distance (km/year) and $f(x)$ returns LTM (km). The function $f(\cdot)$ captures the observed association between annual distance and total distance accumulated at retirement in the Québec deregistration data (Chapter 4), reflecting real-world retirement processes (age limits, wear-and-tear, failures, crashes, and other scrappage factors).

Carsharing life-cycle intensity per passenger-kilometer

Let G_{prod} and G_{eol} denote production and EoL emissions per vehicle (kg CO_2e/vehicle). These upstream impacts are allocated over the expected LTM K_r (km), yielding an upstream intensity per driven kilometer:

$$g_{\text{up},r} = \frac{G_{\text{prod}} + G_{\text{eol}}}{K_r}. \tag{5.24}$$

Use-phase emissions are taken from the LCA inventory as an intensity per passenger-kilometer, denoted g_{use} (kg CO_2e/pkm), and therefore already reflect average occupancy during passenger-carrying travel. However, when empty vehicle movements (deadheading) occur, additional vehicle-kilometers are required to deliver the same passenger service.

To account for this effect, driven vehicle-kilometers are related to delivered passenger-kilometers through a deadheading multiplier:

$$\varphi_r = \begin{cases} 1, & \text{deadheading excluded,} \\ \dfrac{S_r + H_r}{S_r}, & \text{deadheading included and } S_r > 0, \end{cases} \tag{5.25}$$

where S_r denotes delivered shared passenger-kilometers and H_r denotes empty vehicle-kilometers in round r. The multiplier φ_r therefore captures the increase in vehicle-kilometers per delivered passenger-kilometer induced by zero-occupancy travel.

The carsharing life-cycle intensity per passenger-kilometer is then:

$$g_r^{\text{share}} = (g_{\text{up},r} + g_{\text{use}})\ \varphi_r, \tag{5.26}$$

with units kg CO_2e/pkm.

Private travel and system-average intensity

Private-travel intensity is obtained from the user-level private-car LCA. Because private vehicles differ in annual mileage and LTM, each user u is associated with a specific private-car intensity (kg CO_2e/pkm). For a given round r, these user-specific intensities are aggregated over the trips that remain private to obtain a passenger-kilometer–weighted private intensity g_r^{priv}.

The system-average life-cycle intensity is then computed as:

$$g_r^{\text{sys}} = \frac{g_r^{\text{share}} S_r + g_r^{\text{priv}} P_r}{S_r + P_r}, \tag{5.27}$$

where S_r and P_r denote shared and private passenger-kilometers, respectively.

To support reproducibility, the numerical values of all operational and vehicle parameters introduced above are reported in Tables 5.1 and 5.2. The tables summarise the assumptions required to operationalise access, dispatch, and vehicle operation, and reference the equations in which each parameter is applied.

5.4 Study area and trip data

This section describes the spatial context and empirical trip dataset used to apply the operational and life-cycle modelling framework introduced in Section 5.3. It defines the geographic scope of the analysis, the structure of observed travel demand within that area, and the size

Table 5.1 Operational and vehicle parameters used in the assignment model. Parameter values represent conservative assumptions adopted to avoid overstating operational performance.

Parameter	Symbol	Value	Unit	Used in
Access time limit	T_{acc}	900	s	Eq. (5.3)
Baseline walking speed	v^{walk}	1.30	m/s	Eq. (5.3)
Autonomous cruising speed	v^{AV}	30	km/h	Eq. (5.5)
Maximum dispatch time	T_{disp}	600	s	Eq. (5.6)
Battery capacity	B	60	kWh	Eqs. (5.10), (5.15)
Energy consumption rate	c	0.18	kWh/km	Eq. (5.9)
Minimum SOC fraction	$\underline{s}$	0.10	–	Eq. (5.10)
Charging trigger threshold	s_{trig}	0.20	–	Eq. (5.14)
Charger power	P_{ch}	50	kW	Eq. (5.15)

Table 5.2 Walking-speed assumptions by age group in the age-adjusted access scenario. Values are derived from [1, 2] and harmonised to the age bins used in this study.

Age group	$v^{\text{walk}}(a)$ (m/s)	Used in
$<$ 30 years	1.35	Eq. (5.3)
30–59 years	1.20	Eq. (5.3)
60–74 years	1.05	Eq. (5.3)
$\geq$ 75 years	0.90	Eq. (5.3)

and characteristics of the analytical sample.

5.4.1 Central Montréal

The analysis focuses on central and downtown Montréal rather than the entire island. The selected area includes Ville-Marie, Plateau Mont-Royal, Rosemont–La Petite-Patrie, Outremont, Westmount, Villeray–Saint-Michel–Parc-Extension, and parts of Le Sud-Ouest and Côte-des-Neiges–Notre-Dame-de-Grâce.

These neighbourhoods correspond to the spatial footprint in which free-floating carsharing systems currently operate in Montréal. Their dense urban form, mixed land use, and high multimodal accessibility generate short trip lengths and frequent trip turnover, which are essential conditions for shared-fleet feasibility.

The study area is characterised by:

- high residential and employment densities,
- strong public-transport connectivity,
- a high frequency of short-distance motorised trips,
- limited parking availability and high curbside turnover,
- predominantly intra-urban travel with limited long-distance flows.

This spatial context reflects real-world operating conditions for free-floating systems in Montréal and provides an appropriate empirical setting for examining how fleet size and operational constraints shape service feasibility and operational vehicle use. Figure 5.1 shows the boundary of the study area used in this analysis.

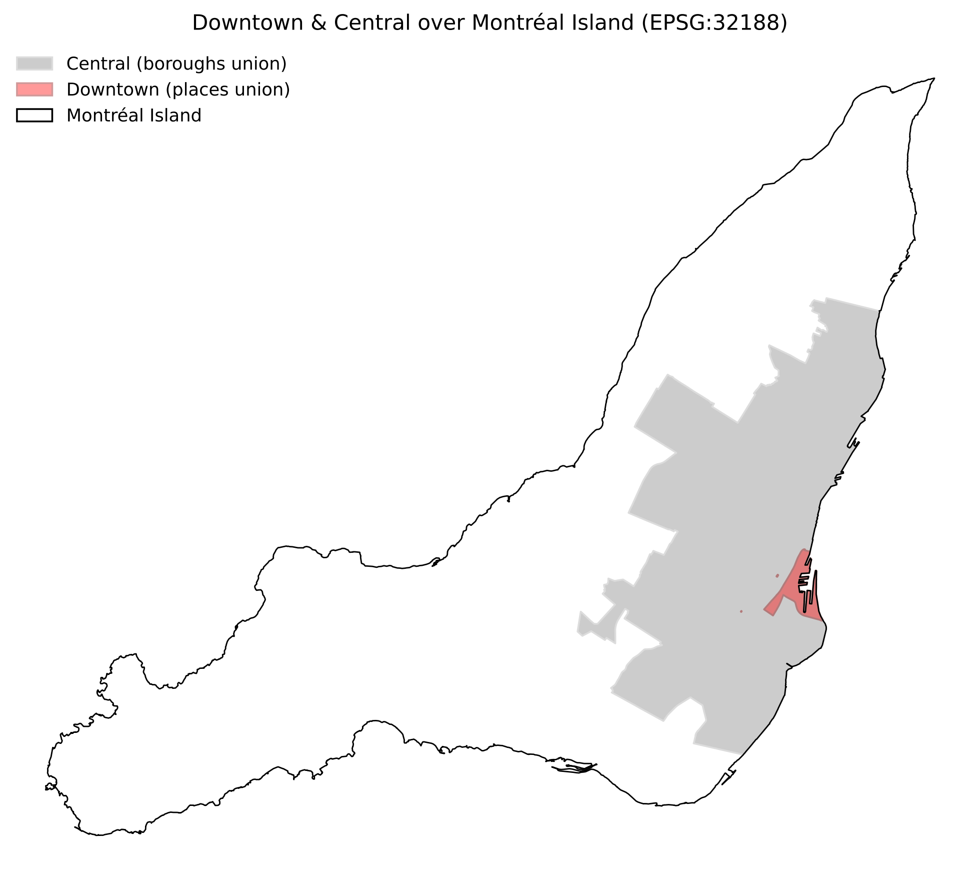

Figure 5.1 Study area covering downtown Montréal and adjacent central neighbourhoods.

5.4.2 Origin–destination structure within the study area

The trip dataset is filtered to retain only trips whose origins and destinations both lie within the study area. This restriction ensures that the analysis represents a closed free-floating service zone and avoids boundary effects associated with vehicles leaving or entering the system.

To characterise the spatial structure of travel demand, trip origins and destinations are aggregated to a 250 m hexagonal grid. Differences between origin and destination densities reveal local imbalances between trip generation and attraction. Such imbalances influence where vehicles tend to accumulate or become scarce, thereby shaping operational feasibility and fleet requirements.

Figure 5.2 illustrates these spatial patterns during morning and evening peak periods. The presence of both generation- and attraction-dominated zones confirms that the selected area exhibits the short, bidirectional, high-intensity flows typical of dense urban travel.

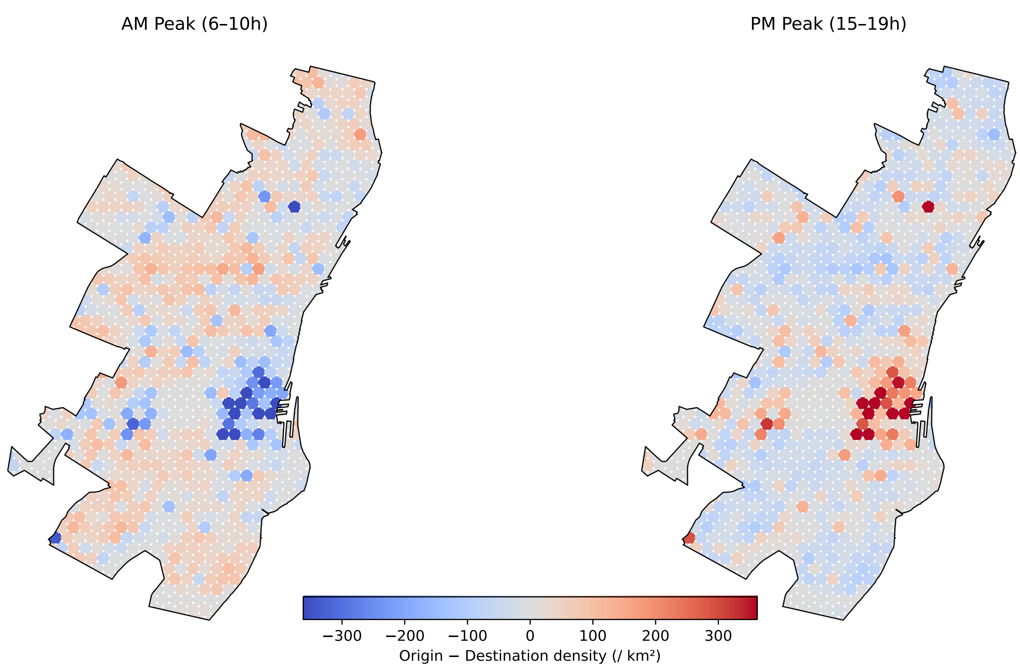

Figure 5.2 Spatial distribution of origin–destination density differences during peak periods. Red hexagons indicate net trip generation, while blue hexagons indicate net attraction.

5.4.3 Trip dataset and analytical sample

The trip data are derived from the synthetic population model developed in Themes 1 and 2. The model reproduces weekday motorised travel demand with explicit trip start times, durations, and spatial coordinates.

After filtering trips to those fully contained within the study area, the analytical sample consists of:

- 319 453 internal motorised trips,
- 141 673 unique users,
- complete temporal and spatial information for each trip.

This dataset provides a temporally ordered and spatially continuous representation of urban motorised travel demand. Its scale and completeness enable detailed simulation of vehicle–trip matching, fleet-averaged vehicle utilisation, and service coverage under explicit operational constraints, as analysed in the following sections.

5.5 Results

This section presents the operational and environmental outcomes of the fleet-size experiment under the three operational assumption families. Results are reported sequentially, following the modelling pipeline described in Section 5.3: first, operational service and vehicle-use outcomes; second, system-level life-cycle emissions; and finally, a comparison of minimum-impact configurations.

For clarity of interpretation at the system level, fleet sizes below 50 vehicles are excluded from the figures. At very small fleet sizes, a limited number of trips are served, which produces artificially high levels of operational vehicle use that are not representative of system-wide performance or environmental outcomes.

5.5.1 Operational service and vehicle utilisation

Figure 5.3 summarises the relationship between fleet size, delivered carsharing service, and vehicle utilisation.

The upper panel shows the number of vehicles used as a function of delivered carsharing passenger-kilometers. In both walking-access scenarios, fleet usage increases almost proportionally with delivered service, reaching more than 35 000 vehicles at the highest service levels. In contrast, the autonomous dispatch scenario delivers comparable or higher passenger-kilometers with substantially fewer vehicles, indicating greater reuse of individual vehicles.

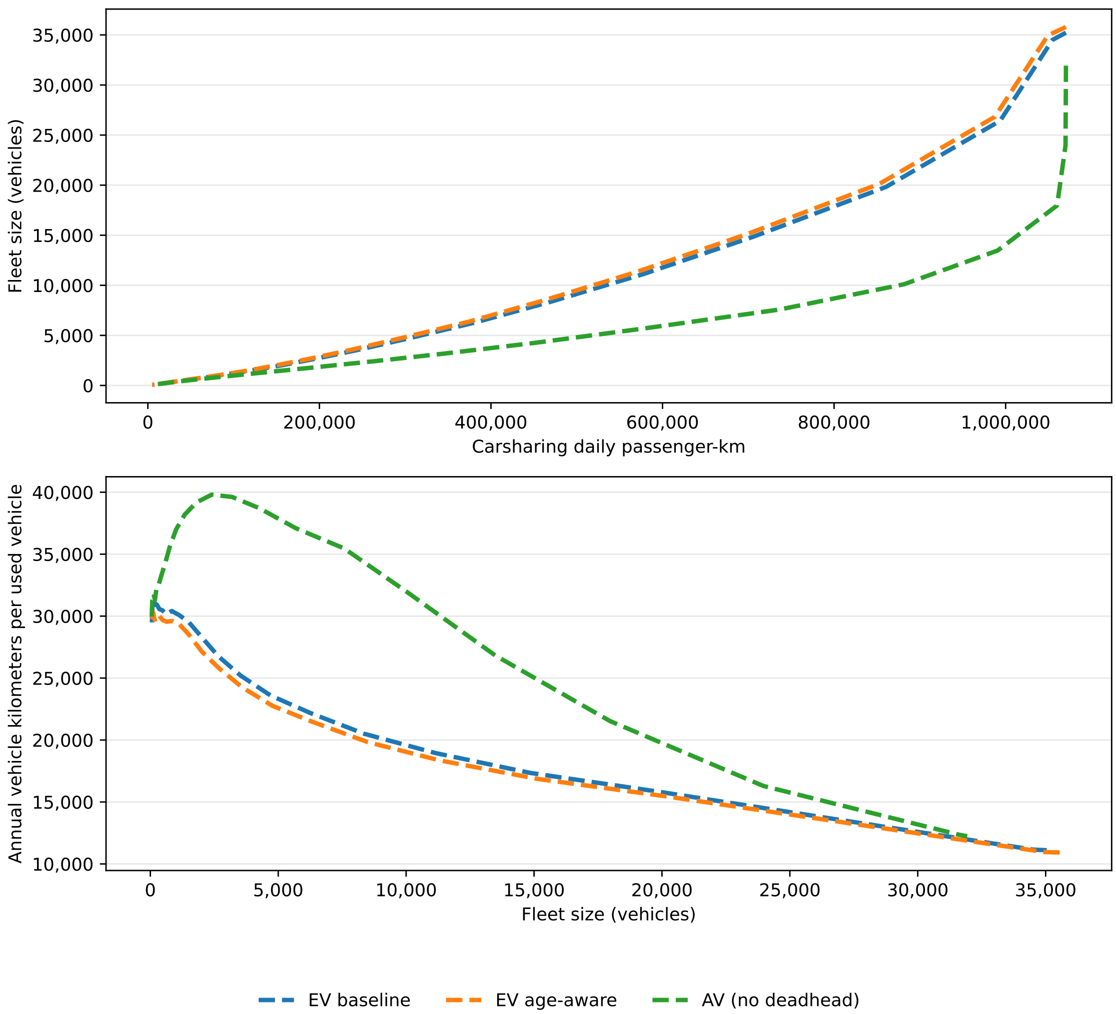

Figure 5.3 Relationship between fleet size, delivered carsharing passenger-kilometres, and vehicle utilisation under different operational assumptions. The upper panel shows vehicles used versus delivered carsharing service, and the lower panel shows annual distance per used vehicle as a function of fleet size.

The lower panel reports annual distance per used vehicle as a function of fleet size. For the walking-access scenarios, annual distance per vehicle decreases monotonically as fleet size increases, reflecting a dilution of operational vehicle use as additional vehicles are introduced. In the autonomous dispatch scenario, annual distance per vehicle initially increases at small fleet sizes, reaches a maximum, and then declines as fleet size grows. Across most of the fleet-size range, vehicles in the autonomous dispatch scenario accumulate substantially higher annual mileage than in the walking-access scenarios, indicating more intensive reuse of vehicles under the same demand conditions.

5.5.2 System-level life-cycle emissions

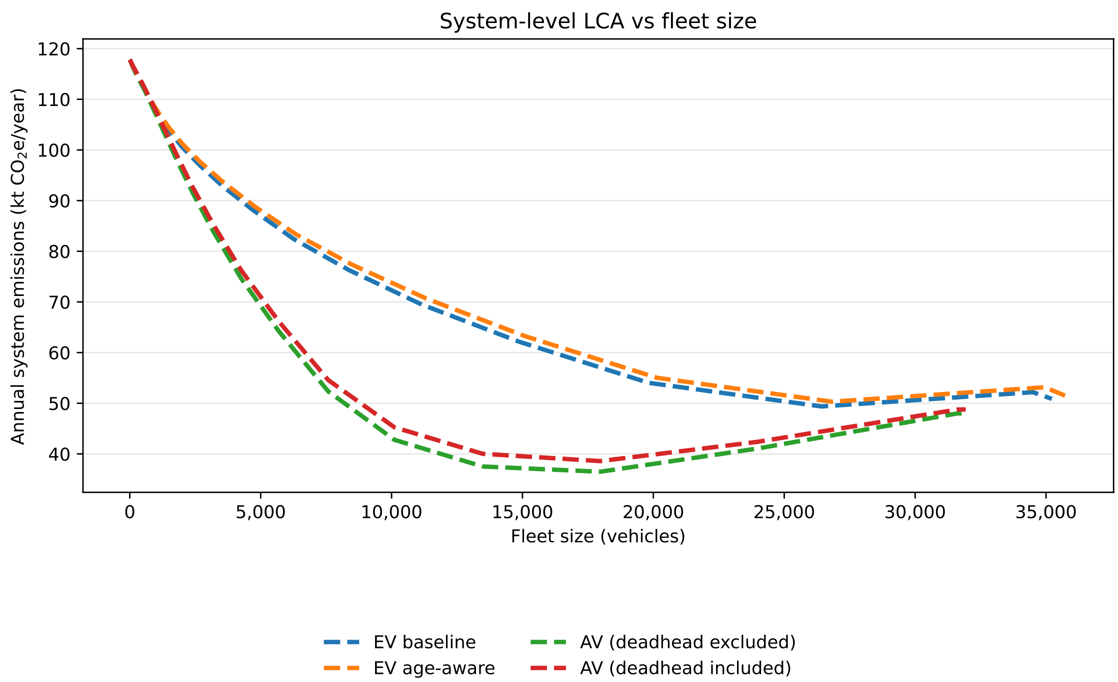

Figure 5.4 Annual system-level carbon footprints as a function of carsharing fleet size under different operational assumptions. Emissions include both shared and remaining private travel and are reported in kilotonnes of CO_2e per year.

Figure 5.4 presents annual system-level carbon footprints as a function of fleet size. Emissions include both shared and remaining private travel and are expressed in kilotonnes of CO_2e per year.

For all scenarios, system emissions decrease as fleet size increases from small values, reflecting the progressive substitution of private travel by carsharing. Emissions reach a minimum at intermediate-to-large fleet sizes and increase slightly thereafter as additional vehicles contribute marginal service gains.

For a given fleet size, the autonomous dispatch scenario exhibits lower system emissions than the walking-access scenarios over most of the range. Accounting for deadheading increases system emissions relative to the no-deadheading case, but the autonomous dispatch scenario with deadheading remains below the walking-access scenarios across the fleet-size range shown.

At large fleet sizes, system emissions across scenarios converge as carsharing service approaches full coverage and remaining private passenger-kilometers become negligible.

5.5.3 Minimum-impact configurations

Table 5.3 compares the configurations that yield the minimum system-level life-cycle intensity for each scenario. Reported values correspond to the fleet size at which total life-cycle emissions per passenger-kilometer are lowest.

The autonomous dispatch scenarios reach their minimum system impacts with substantially smaller fleets than the walking-access scenarios. When deadheading is excluded from accounting, the autonomous dispatch scenario achieves the lowest total life-cycle intensity. Including deadheading increases the carsharing intensity but does not alter the fleet size at which the minimum occurs.

Walking-access scenarios require larger fleets to approach their minimum system impacts and exhibit higher minimum life-cycle intensities than both autonomous dispatch cases.

Table 5.3 Fleet configurations corresponding to minimum system-level life-cycle impact by scenario.

Scenario	**Fleet used**	**Served trips**	**Deadheading km (daily)**	**Total kg CO_2e/pkm**
EV baseline	26 426	295 653	0	0.126
EV age-aware	26 827	293 372	0	0.129
AV (no deadhead)	17 969	316 600	117 170	0.093
AV (with deadhead)	17 969	316 600	117 170	0.099

5.6 Interpretation of results

This chapter examined how operational feasibility conditions shape the environmental performance of shared electric mobility systems when fleet size, access rules, and relocation capabilities are made explicit. By linking a spatial–temporal assignment model to life-cycle accounting, the analysis complements the behavioural and material efficiency perspectives developed in Chapters 3 and 4 and provides a system-level interpretation of carsharing deployment under spatial and temporal constraints.

5.6.1 Methodological contribution: operationally grounded LCA

One of the main contributions of this chapter is methodological. Rather than assuming the functional use of vehicles in the fleet or relying on scarce operator data, the study derives life-cycle outcomes directly from operational feasibility. Annual vehicle distance and LTM are not imposed as exogenous parameters, but are instead derived from the ability of vehicles to reach and serve observed trips under explicit spatial, temporal, and energy constraints.

In much of the carsharing LCA literature, LTM is fixed, scaled heuristically, or inferred from limited empirical samples. This practice largely reflects the lack of publicly available, large-scale carsharing usage data. As a result, vehicle use is often treated as an assumption rather than as an outcome of system design and operational context. The approach developed here demonstrates that life-cycle impacts can instead be computed from operational rules alone, while remaining consistent with empirically observed vehicle retirement behaviour through the LTM function estimated in Chapter 4.

Beyond addressing data limitations, this framework offers an additional analytical advantage. Because vehicle use metric is derived endogenously from fleet operations, the method allows systematic exploration of counterfactual fleet sizes and access rules without requiring new behavioural or usage data. This makes it possible to examine how environmental performance changes as fleets expand or contract, and to identify conditions under which shared mobility shifts from being environmentally beneficial to environmentally counterproductive.

The value of this contribution therefore lies in providing a transparent and reproducible link between fleet operations and life-cycle impacts. It offers a practical alternative for environmental evaluation in contexts where detailed carsharing usage data are unavailable, and a complementary tool for analysing fleet-size trade-offs even when such data exist.

5.6.2 System-level environmental implications

When operational outcomes are translated into life-cycle impacts, system-level emissions decrease with fleet size until a minimum is reached and increase slightly thereafter. This pattern reflects two opposing effects. Increasing fleet size allows more trips to be served by carsharing, reducing reliance on private vehicles. At the same time, larger fleets lower average operational vehicle use and increase the share of production and EoL impacts allocated per passenger-kilometre.

The fleet size associated with minimum system impact differs substantially across scenarios. Autonomous dispatch achieves comparable or greater service with a smaller fleet, leading to lower system-level emissions despite the presence of deadheading. Including deadheading increases use-phase impacts, but does not eliminate the advantage of higher feasible reuse. In contrast, walking-access scenarios require larger fleets to approach similar service levels and exhibit higher minimum life-cycle intensities.

These results show that system-level environmental performance cannot be inferred from vehicle technology or demand alone. It depends critically on how fleet size interacts with operational feasibility. Evaluations that assume vehicle use patterns without linking it to system constraints or neglect upstream impacts risk misrepresenting the true environmental consequences of carsharing deployment.

5.6.3 Implications for planning and policy

From an environmental perspective, the results suggest that fleet size should be treated as a key determinant of life-cycle performance rather than as a purely operational parameter. Oversized fleets dilute vehicle utilisation and increase embedded production and battery impacts per passenger-kilometre, while undersized fleets limit feasible substitution and allow a growing share of trips to revert to private vehicles with higher life-cycle intensities.

At the same time, fleet size is not determined by environmental objectives alone. In practice, operators may deliberately maintain larger fleets to improve service availability, reduce waiting times, deter competitors, or capture market share. These economic and strategic considerations can lead to fleet configurations that are environmentally suboptimal, even in dense urban contexts. The results therefore highlight a structural tension between commercial incentives and climate objectives in shared-mobility deployment.

For public authorities, this tension implies that fleet regulation based solely on access or coverage targets is unlikely to deliver consistent environmental benefits. Performance-based approaches that incorporate realised vehicle utilisation, functional use per vehicle, or the share of unserved demand could better align operational outcomes with climate goals. Such indicators reflect whether shared vehicles are actually replacing private travel at sufficient intensity to offset their production impacts.

More broadly, the findings reinforce that carsharing contributes to decarbonisation only when behavioural suitability, material efficiency, and operational feasibility align. Policies that promote shared mobility without accounting for these interactions may improve access or convenience while inadvertently increasing system-wide life-cycle emissions.

5.6.4 Interpreting utilisation patterns and model artefacts

The operational results reveal distinct patterns of *operationally realised vehicle use* across scenarios. In the walking- access scenarios, annual distance per vehicle decreases monotonically as fleet size increases. This reflects a simple dilution effect: adding vehicles increases coverage but reduces average reuse. In contrast, the autonomous dispatch scenario exhibits a non-monotonic pattern in annual vehicle mileage. Annual distance per vehicle increases at small fleet sizes, reaches a maximum at intermediate fleet sizes, and then declines as additional vehicles are introduced.

It is important to interpret these patterns in light of model structure. At very small fleet sizes, particularly in dense urban conditions, the model allows a limited number of vehicles to serve a long sequence of short trips. This produces very high annual distance per vehicle, but only for a small fleet serving a limited subset of total demand. These configurations are not operationally representative of a viable system and should be understood as artefacts of the feasibility rules rather than as desirable performance states.

In the autonomous dispatch scenario, the peak in annual vehicle mileage reflects a balance between expanded spatial reach enabled by relocation and increasing fleet supply. Dispatch allows individual vehicles to serve more trips by repositioning between bookings, raising functional use per vehicle at intermediate fleet sizes. As fleet size grows further, the marginal benefit of relocation diminishes, demand becomes less binding, and per-vehicle use converges toward the walking-access cases. These results highlight that realised vehicle use is not an intrinsic property of carsharing technology, but an emergent outcome of access rules, relocation capabilities, and the spatial–temporal structure of demand.

5.6.5 Limitations

Several limitations shape the interpretation of the results. First, the analysis is based on private-car trip demand rather than on observed carsharing usage. The temporal distribution, trip chaining, and booking patterns of carsharing users are known to differ from those of private-car travel. Applying private-car demand to a shared-fleet assignment therefore affects absolute fleet-size requirements and levels of operationally realised vehicle use (for example, annual distance per vehicle). The purpose of this modelling choice is not to reproduce current operator performance, but to examine how feasibility constraints shape vehicle reuse and life-cycle outcomes under a fixed and transparent demand structure. The qualitative insights regarding the relationship between fleet size, feasibility, and environmental performance are expected to remain valid even if absolute values shift under carsharing-specific demand profiles.

Second, the spatial focus on central Montréal represents a dense and walkable urban context with short access distances and strong temporal overlap between trips. These conditions favour vehicle reuse and are not representative of suburban or low-density areas, where larger fleets would be required to achieve comparable service coverage. The results should therefore be interpreted as indicative of dense free-floating service zones rather than as city-wide averages.

Third, the assignment model relies on Euclidean distances and does not represent congestion, routing constraints, parking availability, or detailed charging infrastructure constraints. Charging is represented through a simplified downtime rule and does not account for charger availability or queuing effects. These simplifications affect absolute feasibility and per-vehicle use levels but allow clear identification of structural relationships between spatial access, fleet supply, and life-cycle allocation.

Finally, the analysis considers only electric shared vehicles. Other powertrains or mixed fleets would alter absolute impact levels, particularly in the use phase. However, the central mechanism identified in this chapter—namely that life-cycle impacts depend on whether operational conditions allow sufficient functional use per vehicle—is expected to remain relevant across vehicle technologies.

5.7 Summary and implications

This chapter examined whether the levels of vehicle utilisation required for material-efficient carsharing can be realised once shared EVs operate under explicit spatial, temporal, and operational constraints. By linking a spatial and temporal fleet assignment model to LCA, the analysis showed how fleet size and access rules shape operationally feasible vehicle use and, in turn, system-level life-cycle carbon footprints.

The results demonstrate that material efficiency cannot be inferred from behavioural change or LTM alone. Although earlier chapters showed that certain user groups and utilisation levels are environmentally favourable under idealised access assumptions, the present analysis indicates that these conditions do not automatically translate into realised system performance. High vehicle use arises only when shared vehicles can repeatedly reach trips within realistic time and distance limits. When these conditions are not met, vehicles either accumulate insufficient annual distance to offset production impacts or a growing share of trips remains unserved and reverts to private vehicles with higher life-cycle intensities.

By making operational feasibility explicit, this chapter clarifies the relationship between vehicle use and environmental performance. Vehicle LTM is not an independent design choice but the outcome of whether trips can be feasibly chained under given access rules and fleet-supply conditions. Autonomous relocation expands the set of feasible trip sequences and allows comparable service with fewer vehicles, while introducing additional empty travel that must be accounted for in life-cycle impacts. Walking-access systems, in contrast, require larger fleets to approach similar coverage, which lowers average vehicle reuse and increases embedded emissions per passenger-kilometre.

A central contribution of this chapter is methodological. Rather than assuming utilisation or relying on scarce operator data, the study derives life-cycle outcomes directly from operational feasibility and links them to empirically observed vehicle retirement behaviour through a LTM function. This approach complements integrated transport models by isolating the role of operational constraints in shaping life-cycle impacts and by providing a transparent framework for evaluating fleet design choices in contexts where detailed carsharing usage data are unavailable.

From a planning perspective, the findings indicate that the environmental performance of carsharing depends on how fleet size aligns with feasible vehicle reuse rather than on fleet expansion alone. Deployments in dense and multimodal areas are more likely to support intensive use per vehicle and lower life-cycle emissions, while larger fleets in less suitable contexts risk increasing upstream impacts without proportionate substitution of private travel. Evaluations of shared mobility therefore need to incorporate operational feasibility and upstream emissions alongside service coverage objectives.

In the context of the dissertation as a whole, this chapter completes the analytical framework by showing that the climate performance of carsharing depends jointly on three determinants. Behavioural change determines who adopts shared mobility. Material efficiency determines how realised vehicle use translates into life-cycle impacts. Operational feasibility determines whether these levels of vehicle use can be achieved in practice. Meaningful decarbonisation from shared electric mobility requires alignment across all three.

Supplementary data

The Python notebook and data required to reproduce the results are provided in Appendix C.

CHAPTER 6 CONCLUSION

This chapter synthesises the findings of the dissertation and discusses their implications for research, policy, and practice. The dissertation examined carsharing through a system-level life-cycle perspective and addressed a single guiding question: under what behavioural, material efficiency, and operational conditions can large-scale carsharing reduce the environmental impacts of urban mobility, and what limitations arise as adoption expands.

The empirical chapters examined three determinants that shape environmental performance. Chapter 3 analysed behavioural responses across plausible adopter groups under unconstrained service availability. Chapter 4 isolated the material efficiency mechanism by examining how annual driving distance and LTM affect life-cycle emissions when demand is fixed and access is idealised. Chapter 5 introduced spatial and temporal feasibility by applying a trip-to-vehicle assignment framework and deriving realised vehicle use and trip coverage under explicit access and fleet-size conditions.

A central methodological choice of the dissertation is that these determinants are examined separately before being interpreted jointly. This choice does not imply that integrated models are incorrect or unnecessary. Integrated approaches are often essential for forecasting, optimisation, and detailed scenario planning. The contribution of this dissertation is different. By analysing each determinant under controlled assumptions, the work clarifies which mechanisms drive environmental outcomes, why results can diverge across studies, and which levers are most relevant for policy design and fleet planning.

It is important to acknowledge that the analyses developed in this dissertation are not intended to reproduce the full complexity of real-world carsharing systems. Behavioural change, material efficiency through high functional use of vehicle (as reflected in annual distance and LTM), and operational decisions are examined under simplified and controlled assumptions, and their interactions are analysed sequentially rather than simultaneously. In this sense, the framework does not aim to function as a fully realistic or predictive model of observed systems.

This analytical simplification is a deliberate and practical choice. Fully integrated models that combine behaviour, operations, and environmental accounting require extensive data, calibration, and modelling effort, and their results can be difficult to interpret or transfer across contexts. In many planning and policy settings, particularly in early-stage deployment, exploratory analysis, or comparative assessment, such complexity is neither feasible nor necessary.

The approach adopted here therefore prioritises practical interpretability over exhaustive realism. It allows decision makers and researchers to explore how specific assumptions about adopters, vehicle use, or service constraints influence environmental outcomes, without requiring a complete representation of all system interactions. This makes the framework particularly useful for identifying leverage points, screening policy options, and clarifying the conditions under which carsharing is likely to deliver environmental benefits or produce counterproductive effects.

6.1 Revisiting the dissertation's hypotheses

The dissertation was guided by three hypotheses that reflect the three determinants examined across the empirical chapters. These hypotheses do not correspond one-to-one with individual chapters, but instead structure the staged analytical design adopted in the thesis.

> **H1:** The environmental outcomes of large-scale carsharing depend strongly on the distribution of behavioural responses across user groups.

> **H2:** Under large-scale adoption, service-delivery constraints and the balance between supply and demand can limit or erode environmental gains that appear under simplified assumptions.

> **H3:** Environmental assessments that represent vehicle use (annual distance and implied LTM) as an outcome of behavioural or operational processes yield different system-level outcomes than assessments based on static or average use assumptions.

The following sections clarify how each hypothesis is addressed and the scope of inference supported by the dissertation. Hypothesis H1 is evaluated through direct within-study comparisons in Chapter 3, where alternative adopter compositions, adoption orders, and spatial distributions are examined under identical behavioural assumptions. Hypotheses H2 and H3 concern contrasts with alternative modelling assumptions that are not implemented as matched counterfactual baselines within the same modelling context in every chapter. Their support therefore rests on a combination of within-study evidence that demonstrates sensitivity to service-delivery and utilisation mechanisms, and consistency with established assumptions and findings in the literature.

This distinction is made explicit to avoid overstating the extent of hypothesis testing within a single modelling framework, while still allowing the staged results to be interpreted coherently at the system level.

6.2 Summary of contributions by determinant

Before revisiting implications, this section summarises what each determinant contributes to understanding carsharing's environmental performance and why the three chapters form a coherent progression.

6.2.1 Theme 1: Behavioural responses at population scale (Chapter 3)

Chapter 3 examined how empirically documented behavioural responses, when applied to a full metropolitan population, translate into system-level life-cycle outcomes. The chapter does not estimate behavioural parameters from the synthetic dataset and does not claim to represent a single "true" response. Instead, it applies literature-based behavioural adjustments under unconstrained service availability in order to isolate how individual-level effects aggregate as adoption expands.

A central novelty is that adoption is treated as a progressive policy variable rather than a single uptake point. Adoption is scaled from 0 to 100% within each eligible adopter group, which makes it possible to trace how impacts evolve as participation expands beyond early adopters. The analysis also makes explicit that aggregation depends on adoption structure, not only on average effects.

The chapter operationalises adoption structure along two dimensions that are typically implicit in system-level interpretations. First, adopters are differentiated by **baseline travel demand**. Second, adoption is spatially structured using **residential density quintiles** defined at the census-tract level. In the main adoption sequence, adoption is prioritised among lower-demand individuals living in higher-density areas, reflecting how services are often concentrated in dense neighbourhoods. Sensitivity analyses then vary adoption order, including demand-first variants and randomised selection, while keeping behavioural adjustments and fleet assumptions constant.

The results show that system-level outcomes depend on adopter composition and on how adoption unfolds. Occasional car users, defined as individuals with intermittent household-car access, tend to substitute private-car driving and generate emission reductions under the adopted behavioural adjustments. By contrast, individuals without prior car access tend to increase motorised travel when given carsharing access, which can increase their life-cycle emissions even with a low-carbon electricity mix. In addition, structured adoption sequences can yield non-linear system-level trajectories relative to random adoption because adoption order correlates with baseline demand and spatial context. These findings support the interpretation that behavioural heterogeneity, adoption order, and spatial context are first-order determinants of system-level outcomes when carsharing is evaluated as a large-scale policy intervention.

6.2.2 Theme 2: Material efficiency and vehicle utilisation heterogeneity (Chapter 4)

Chapter 4 isolated the material efficiency mechanism by holding behaviour constant and analysing how annual driving distance and LTM influence life-cycle carbon intensity. The chapter combines empirical relationships derived from end-of-life vehicle data with a harmonised LCA framework to quantify how embedded emissions from vehicle manufacturing and EoL are amortised across functional use.

The novelty of this chapter is not the claim that average-based LCA is wrong. Average representations are useful for describing a typical vehicle. The contribution here is to show how heterogeneity in annual driving distance implies heterogeneity in lifetime use, and why this heterogeneity matters for carsharing, which reallocates functional use across fewer vehicles.

The results identify a clear material efficiency logic: low- and mid-mileage private car users tend to underuse vehicles relative to feasible LTM, so consolidating their mobility onto shared vehicles can reduce carbon intensity by spreading embedded emissions across more service. High-mileage users already distribute embedded emissions across high functional use, so the incremental material efficiency gain from switching to carsharing is smaller and can be sensitive to fleet sizing and service conditions.

6.2.3 Theme 3: Operational feasibility and realised vehicle use under constraints (Chapter 5)

Chapter 5 introduced spatial and temporal constraints through a trip assignment framework applied to a dense study area on Montréal Island. The core contribution is an operationally grounded life-cycle evaluation in which key operational outputs required by LCA, including realised annual distance per used vehicle, trip coverage, and (where applicable) deadhead, are derived from explicit feasibility rules rather than imposed as assumptions.

It is important to be precise in terminology. The model is not calibrated as a full operational representation of a specific operator and does not aim to predict observed service performance. It is a feasibility-based assignment that determines whether vehicles can reach and serve trips under explicit constraints, including spatial reachability, temporal overlap, accessibility rules, and a specified fleet size. This design makes it possible to quantify how service-delivery constraints bound achievable vehicle use and how changes in fleet size shift the balance between underuse of vehicles and unmet demand.

The results show that fleet size is an environmental lever, but not one that yields a universal optimum independent of context and objectives. Increasing fleet size improves availability but can reduce average functional use per vehicle, which raises the embedded life-cycle burden per unit of service. Reducing fleet size concentrates demand and can increase vehicle use, but stricter feasibility constraints lead to unmet trips that remain private. In the AV-dispatch configuration, allowing vehicles to reposition can increase feasible coverage, but introduces deadhead kilometres that must be accounted for explicitly in LCA. Together, these results demonstrate that operational constraints shape the achievable level of vehicle use and coverage conditions required for environmental gains.

6.3 Assessment of the dissertation's hypotheses

6.3.1 H1: Behavioural heterogeneity and environmental outcomes

Chapter 3 provides direct support for Hypothesis H1 through within-study scenario comparisons. Using a metropolitan-scale synthetic travel-demand dataset and empirically grounded behavioural adjustments, the chapter evaluated how life-cycle impacts change when adoption is attributed to different plausible adopter profiles.

The results show that environmental outcomes depend on which users adopt and how their mobility patterns shift. Occasional car users with intermittent household-car access tend to substitute private-car travel and can reduce life-cycle emissions when adopting carsharing. In contrast, users without prior car access can increase motorised travel under carsharing access, which can offset or reverse benefits even with a low-carbon electricity mix. The implication is not that one group is "good" or "bad", but that behavioural heterogeneity is a first-order determinant of environmental performance at large scale.

6.3.2 H2: Service-delivery constraints as bounds on environmental performance

Chapter 5 provides support for Hypothesis H2 by showing that spatial and temporal constraints place binding limits on trip coverage and realised vehicle use under a free-floating EV feasibility framework. The chapter evaluates how changes in fleet size and access rules affect (i) the share of demand that can be served by the shared fleet and (ii) the realised functional use per used vehicle, which jointly determine life-cycle outcomes.

The key insight is that service-delivery constraints are not secondary implementation details. They shape whether sufficient trip substitution and vehicle use are feasible in the studied area under the assumed access and assignment rules. When fleets are small relative to the spatiotemporal structure of demand and the adopted constraints, unmet trips remain private and can dominate system-level impacts. When fleets are large, many vehicles can remain underused, increasing embedded impacts per unit of service. This chapter therefore demonstrates the existence of a trade-off between underuse and unmet demand under realistic constraints, while avoiding claims of a universal city-wide optimum that would require matched counterfactual baselines and explicit economic modelling.

6.3.3 H3: Utilisation-sensitive representation and life-cycle outcomes

Chapter 4 supports Hypothesis H3 by showing that life-cycle outcomes change when utilisation is represented through observed heterogeneity in annual driving distance and implied LTM, rather than treated as a fixed or average parameter. The chapter quantified how production and end-of-life burdens are allocated across functional output for users with different driving profiles.

Because the chapter does not implement a matched “static utilisation” counterfactual under the same context as a side-by-side experimental baseline, the evidence for H3 is interpreted as follows. The analysis demonstrates that utilisation-sensitive accounting reveals large variation across users and consolidation levels and therefore changes which users and fleet configurations appear environmentally favourable. This finding is consistent with the broader LCA literature where assumed LTM and annual distance strongly influence per-kilometre intensities. The contribution of Chapter 4 is to make that dependence explicit and policy-relevant by grounding utilisation in empirical vehicle lifetime-use patterns rather than in a single assumed value.

6.3.4 Synthesis: What the three hypotheses establish within the dissertation’s scope

Within the scope of the staged design, the dissertation establishes three points. First, behavioural heterogeneity determines the direction and magnitude of environmental change under large-scale adoption scenarios (H1). Second, utilisation-sensitive representation changes which users and consolidation strategies appear environmentally favourable (H3). Third, service-delivery constraints bound what utilisation and trip substitution are feasible under explicit spatial and temporal conditions (H2). These findings motivate a determinant-based interpretation of carsharing in which environmental performance depends on who adopts, how vehicles are used over their lifetime, and whether operations can sustain the realised use needed for material efficiency.

6.4 Integrated interpretation without conflating determinants

The staged design makes it possible to combine insights across determinants while keeping interpretation transparent.

First, Chapter 3 shows that adopter composition is decisive. If adoption expands primarily among occasional car users, substitution of private-car travel is plausible and environmental benefits can arise. If adoption expands primarily among users without prior car access, induced driving can dominate and offset technology gains.

Second, Chapter 4 shows why material efficiency is central even under electrification. Shared EVs can reduce use-phase emissions, but embedded emissions from manufacturing and EoL remain significant and depend on lifetime functional use. Carsharing can reduce embedded emissions per person-kilometre only if it increases lifetime functional use per vehicle.

Third, Chapter 5 shows that operational feasibility conditions whether higher vehicle lifetime functional use can be realised in practice. Even if the right users are targeted and the material efficiency logic is favourable, service-delivery constraints can limit trip coverage or lower realised vehicle use if fleet size and access conditions are not aligned with demand density.

This synthesis does not replace integrated modelling. Instead, it clarifies what integrated models must represent and which mechanisms should not be conflated. Integrated assessment becomes more informative when its results can be traced back to behavioural composition, utilisation mechanisms, and operational feasibility rather than being treated as a single black-box outcome.

6.5 Summary tables for interpretation and policy relevance

Table 6.1 summarises the determinants, what each chapter delivers, and how each translates into decision-relevant interpretation.

Table 6.2 summarises policy and operator levers that correspond to each determinant. These levers are phrased as actionable directions rather than prescriptions.

6.6 Interpretation and implications for decision makers and researchers

This section interprets the dissertation's findings for three audiences: cities and planners, carsharing operators, and researchers. Rather than separating interpretation from policy implications, the discussion integrates both. For each audience, the results are first interpreted conceptually and then translated into practical implications, while keeping assumptions and

Table 6.1 Determinants, chapter outputs, and decision relevance

Determinant	What is quantified in this dissertation	Why it matters for decisions
Behavioural responses	Population-scale life-cycle outcomes under empirically grounded adopter scenarios	Identifies which adopter compositions yield reductions and where rebound risk is plausible
Material efficiency	Heterogeneity in vehicle lifetime use (annual distance and LTM) and its life-cycle implications	Shows when consolidating vehicles reduces embedded emissions per person-kilometre
Operational feasibility	Fleet-size scaling relationships linking trip coverage, realised vehicle use (annual distance per used vehicle), and dispatch overheads (deadhead where applicable) under explicit access rules	Supports fleet planning and policy design by revealing trade-offs between service coverage, vehicle underuse, and environmental performance

scope explicit.

6.6.1 Cities and planners: governing carsharing as a conditional climate instrument

From a city and planning perspective, the central message of this dissertation is that carsharing should be understood as a conditional climate instrument rather than a universal policy target. Environmental performance depends on who adopts the service, how intensively vehicles are used over their lifetime, and whether operational conditions allow shared vehicles to reliably substitute private-car travel within the intended service area.

The results show that city-wide targets based solely on membership counts, fleet size, or the presence of shared electric vehicles can be misleading. Behavioural composition matters. Carsharing contributes to emission reductions primarily when adoption replaces existing private-car travel, particularly among occasional car users and low- to mid-mileage drivers. Adoption among users without prior car access, while relevant for accessibility and social objectives, does not generate comparable climate benefits and can increase life-cycle emissions when motorised travel expands.

Material efficiency further conditions these outcomes. Shared vehicles reduce environmental intensity only when they deliver substantially more lifetime transport service per vehicle

Table 6.2 Decision levers aligned with the determinants

Determinant	Levers suggested by the results	Primary actors
Behavioural responses	Target adoption and outreach toward occasional car users and underusing households; avoid strategies that mainly expand access for users without prior car access if the goal is carbon footprint reduction; interpret impacts as sensitive to adoption order and spatial context	Cities, operators
Material efficiency	Manage shared EVs deployment to support high functional use per vehicle over its service life; prioritise maintenance, refurbishment, and extended vehicle lifespan; avoid fleet expansion that reduces functional use per vehicle and increases embedded impacts per PKT	Operators, cities
Operational feasibility	Treat fleet sizing as a trade-off between vehicle underuse and unmet demand under explicit spatial and temporal access rules; use feasibility-based indicators such as trips served, unserved demand, functional use per vehicle, charging feasibility, and deadhead kilometres (when dispatch or relocation is enabled); recognise that the environmentally preferred fleet size can differ from the economically preferred fleet size	Operators, cities

than private cars. This condition is not guaranteed by electrification alone. Deploying large numbers of shared electric vehicles in contexts with limited demand density or weak multimodal alternatives risks producing underused assets with high embedded emissions.

Operational feasibility places an additional constraint on policy expectations. Even when behavioural and material conditions are favourable, spatial and temporal demand patterns limit how many trips shared vehicles can feasibly serve under given access rules. Expanding service areas or increasing availability can improve coverage, but often at the cost of lower realised use per vehicle or higher empty travel.

Taken together, these findings imply that cities should avoid framing carsharing as a uniform city-wide solution. A more robust approach is to govern carsharing through differentiated expectations and targeted deployment. Adoption strategies, lifetime vehicle use performance, and service coverage constraints should be treated as distinct but aligned levers. Cities can use the results of this dissertation to identify where carsharing is most likely to substitute private-car travel, where lifetime vehicle use can be increased through consolidation, and where operational constraints are likely to limit environmental effectiveness. This supports geographically differentiated policies and realistic climate expectations rather than a single aggregate target.

6.6.2 Operators: environmental fleet performance versus economic optimisation

For carsharing operators, the dissertation clarifies that environmental fleet performance and economic fleet optimisation are related but distinct objectives. Chapter 5 evaluates fleet size and service configurations from an environmental perspective using life-cycle impacts under explicit service-delivery constraints. This perspective differs from the criteria that typically guide operational decision making.

From an environmental standpoint, fleet performance improves when shared vehicles achieve high realised use and when trips served by carsharing substitute private-car travel. Underuse dilutes embedded manufacturing emissions across fewer kilometres, while unmet demand leads to continued private-car use with higher life-cycle intensities. Both mechanisms affect system-level outcomes, even when fleets are electrified.

From an operator perspective, however, fleet sizing decisions must balance additional considerations. These include revenue stability, user search time, service reliability, charging logistics, staff capacity, repositioning strategies, and risk management. Operators may therefore rationally choose fleet sizes or service configurations that prioritise customer experience or market share, even if these choices reduce average vehicle use and increase embedded emissions per unit of service.

The results of this dissertation should therefore not be interpreted as prescribing an economically optimal fleet size. Instead, they clarify how environmental performance responds to utilisation (as reflected in realised vehicle use) and service feasibility under controlled assumptions. The gap between environmental and economic optima helps explain why voluntary operator behaviour alone may not align with climate objectives. This creates a role for cities to consider performance-based regulation or incentives that reward functional use per vehicle, reliable service in priority areas, or electrification pathways that preserve high lifetime utilisation.

6.6.3 Researchers: implications for interpretation and modelling practice

For researchers, the primary contribution of this dissertation lies as much in its interpretive insights as in its methodological structure. The analyses show that divergent conclusions in the carsharing literature do not necessarily arise from conflicting empirical evidence, but often from differences in how behavioural responses, utilisation, and operational feasibility are represented and scaled.

The dissertation does not attempt to identify the real-world causal mechanisms that determine how individuals adopt carsharing or how operators optimise services. Instead, it demonstrates that system-level environmental outcomes can diverge substantially even when studies rely on similar behavioural elasticities, similar vehicle technologies, or similar service concepts. Differences emerge because assumptions about adopter composition, lifetime vehicle use, and service feasibility interact differently when they are extrapolated beyond small samples or idealised contexts.

By isolating behavioural responses, material efficiency, and operational feasibility under controlled assumptions, the dissertation shows where aggregation and representation choices matter most. For example, average behavioural effects remain informative at the individual level, but they do not determine system-level outcomes unless adoption structure is specified. Similarly, utilisation assumptions strongly influence life-cycle results, yet utilisation itself depends on whether demand can be feasibly served under spatial and temporal constraints.

The key insight for research is therefore not that one modelling approach is correct and others are wrong, but that different approaches answer different questions. Behavioural studies, utilisation-focused assessments, and operational models each capture valid aspects of carsharing systems, but their results are not directly interchangeable. Making assumptions explicit, and clarifying the scale and scope at which conclusions apply, is essential for meaningful comparison and synthesis across studies.

This determinant-based perspective offers a complementary analytical framework to existing integrated models, rather than a replacement for them. It is particularly suited to contexts where the objective is to clarify mechanisms, explore boundary conditions, or inform early-stage or targeted policy decisions under limited data availability.

Rather than embedding behaviour, utilisation, and operations within a single black-box framework, the dissertation demonstrates the value of examining these determinants separately under controlled assumptions. Preserving this conceptual separation improves transparency in how results are generated, supports clearer attribution of system-level outcomes to specific assumptions, and facilitates comparison across studies that focus on different aspects of carsharing systems.

In this sense, the contribution of the dissertation is not to prescribe a universal modelling architecture, but to provide an alternative and complementary way of reasoning about system-level environmental evaluation of shared mobility. This perspective helps align the choice of analytical approach with the research question, policy objective, and data context, while avoiding overinterpretation of results derived from highly aggregated or implicitly integrated models.

6.7 Limitations and future research

Several limitations arise from the staged analytical design and from data availability. These limitations are inherent to the deliberate choice to analyse behavioural responses, material efficiency, and operational feasibility separately in order to preserve interpretability.

First, behavioural responses in Theme 1 are imposed exogenously using effect sizes drawn from the empirical literature. Behavioural change is not modelled endogenously and does not adapt to service quality, pricing, availability, or reliability. Adoption decisions and diffusion processes are likewise not modelled. This design choice allows behavioural aggregation and adoption order to be examined transparently, but it does not capture feedback mechanisms through which users might adjust behaviour in response to evolving service conditions.

Second, Theme 2 isolates material efficiency by holding behaviour and access conditions fixed. Operational constraints such as vehicle availability, spatial reach, charging constraints, and temporal mismatch between demand and supply are intentionally excluded. As a result, the analysis quantifies how utilisation and LTM affect life-cycle outcomes in principle, rather than whether such utilisation levels can be achieved in practice under real-world service conditions.

Third, Theme 3 derives realised vehicle use from explicit spatial and temporal feasibility rules, but does not represent the full operational complexity of a real carsharing operator. Elements such as dynamic pricing, demand management, profit maximisation, charging optimisation, staffing constraints, or strategic long-term relocation policies are outside the scope of the model. The results therefore reflect environmental feasibility under defined access and assignment rules, not an economically optimised or operationally calibrated service design.

The empirical context also constrains interpretation. All analyses are conducted for Montréal, a city characterised by a dense central area and a low-carbon electricity mix. While the determinant-based logic developed in this dissertation is transferable, quantitative results, including realised annual vehicle use and fleet performance outcomes, are context dependent. Cities with different urban forms, travel behaviour, or electricity generation mixes may exhibit different balances between behavioural effects, material efficiency, and operational constraints.

Several directions for future research follow from these limitations. A first priority is the development of matched within-context counterfactual analyses that hold demand and spatial structure fixed while varying behavioural assumptions, utilisation representations, or operational rules. Such designs would strengthen causal attribution and allow more direct comparison between idealised and constrained representations within a single modelling context.

Further extensions could incorporate dynamic behavioural responses to service quality and pricing, richer temporal coverage including weekends and seasonal variation, and explicit representation of charging logistics and relocation strategies. Importantly, these extensions would benefit from a modular design that preserves the conceptual separation between behavioural responses, material efficiency, and operational feasibility, rather than collapsing all mechanisms into a single opaque integrated model.

Together, these directions point toward a next generation of integrated yet interpretable assessment tools that build on the determinant-based framework developed in this dissertation.

6.8 Final reflection

This dissertation set out to clarify under what conditions carsharing reduces the environmental impacts of urban mobility. It shows that outcomes depend on determinants rather than on technology alone.

Behavioural composition determines whether carsharing substitutes private-car travel or induces new motorised travel. Material efficiency determines whether embedded vehicle impacts are distributed across sufficient lifetime functional use. Operational feasibility determines whether vehicles can serve trips in time and space, and therefore whether high functional use per vehicle can be achieved without excessive unmet demand or deadhead.

The determinant-based approach developed in this dissertation does not aim to replace integrated modelling of carsharing systems. Instead, it complements integrated assessments by making explicit the assumptions and mechanisms that are often implicit when behavioural and operational processes are combined within a single LCA framework. By examining behavioural composition, vehicle lifetime functional use as a material-efficiency mechanism, and operational feasibility under transparent assumptions, the dissertation clarifies how each determinant contributes to system-level outcomes and why results can diverge across studies and contexts. This interpretive scaffold supports more robust, policy-relevant reading of car-sharing evidence, helps avoid overinterpretation driven by hidden scaling assumptions, and facilitates comparison across analyses that emphasise different determinants.

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APPENDIX A SUPPORTING MATERIALS FOR CHAPTER 3

Passenger-vehicle fleet composition and mass diagnostic

This appendix documents the descriptive analysis of the passenger-vehicle fleet used to parameterize vehicle size and mass in the life-cycle assessment. The objective is twofold: (i) to report the composition of the fleet by vehicle size and fuel type in the Greater Montréal Area (GMA), and (ii) to assess whether fuel-specific differences in vehicle mass within a given size class are sufficiently large to warrant explicit modelling.

Fleet composition by size and fuel

The analysis is based on the 2022 registry of vehicles in circulation, restricted to passenger vehicles (classification `PAU`) registered in the administrative regions corresponding to Montréal (06), Laval (13), and Montérégie (16). Fuel types are classified as petrol, diesel, or electric based on the recorded powertrain category. Vehicle size classes are defined using net vehicle mass as follows: *Small* (<1500 kg), *Mid-size* (1500–1999 kg), and *Large* (≥2000 kg).

Table A.1 reports the resulting fleet composition. Small vehicles represent just over half of the fleet, followed by mid-size vehicles, while large vehicles account for less than 10% of the total fleet. Across all size classes, petrol vehicles dominate, with diesel and electric vehicles representing comparatively small shares. Electric vehicles remain concentrated in the mid-size and large segments, but their overall share of the fleet remains limited.

Table A.1 Passenger-vehicle fleet composition in the Greater Montréal Area (GMA) by size class and fuel type. Fuel shares are reported within each size class.

Size class	N	Share of fleet (%)	Petrol (%)	Diesel (%)	Electric (%)
Small	971,781	51.52	98.9	0.6	0.5
Mid-size	738,626	39.16	95.5	0.5	4.0
Large	175,636	9.31	87.5	7.7	4.8

Average vehicle mass by size class

For each size class, the average net vehicle mass is computed across all vehicles belonging to that class, independent of fuel type. The resulting average masses are 1285 kg for small vehicles, 1690 kg for mid-size vehicles, and 2258 kg for large vehicles. These averages are used to parameterize vehicle mass in the life-cycle assessment.

Diagnostic of fuel-specific mass differences

To assess whether fuel-specific vehicle mass should be modelled explicitly within each size class, a diagnostic comparison was performed. For each size class and fuel type, the mean vehicle mass was computed and expressed as a ratio relative to the corresponding size-average mass. A ratio of 1 therefore indicates no deviation from the size-average value.

Table A.2 reports the resulting ratios.

Table A.2 Ratio of fuel-specific average vehicle mass to size-average mass. Values greater than 1 indicate heavier vehicles relative to the size-class average.

Size class	**Petrol**	**Diesel**	**Electric**
Small	0.999	1.073	1.043
Mid-size	1.000	1.028	0.995
Large	0.988	1.169	0.949

The diagnostic shows that fuel-specific deviations from the size-average mass are small for the dominant mid-size segment, which accounts for nearly 40% of the fleet. Larger deviations are observed for diesel vehicles in the large size class; however, this segment represents a limited share of the overall fleet. Electric vehicles are not systematically heavier than their size-class average in this dataset, and in the large class are slightly lighter on average.

Implications for life-cycle modelling

Given that (i) fuel-specific mass deviations are small in the most prevalent size class, and (ii) larger deviations occur only in segments with limited fleet shares, vehicle mass is parameterized at the size-class level without fuel-specific differentiation in the life-cycle assessment. Differences between fuel types are instead captured through powertrain- and energy-specific life-cycle inventories.

This modelling choice improves transparency and robustness while avoiding unnecessary complexity, and it does not materially affect system-level environmental results.

Vehicle occupancy assumptions

Vehicle occupancy is assumed to be equal to one for passenger cars throughout the analysis. This choice reflects the focus on vehicle-based service provision and avoids introducing additional behavioural assumptions regarding carpooling or shared rides within a single vehicle. Occupancy therefore does not vary across private and shared passenger-car travel and does not contribute to differences in life-cycle impacts between scenarios.

For public transport modes, including buses and trains, occupancy assumptions follow the default values embedded in the *ecoinvent* life-cycle inventory. These values represent average operating conditions and are consistent with standard practice in attributional LCA. Maintaining these defaults ensures internal consistency of upstream inventories while keeping the analysis focused on differences arising from carsharing deployment rather than from mode-specific occupancy variation.

Material intensity per lifetime kilometre

This appendix reports vehicle and battery material intensity per lifetime kilometre travelled for private passenger vehicles and carsharing vehicles. Lifetime mileage (LTM) is used as the material efficiency denominator, representing total functional use delivered over a vehicle's life.

Lifetime mileage assumptions

Private passenger vehicles are assumed to have a lifetime mileage of 110,490 km, based on deregistered-vehicle data. Carsharing vehicles are assumed to achieve twice this lifetime mileage, reflecting higher utilisation:

$$\mathrm{LTM}_{\mathrm{priv}} = 110{,}490 \text{ km}, \qquad \mathrm{LTM}_{\mathrm{cs}} = 220{,}980 \text{ km}. \tag{A.1}$$

Private passenger vehicles

Table A.3 reports vehicle and battery mass per lifetime kilometre by size class for private cars.

Table A.3 Vehicle and battery mass per lifetime kilometre for private passenger vehicles.

Size class	Vehicle mass / LTM (kg/km)	Battery mass / LTM (kg/km)
Small	0.01163	0.00290
Mid-size	0.01530	0.00435
Large	0.02045	0.00498

Carsharing vehicles

Table A.4 reports the same indicators for the Communauto carsharing fleet. Due to higher utilisation, material intensity per kilometre is approximately halved relative to private vehicles.

Table A.4 Vehicle and battery mass per lifetime kilometre for carsharing vehicles.

Size class	**Vehicle mass / LTM (kg/km)**	**Battery mass / LTM (kg/km)**
Small	0.00582	0.00145
Mid-size	0.00765	0.00217

These results illustrate how increasing lifetime functional use reduces embedded material intensity per kilometre, independent of vehicle technology.

Battery lifetime and vehicle retirement

Battery lifetime is assumed to coincide with vehicle lifetime. In the analysis, traction batteries are retired at the same time as the vehicle and no battery replacement during the vehicle's service life is modelled. Battery-related production and end-of-life impacts are therefore allocated across the same lifetime mileage as the vehicle itself.

This assumption reflects a conservative and transparent modelling choice given the uncertainty surrounding battery replacement rates, second-life applications, and reuse pathways at scale. While battery replacement or repurposing could alter the allocation of battery impacts across functional use, explicitly modelling these processes would require additional assumptions that are outside the scope of the present system-level analysis. The adopted approach ensures consistency across scenarios and aligns battery impacts directly with realised vehicle use and retirement.

Fuel mass intensity per kilometre

This appendix reports fuel mass consumption per kilometre for petrol and diesel vehicles by size class. The same fuel-efficiency parameters are applied to both private and carsharing fleets to ensure consistency and to avoid model-specific disclosure.

Conversion assumptions

Fuel consumption values are expressed in litres per 100 km and converted to fuel mass per kilometre using standard fuel densities:

$$\rho_{\text{petrol}} = 0.745 \text{ kg/L}, \qquad \rho_{\text{diesel}} = 0.832 \text{ kg/L}. \tag{A.2}$$

Fuel mass intensity is computed as:

$$m_{\text{fuel}} = \frac{\text{Fuel consumption (L/100 km)} \times \rho}{100}. \tag{A.3}$$

Fuel mass per kilometre

Table A.5 reports the resulting fuel mass intensity by vehicle size class.

Table A.5 Fuel mass consumption per kilometre by vehicle size class.

Size class	**Petrol (kg/km)**	**Diesel (kg/km)**
Small	0.0536	0.0483
Mid-size	0.0641	0.0582
Large	0.0820	0.0749

These mass-based intensities are used for life-cycle impact calculations and are independent of vehicle lifetime mileage assumptions.

Public transport and active modes: background data sources

Environmental impacts for urban public transport and active modes are modelled using background processes from the ecoinvent database. These modes are not parameterised through vehicle mass and lifetime mileage in the same way as private or shared cars. Instead, impacts are derived directly from ecoinvent transport service processes, which already embed vehicle production, infrastructure use, energy consumption, and maintenance per unit of passenger transport.

Urban passenger rail

Urban rail transport is modelled using the ecoinvent process *"transport, passenger train, urban"*. Electricity supply is adapted to reflect the Québec context. Traction electricity is modelled using high-voltage electricity for Québec (CA-QC), consistent with the electricity supply characteristics of rail systems:

- Transport process: *transport, passenger train, urban*
- Electricity supply: *electricity, high voltage, CA-QC*

This choice ensures that upstream electricity generation reflects Québec's low-carbon grid while maintaining consistency with the voltage level used for rail traction in ecoinvent.

Urban bus transport

Urban bus services are modelled using the ecoinvent process *"transport, regular bus"*. Energy supply for buses is assumed to be diesel fuel, using a global average (Rest-of-World, ROW) dataset, reflecting the absence of Québec-specific diesel production data in the database:

- Transport process: *transport, regular bus*
- Fuel supply: *diesel, low-sulfur, ROW*

This assumption is consistent with common practice in attributional LCA studies of urban bus transport and preserves comparability with the literature.

Bicycle transport

Cycling is modelled using the ecoinvent process *"transport, passenger, bicycle"*. This process represents bicycle manufacturing, maintenance, and infrastructure use per passenger-kilometre, without direct energy consumption during operation:

- Transport process: *transport, passenger, bicycle*

No additional electricity or fuel inputs are required at the use phase.

Electricity and fuel background assumptions

Electricity and fuel background processes are harmonised across modes to ensure internal consistency:

- Low-voltage electricity (e.g. for electric vehicles): *electricity, low voltage, CA-QC*
- High-voltage electricity (rail traction): *electricity, high voltage, CA-QC*
- Diesel fuel: *diesel, low-sulfur, ROW*
- Petrol fuel: *petrol, low-sulfur, ROW*

Using Québec-specific electricity mixes preserves the low-carbon characteristics of the regional grid, while ROW fuel datasets are used where region-specific datasets are unavailable. These choices affect absolute emission intensities but do not alter the relative comparison between modes, which remains robust to reasonable variations in background data.

Mode-specific life-cycle intensities and background data

This appendix reports the life-cycle greenhouse-gas intensities used for car-based modes (private car and carsharing) disaggregated by fuel type and vehicle size class, as well as the intensities adopted for key non-car modes (urban bus, bicycle, and urban passenger rail).

Car-based modes: private car and carsharing

Table A.6 summarises the car-based intensities by fleet type (private vs. carsharing), fuel type, and vehicle size class.

Table A.6 Life-cycle intensity values (kg CO2e/pkm) for car-based modes by fleet, fuel type, and vehicle size class.

Fleet	**Fuel type**	**Size class**	**Intensity**
Private car	Petrol	Large	0.461
Private car	Diesel	Large	0.433
Private car	Petrol	Medium	0.371
Private car	Diesel	Medium	0.339
Private car	Petrol	Small	0.296
Private car	Diesel	Small	0.259
Private car	Electric	Large	0.207
Private car	Electric	Medium	0.163
Private car	Electric	Small	0.124
Carsharing	Petrol	Medium	0.319
Carsharing	Petrol	Small	0.257
Carsharing	Electric	Medium	0.090
Carsharing	Electric	Small	0.070

Non-car modes: bus, bicycle, and urban rail

Table A.7 reports the intensity values adopted for diesel bus, bicycle, and urban passenger rail.

Table A.7 Life-cycle intensity values (kg CO2e/pkm) for selected non-car modes.

Mode	**Intensity**
Diesel bus	0.108
Bicycle	0.011
Urban train	0.009

Guide to reproducing the sampling and scenario analysis

This appendix documents the workflow used to generate the behavioural-scenario outputs used in Theme 1. The objective is to (i) prepare individual daily distance data, (ii) segment and filter the target adopter populations, (iii) assign carsharing membership deterministically under multiple adoption levels, (iv) apply literature-based behavioural adjustments under Low/Medium/High bounds, and (v) aggregate results by density quintile for plotting and interpretation.

The workflow is deterministic (no Monte Carlo): for a given input dataset and parameter set, it produces identical outputs.

Inputs and overall structure

Three input files are required:

- `mode_distances_with_attributes.csv`: individual daily travel distances by mode, plus user attributes (licence, car availability).
- `person_to_ct.csv`: mapping from `person_id` to census tract identifier `CTUID`.
- `ct_density_quintiles.csv`: mapping from `CTUID` to density quintile `dens_q` (Q1–Q5).

The main outputs are:

- `scenario_quintile_raw.csv`: scenario-induced *changes* in kilometres by mode and density quintile.
- `scenario_quintile_levels.csv`: *absolute* before/after mode totals for adopters by density quintile (used for stacked plots).

Adoption is evaluated at eleven discrete levels from 0% to 100%:

$$a \in \{0.0, 0.1, \ldots, 1.0\}.$$

For each adoption level a and each behavioural scenario (Low/Medium/High), the workflow selects adopters, applies behavioural changes to adopters only, and then aggregates impacts by density quintile.

Step 1: Load, validate, and harmonise travel-distance variables

The analysis begins by loading `mode_distances_with_attributes.csv`. Distance columns are verified and coerced to numeric. If a modal distance column is missing, it is created and set to zero. The modal distance set used throughout Theme 1 is:

$$\{\text{car},\ \text{car-passenger},\ \text{pt},\ \text{bike},\ \text{walk},\ \text{cs}\}.$$

User attributes are standardised to ensure consistent group definitions: `hasLicense` is mapped to `yes/no`, and `carAvail` is mapped to the canonical categories `never/sometimes/always`. This prevents inconsistent spelling or coding (e.g., `1/2`, `true/false`) from changing group membership.

A baseline daily total distance (excluding carsharing) is computed for each individual:

$$d_i^{\text{base}} = d_{i,\text{car}} + d_{i,\text{carpass}} + d_{i,\text{pt}} + d_{i,\text{bike}} + d_{i,\text{walk}}. \tag{A.4}$$

This baseline total is used for deterministic ranking when assigning carsharing membership.

Step 2: Attach spatial attributes and define density quintiles

Spatial analysis requires linking each person to a density quintile. This is done in two joins:

$$\texttt{person\_id} \rightarrow \texttt{CTUID} \rightarrow \texttt{dens\_q}.$$

Individuals without an assigned `dens_q` are removed to ensure that subsequent spatial summaries (by Q1–Q5) are complete and comparable.

Density quintiles are treated as an ordered categorical variable:

$$\texttt{dens\_q} \in \{\text{Q1}, \text{Q2}, \text{Q3}, \text{Q4}, \text{Q5}\},$$

where Q5 corresponds to the highest-density quintile.

Step 3: Define eligible adopter groups and apply minimum-usage filters

Theme 1 focuses on two potential adopter populations based on car availability:

- **Carless users**: `carAvail = never`
- **Occasional car users**: `carAvail = sometimes`

Only individuals with a valid driving licence (`hasLicense = yes`) are eligible to become carsharing members in the scenario analysis. This restriction is applied consistently to both groups.

A minimum-usage filter removes extremely low-activity records that can create zero-inflation and unstable percentage changes. The filter is applied only to licensed users (i.e., within the eligible population):

- **Carless users:** drop individuals with $d_{\text{carpass}} < 1$ km/day.
- **Occasional car users:** drop individuals with $d_{\text{car}} < 1$ km/day.

Finally, for conceptual consistency, carless users are forced to have zero private-car driving as a driver:

$$d_{i,\text{car}} = 0 \quad \forall i \in \text{carless}.$$

Baseline totals d_i^{base} are recomputed after this adjustment (Equation A.4).

Step 4: Assign carsharing membership under adoption levels

For each adoption level a, a subset of eligible users becomes carsharing members. Membership is assigned deterministically to avoid random noise and to ensure exact reproducibility.

The primary rollout strategy used in Theme 1 is **core-first adoption**:

- density quintiles are filled in the order Q5 → Q4 → Q3 → Q2 → Q1,
- within each quintile, lower baseline total distance joins first (ties broken deterministically).

Let N be the number of eligible users in a group (carless or occasional). At adoption level a, the number of members is:

$$N_{\text{mem}} = \lfloor a\, N \rfloor .$$

All selected members are treated as *active* in the current implementation (active share = 1.0), meaning behavioural changes apply to all members. (The workflow supports selecting an active subset among members, but this feature is not used in the main results.)

Step 5: Define behavioural scenarios (Low, Medium, High)

Behavioural changes are applied to *active members only.* Non-members retain baseline travel distances.

Three scenarios are evaluated:

- **Medium**: literature-based reference effects.
- **Low**: a uniform −25% reduction in effect magnitude relative to Medium.
- **High**: a uniform +25% increase in effect magnitude relative to Medium.

The scenarios are implemented as multiplicative factors and shares that control (i) shifts from an existing mode into carsharing and (ii) proportional changes in non-car modes (pt/bike/walk). Total travel is allowed to change as a result of these adjustments (i.e., changes are not renormalised to keep totals fixed).

Carless users (car-passenger to carsharing; non-car mode scaling)

For carless users who become active members:

- A share of car-passenger travel shifts to carsharing:

$$\Delta d_{i,\text{cs}} = \alpha_{\text{cp}\to\text{cs}}\, d_{i,\text{carpass}}, \qquad d'_{i,\text{carpass}} = (1 - \alpha_{\text{cp}\to\text{cs}})\, d_{i,\text{carpass}}.$$

- Public transport, cycling, and walking are scaled:

$$d'_{i,m} = \beta_m\, d_{i,m}, \qquad m \in \{\text{pt}, \text{bike}, \text{walk}\}.$$

Occasional car users (car reduction; remaining car share to carsharing; non-car mode scaling)

For occasional car users who become active members:

- Private-car driving is reduced:

$$d^*_{i,\text{car}} = (1 - \gamma_{\text{car}})\, d_{i,\text{car}}.$$

- A share of the remaining car travel shifts to carsharing:

$$\Delta d_{i,\text{cs}} = \alpha_{\text{car}\to\text{cs}}\, d^*_{i,\text{car}}, \qquad d'_{i,\text{car}} = d^*_{i,\text{car}} - \Delta d_{i,\text{cs}}.$$

- Public transport, cycling, and walking are scaled as above:

$$d'_{i,m} = \beta_m\, d_{i,m}, \qquad m \in \{\text{pt}, \text{bike}, \text{walk}\}.$$

Scenario parameters

Table A.8 summarises the parameters used in the three scenarios. The Medium scenario corresponds to the reference values used in Theme 1; Low and High apply a uniform ±25% scaling of effect magnitude.

Table A.8 Behavioural scenario parameters applied to active members.

Group	Parameter	Low	Medium	High
Carless	$\alpha_{\text{cp}\to\text{cs}}$ (share car-passenger → cs)	0.143	0.190	0.238
Carless	β_{pt} (PT factor)	0.750	1.000	1.250
Carless	β_{bike} (bike factor)	0.765	1.020	1.275
Carless	β_{walk} (walk factor)	0.803	1.070	1.338
Occasional	γ_{car} (car reduction share)	0.188	0.250	0.313
Occasional	$\alpha_{\text{car}\to\text{cs}}$ (share remaining car → cs)	0.041	0.054	0.068
Occasional	β_{pt} (PT factor)	0.750	1.000	1.250
Occasional	β_{bike} (bike factor)	0.765	1.020	1.275
Occasional	β_{walk} (walk factor)	0.803	1.070	1.338

Step 6: Recompute scenario totals and quantify changes

After behavioural adjustments are applied to active members, scenario totals are recomputed including carsharing:

$$d_i^{\text{scen}} = d'_{i,\text{car}} + d'_{i,\text{carpass}} + d'_{i,\text{cs}} + d'_{i,\text{pt}} + d'_{i,\text{bike}} + d'_{i,\text{walk}}. \tag{A.5}$$

For reporting, the workflow computes changes for adopters as differences between scenario distances and baseline distances. For carless users, key reported quantities include:

- reduction in car-passenger travel,
- change in PT/bike/walk,
- carsharing kilometres gained,
- total kilometres change.

For occasional users, the analogous quantities include the reduction in private car driving rather than car-passenger travel.

Step 7: Aggregate results by density quintile

All adopter-level results are aggregated by density quintile to support spatial interpretation and plotting. Two complementary summaries are produced for each group (carless and occasional), scenario (Low/Medium/High), adoption level a, and density quintile Q1–Q5:

- **Change table (deltas):** sums of mode-specific changes across adopters within each quintile (saved to `scenario_quintile_raw.csv`).
- **Levels table (before/after):** absolute sums of baseline and scenario distances by mode for adopters within each quintile (saved to `scenario_quintile_levels.csv`). This table is used directly to generate stacked before/after plots.

In both outputs, adopter counts are recorded by quintile to enable conversion to per-adopter quantities (e.g., kilograms per adopter per year) during the LCA post-processing stage.

Interpretation of the outputs

The change table supports interpreting *mechanisms* (which modes increase or decrease, and by how much), while the levels table supports interpreting *composition* (how the modal distance mix of adopters differs across space and between baseline and scenario conditions). Together, these outputs provide the behavioural activity inputs required to apply the mode-specific life-cycle intensities described in Appendix A and to compute city-wide impacts under different adoption trajectories and behavioural bounds.

Python script for scenario analysis

The full Python script used to reproduce all preprocessing steps, filtering operations, and carsharing scenario calculations can be downloaded from the following link:

`https://osf.io/fer6z/overview?view_only=23600bbc44fc45c6be452a8a64631f8e`

APPENDIX B SUPPORTING MATERIALS FOR CHAPTER 4

This document provides a guide to prepare SAAQ data for lifetime mileage estimation, a table summarizing the statistics of the lifetime mileage, and two figures illustrating the curve fitting for the analysis. The document also provides guide for reproducing the data for the analysis.

Guide to reproducibility of data processing

Data collection and initial dataset overview

- Obtain the dataset of retired vehicles from the Société de l'assurance automobile du Québec (SAAQ).
- The dataset consists of a random 0.5% sample of all deregistered vehicles in Quebec from 2011 to 2022.
- The dataset includes light-duty, medium-duty, and heavy-duty vehicles, further classified by:
  - Private automobiles
  - Commercial automobiles
  - Taxis
  - Motorcycles and scooters
  - Camping vehicles
  - Service vehicles
  - Agricultural vehicles
- Ensure inclusion of the following key attributes:
  - Odometer reading at end-of-life (Lifetime Mileage, LTM)
  - Production year and retirement year
  - Curb mass
  - Fuel type
  - Vehicle model

Validation of curb mass distribution

- Verify that the dataset captures the mass range of light-duty cars and trucks (e.g., pickups, vans, multipurpose 4x4 vehicles).
- Compare the curb mass distribution to historical vehicle sales trends in Quebec over the past five years.

Filtering and processing the data

Address missing data

- Remove vehicles with missing:
  - **Curb mass** (dataset reduced to 11,005).
  - **Odometer mileage** (dataset reduced from 11,005 to 10,130).

Compute core variables

- **Calendar age:**

$$\text{Calendar Age} = \text{Retirement Year} - \text{Registration Year}$$

- **Annual driving distance:**

$$\text{Annual Driving Distance} = \frac{\text{Lifetime Mileage (LTM)}}{\text{Calendar Age}}$$

- Assumption: vehicles maintain a constant rate of use throughout their lifespan.

Apply vehicle category and fuel-type filters

- Retain only gasoline and electric vehicles (excluding other fuel types).
  - Resulting dataset size: 9,748 records.
- Keep only private, commercial, and taxi automobiles (excluding motorcycles, service vehicles, etc.).
  - Resulting dataset size: 9,606 records.

Remove outliers

To reduce the influence of extreme observations and ensure that the analysed vehicles reflect plausible real-world use patterns, a statistical outlier-filtering procedure was applied prior to analysis.

- Vehicles were retained only if both calendar age and annual driving distance fell within the interval defined by the sample mean ± two standard deviations.
- This criterion was applied independently to each variable, thereby excluding vehicles exhibiting implausibly low or high usage or age profiles likely arising from reporting errors, atypical use cases, or incomplete records.
- After filtering, the final analytical sample comprises **8,639 vehicles**.
- The resulting distribution of lifetime mileage is summarised in Table B.1.

This filtering approach represents a conservative data-cleaning step intended to improve the robustness of subsequent statistical analysis while preserving the overall structure and variability of observed vehicle lifetime use.

Table B.1 Lifetime Mileage Statistics (2011–2022, Quebec)

Statistic	**Value**
Mean	225,550 km
Standard deviation	82,103 km
Minimum	9,945 km
25th percentile	170,623 km
Median (50th percentile)	219,785 km
75th percentile	273,277 km
Maximum	748,968 km

Guide for LTM analysis and curve fitting

LOWESS (Locally Weighted Scatterplot Smoothing)

- Apply LOWESS regression to generate a smoothed trend of annual distance vs. lifetime mileage.
- Select an appropriate smoothing parameter (fraction) to obtain a stable curve.
- Inspect confidence intervals to validate the LOWESS trend.

Polynomial and Logarithmic Curve Fitting

- Fit the following models to the data:
  - Quadratic (degree 2): $y = ax^2 + bx + c$
  - Cubic (degree 3): $y = ax^3 + bx^2 + cx + d$
  - Quartic (degree 4): $y = ax^4 + bx^3 + cx^2 + dx + e$
  - Logarithmic: $y = a\log(x) + b$
- Compare visual alignment with LOWESS output.

Model evaluation using R^2

- Compute the coefficient of determination (R^2) for each fitted model.
- Compare R^2 values to identify the best-performing model.
- Select the curve with the highest R^2 as the optimal representation.

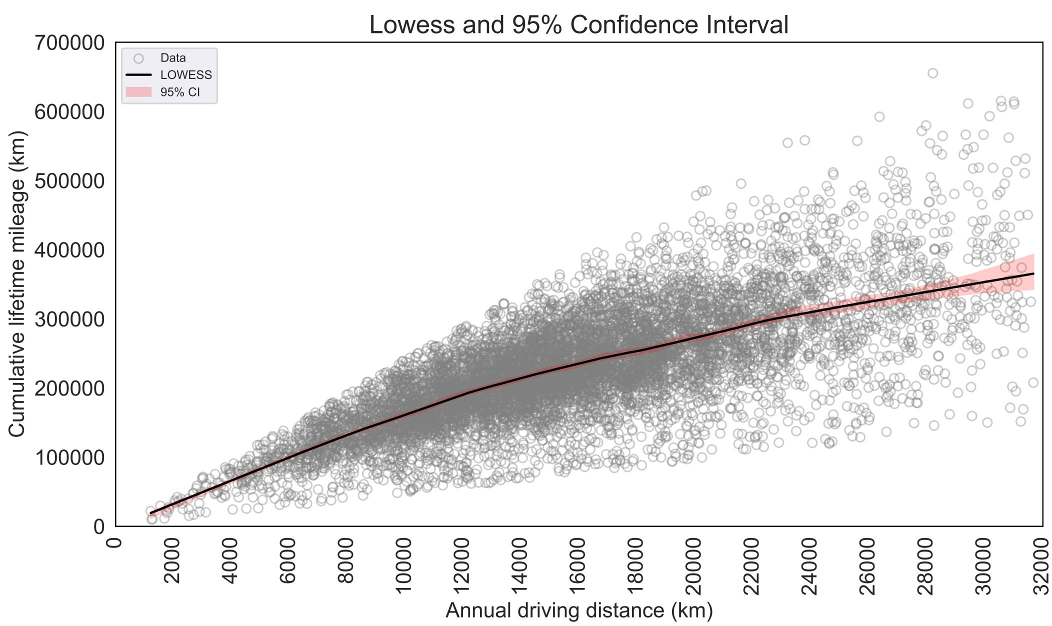

Figure B.1 LOWESS smoothing with confidence bounds for the relationship between annual driving distance and lifetime mileage.

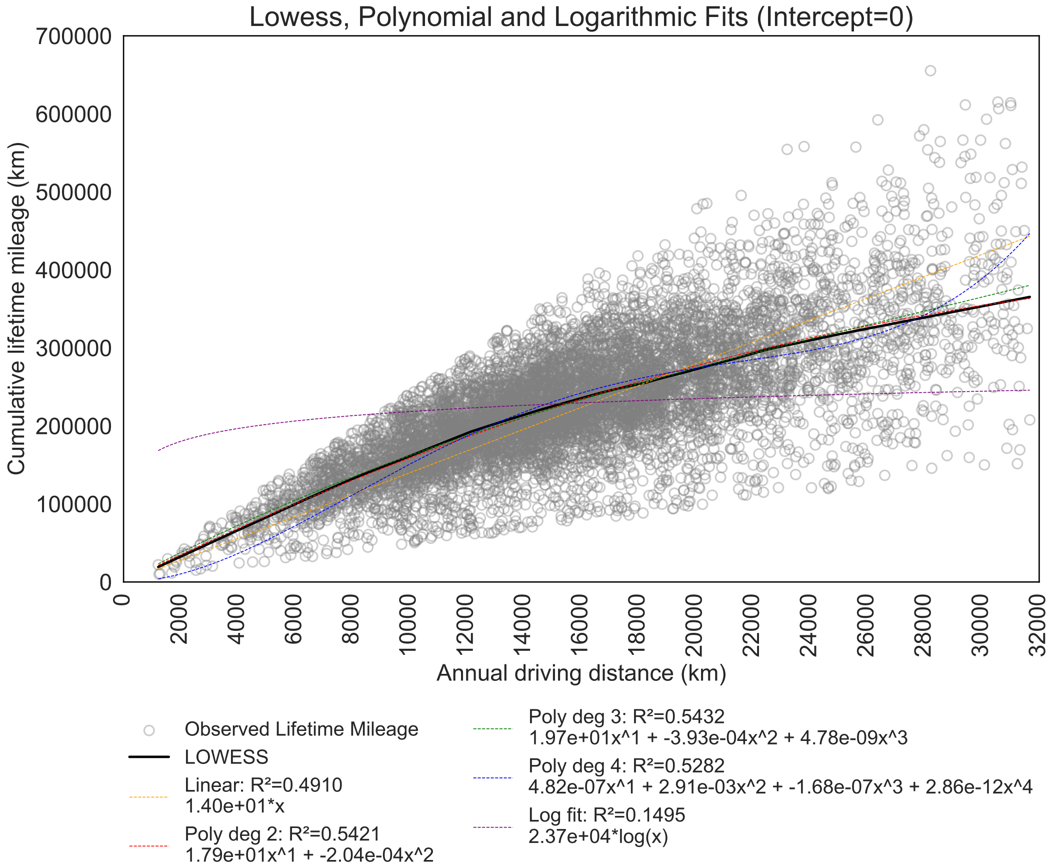

Figure B.2 Comparison of LOWESS, polynomial (degree 2–4), and logarithmic fitting models under the constraint of zero intercept.

Guide to reproducibility of LCA model

The full Python script in jupyternotebook format used to reproduce all preprocessing steps, filtering operations, and performing the analysis can be downloaded from the following link:

`https://doi.org/10.1016/j.trd.2025.105037`

Additional LCA results

This document provides detailed figures illustrating the lifecycle impacts of private car usage and carsharing usage. It includes results for all midpoint impact indicators for both private car and carsharing of battery electric vehicles (BEV) and internal combustion engine vehicles (ICEV-p).

Legend: Blue = End-of-Life (EoL); Orange = Direct exhaust emissions; Green = Direct non-exhaust emissions; Red = Energy chain / upstream supply; Purple = Energy storage (fuel tank or battery); Brown = Glider; Pink = Maintenance; Grey = Powertrain components.

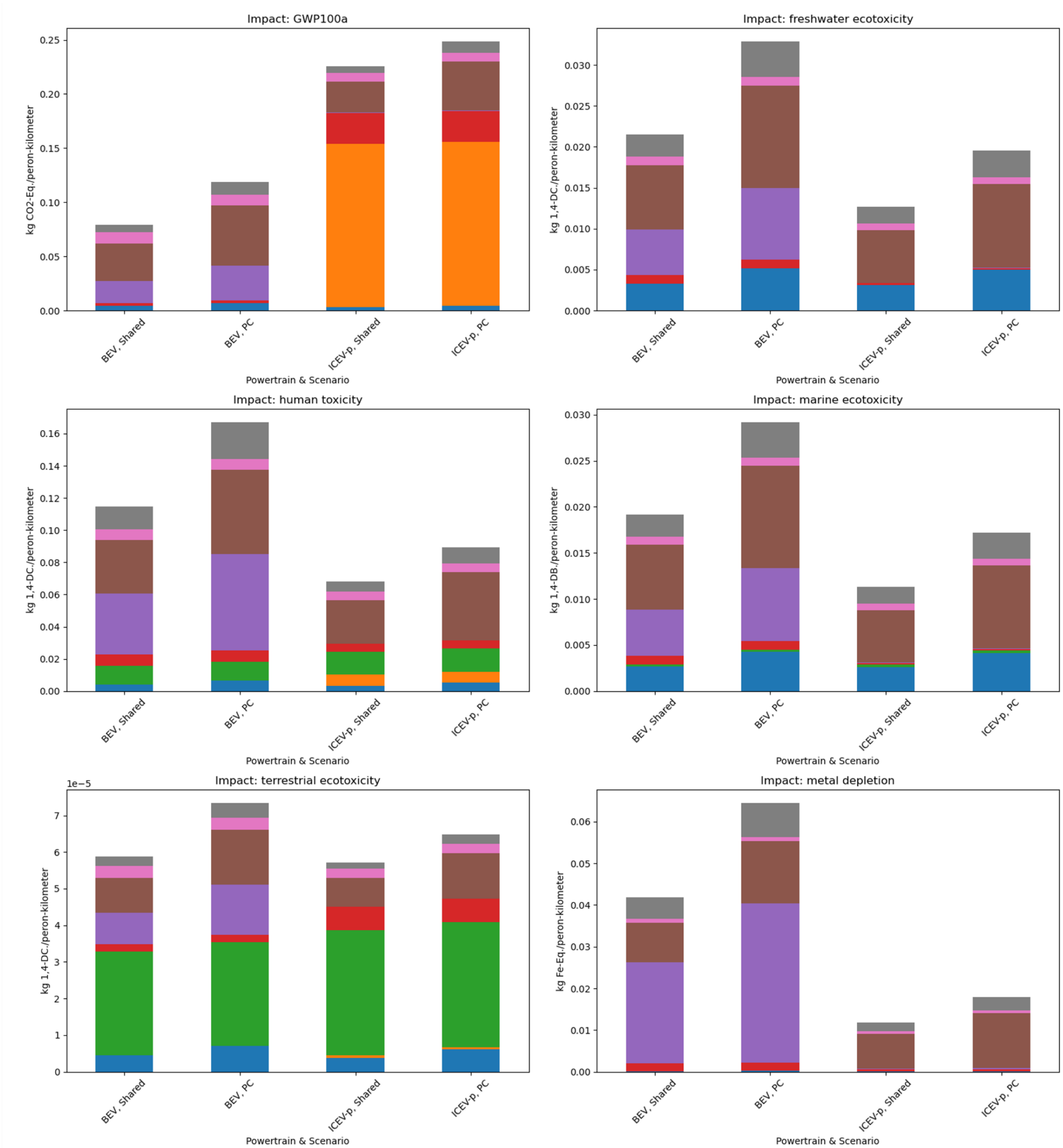

Figure B.3 Lifecycle impacts of private car usage and carsharing for an average user, assessed across the categories of GWP100a, Freshwater Ecotoxicity, Human Toxicity, Marine Ecotoxicity, Terrestrial Ecotoxicity, and Metal Depletion.

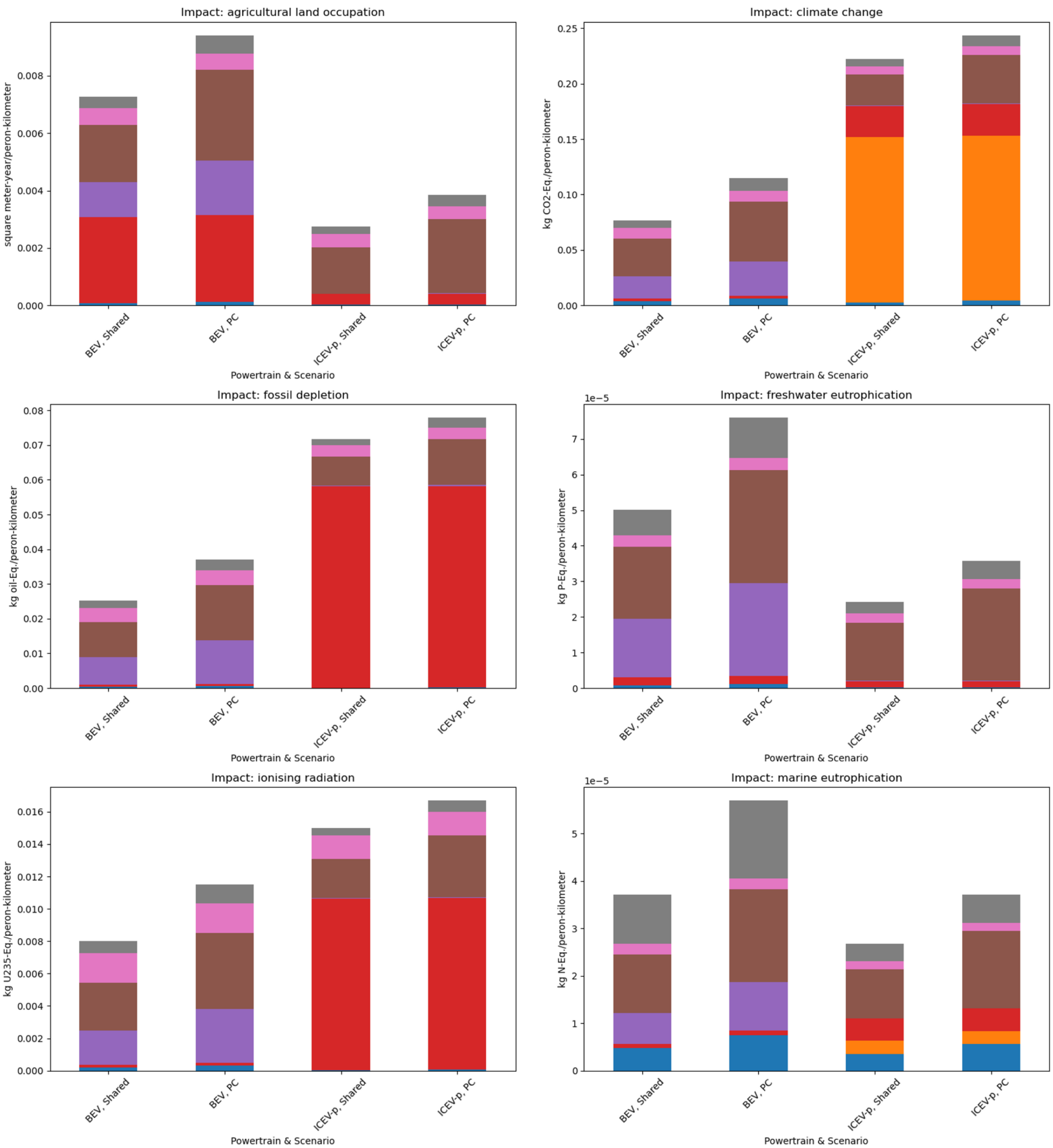

Figure B.4 Lifecycle impacts of private car usage and carsharing for an average user, assessed across the categories of Agricultural Land Occupation, Climate Change, Fossil Depletion, Freshwater Eutrophication, Ionizing Radiation, and Marine Eutrophication.

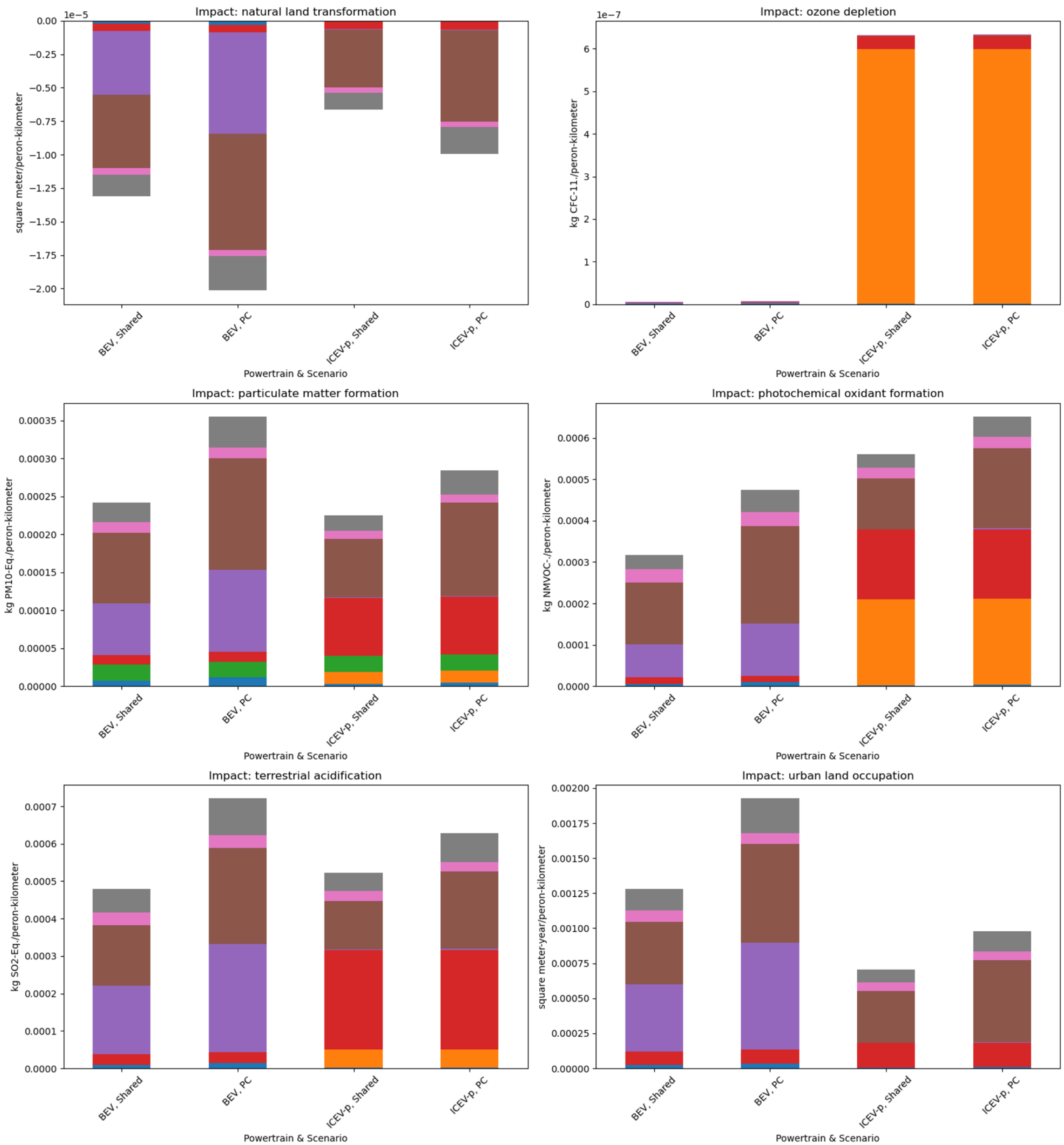

Figure B.5 Lifecycle impacts of private car usage and carsharing for an average user, assessed across the categories of Natural Land Transformation, Ozone Depletion, Particulate Matter Formation, Photochemical Oxidant Formation, Terrestrial Acidification, and Urban Land Occupation.

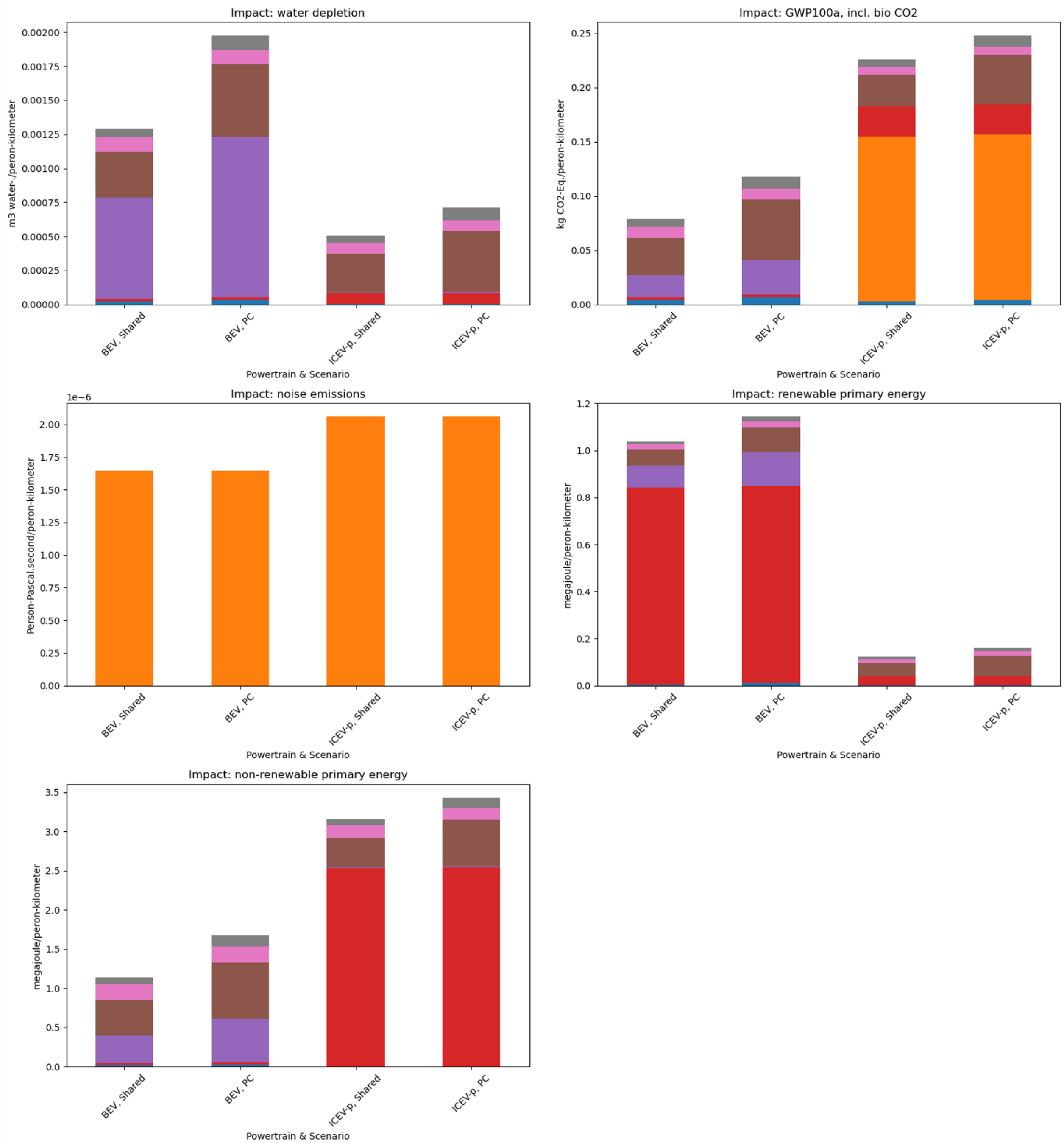

Figure B.6 Lifecycle impacts of private car usage and carsharing for an average user, assessed across the categories of Water Depletion, GWP100a including biogenic CO_2, Noise Emissions, Renewable Primary Energy, and Non-renewable Primary Energy.

APPENDIX C SUPPORTING MATERIALS FOR CHAPTER 5

The full Python script in jupyternotebook format used to reproduce all preprocessing steps, filtering operations, and performing the analysis can be downloaded from the following link:

`https://osf.io/uc98v/overview?view_only=5b3f1a4b5bf040f2b71f418c1e7b34bf`

Procedure for constructing the car trip sample

This appendix describes the procedure used to construct the sample of car trips. The aim is to obtain a clean and realistic subset of trips representative of car travel within the dense central area of Montréal, where large-scale carsharing is most relevant. The final script is provided separately; this section explains the logic behind each step.

Starting dataset

The procedure begins with a dataset that already contains only trips whose origin or destination lies on the Island of Montréal. Each record includes origin and destination coordinates, departure and arrival times, travel time, distance, mode, and person identifier.

Defining the spatial study area

A multi-step approach is used to construct the geographic area from which calibration trips will be drawn.

1. **Island boundary.** A polygon representing the Island of Montréal is constructed and used to ensure that all subsequent areas remain strictly within the island.

2. **Downtown neighbourhoods.** Several recognised neighbourhoods (e.g., Downtown, Golden Square Mile, Old Montréal, Chinatown, Quartier des spectacles) are combined to form a single downtown polygon. Multiple French/English name variants are used for robustness. If a neighbourhood boundary cannot be identified reliably, a small buffer around a known central point is used instead. This avoids failures due to ambiguous or missing place names.

3. **Central boroughs.** A polygon of the "central" area is built by merging a list of boroughs such as Ville–Marie, Plateau–Mont–Royal, Rosemont–La Petite–Patrie, and others representing the dense urban core.

4. **Clipping and union.** Dowtown and central polygons are clipped to the island and then merged into one unified *Central+Downtown* polygon. This area defines the sampling region.

The guiding logic is to focus on the dense inner city where walking, transit, and carsharing are all realistic substitutes. This avoids peripheral areas and ensures consistency in the calibration sample.

Selecting trips by location

Trips are then filtered using their origin and destination coordinates:

- A preliminary bounding-box check first removes trips clearly outside the central area.
- A precise point-in-polygon test is then applied.

For the calibration sample:

> **A trip is kept only if *both* its origin and destination lie inside the Central+Downtown area.**

This removes long cross-island commutes that only touch the central area at one end and focuses the sample on internal urban trips for which carsharing is most applicable.

Removing duplicate trips

After spatial filtering, duplicates are removed:

- If a unique trip identifier is available, duplicates are removed based on this field.
- Otherwise, exact duplicate rows are removed.

This ensures that each trip appears only once, even if it was selected by more than one spatial filter earlier in the pipeline.

Cleaning distance, duration, and mode

The remaining trips are cleaned to ensure internal consistency.

1. **Mode selection.** Only car trips are retained. This matches the purpose of the sample, which is to calibrate driving patterns.

2. **Time fields.** Departure and arrival times are parsed consistently. Travel time is converted to a duration measure, allowing further use of start times (e.g., weekday vs weekend).

3. **Distance and duration ranges.** Extremely short or extremely long trips are removed (e.g., less than a few hundred metres or more than several hundred kilometres; similarly for travel durations). These filters remove data errors and implausible records without making behavioural assumptions.

4. **Missing values.** Trips missing essential information (identifier, times, coordinates, distance, or travel time) are removed.

5. **Consistent naming.** Columns are renamed to match the naming conventions used in the carsharing simulation framework (e.g., `person_id` becomes `user_id`; origin/destination coordinates become `start_x`, `start_y`, `end_x`, `end_y`).

These steps ensure a clean, consistent dataset that feeds directly and reliably into the calibration process.

Weekend indicator

A simple flag is created to distinguish weekday from weekend trips, based on the departure time. This allows peak/off-peak analyses in later stages but does not affect which trips are retained.

Notes on consistency and repetitions

Earlier iterations of the script contained minor redundancies (e.g., applying a distance filter before a mode filter and then overwriting the result). In the final version used for the dissertation, each action—mode filtering, spatial selection, distance/time cleaning, and deduplication—is performed exactly once and in a clear sequence.

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The final cleaned sample represents realistic car trips internal to Montréal's dense central area and serves as the input for car usage behaviour and travel times in the carsharing assignment framework.