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Investigating Anticipated Changes in Post-Pandemic Travel Behavior: Latent Segmentation-Based Logit Modeling Approach Using Data From COVID-19 Era

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Abstract

The unprecedented situation created by the COVID-19 pandemic in the year 2020 has drastically changed daily mobility patterns around the world. Various measures were implemented to prevent the transmission of the virus, which have resulted in short- and long-term impacts on the activity systems and daily travel. To capture the impacts of the pandemic on travel behaviors and activity systems, a web-based survey was designed and administered in April–May 2020 in Montreal, Canada. In addition to questioning on pre- and during COVID-19 behaviors, it included a section on how people expected to travel, telework, shop online, and so forth in the post-pandemic era. Using data from this survey, which gathered 1,620 completed questionnaires, this paper proposes insights into how people are planning to travel in a post-COVID-19 world using latent segmentation-based logit modeling technique. Three models are estimated to identify factors related to expected trip frequency, expected transit usage, and expected bike usage. Undertaking such modeling approach provides opportunity to understand different types of individuals' preferential behaviors. This study probabilistically identifies two latent segments, suburbanite and urbanite people, and finds considerable heterogeneity across sample individuals. For example, urbanite people tend to increase their expected number of trips after COVID-19 if they have at least one bike in their household. Suburbanite people exhibit an opposite relationship, and they are more likely to keep their trip frequency the same as before. Findings of this study will assist decision makers in developing effective policy measures to better prepare for the changes in travel behaviors after COVID-19.

Keywords: COVID-19, expected travel behavior, trip frequency, transit usage, bike usage, latent segmentation-based logit model

Introduction

The unprecedented situation created by the COVID-19 pandemic in the year 2020 has drastically changed daily mobility patterns around the world. COVID-19 is an infectious respiratory-based disease, which is caused by a novel virus called severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) (1). The virus first appeared in Wuhan, China at the end of the year 2019 (2). It is highly transmissible, and the transmission primarily occurs by breathing droplets from coughs and sneezes, person-to-person direct contact, and via infected surfaces (3). It has a significant fatality rate and can cause societal and financial disruptions worldwide (3). COVID-19 was pronounced a worldwide pandemic by the World Health Organization (WHO) on March 11, 2020 (2). This resulted in strict lockdown, social distancing, quarantine measures, and so forth to avoid the spread of the virus and to protect public health, combined with restrictions on travel (4). The pandemic has influenced long-term decisions in households, but short-term activities and travel decisions have experienced even more impacts across the world.

Measures taken to stop the transmission ultimately decreased people's overall mobility and had significant impacts on typical travel behaviors. To understand the changes in individuals' daily mobility related to COVID-19, it is important to explore the relationships between pandemic and transportation. A transportation system works as a connecting hub of travelers' activities and destinations, which makes it a potential source of infectious disease outbreak (5). Therefore, during the outbreak, people started to avoid going out to participate in activities and restricted their mobility to reduce the chances of becoming infected by the virus, which influenced the overall travel patterns of whole regions (6). The number of daily trips undertaken was reduced significantly (7, 8). This subsequently yielded less traffic in the network and lower congestion during peak hours (9). Although distance traveled was found to decrease at the initial stage of the outbreak, it started to increase with the reopening phases—mostly by active modes such as cycling and walking (10). In particular, bike usage has seen an exceptional surge during the COVID-19 pandemic (11). People were also more inclined toward private auto usage since it enabled them to have limited contact with other people (12). The public transport and active transportation sectors were more affected, with a considerable decrease in public transport usage (9). De Vos (13) confirms that various measures implemented during COVID-19 resulted in overall reduction in travel demand, where public transportation was the most affected. Zhang and Lee (7) reported similar behaviors—the usage of public transport decreased significantly and was mostly replaced by walking and cycling. Shamshiripour et al. (14) found that usage of public transit, taxi, and ridehailing services decreased significantly during COVID-19 because of medium to extremely high risk of exposure to the virus in these modes. Similar findings were observed by Nian et al. (15), where they explored lower share of ridehailing services and transit during COVID-19. The primary reason for such changes in regular travel behavior during COVID-19 was fear of being infected with the virus, which ultimately led to increasing telecommuting and online education, and lower participation in public activities and events during the pandemic (7, 13).

Most existing studies on COVID-19 and transportation have explored the impacts of COVID-19 on current travel behavior. It is not clear in the existing studies how people anticipate their daily travel to be in the post-pandemic period. With the ongoing vaccination process across many countries, it is of high importance to assess how people expect to accommodate their travel behavior in the post-pandemic time. This has not yet been explored adequately in the existing literature. It is obvious that with the changes in people's travel behavior during the COVID-19 outbreak, there will be prevalent impacts on the way people will interact and travel in the post-COVID time. There could be radical consequences from the measures taken during COVID-19. Few studies have attempted to investigate how people expect to travel in the post-pandemic world. It has been found that even after the pandemic, people may travel less, usage of public transport may remain lower than before COVID-19, and a significant reduction in shared transportation services may occur because of the fear of virus exposure (13, 16). In contrast, walking and cycling may gain considerable importance (17). De Haas et al. (18) presented a descriptive analysis of expected travel behavior based on the Netherlands Mobility Panel survey. They found that most respondents expect to use all travel modes just as much as they did before COVID-19; however, travelers' attitudes toward choosing private cars is expected to improve while public transport would become notably less favorable in the post-COVID time. Conway et al. (19) conducted a survey on highly-educated adults in the United States in spring 2020, which found that public transport may not completely recover to pre-COVID ridership levels, and people are more likely to walk and cycle than before in the post-pandemic time. However, most of these studies until now have focused on the descriptive analysis of the impacts of COVID-19 on future travel behaviors.

Contribution of the Study

The future of travel behavior during the post-pandemic era is uncertain. Different studies have explored different outcomes based on travelers' opinions using descriptive statistics. However, there is a gap in understanding the behavioral insights such as whether travel behaviors return to normal or transform into a new normal with significant changes in trip frequency and mode choices after a massive pandemic event like COVID-19. Using a descriptive analysis approach, it may not be entirely possible to statistically demonstrate the relationships between choices made by a person and the attributes of the person and/or the choices. In this regard, a discrete choice analysis, that is, an econometric modeling-based micro-behavioral analysis that explores the critical determinants to understand different types of individuals' expected inherent travel behavior, is warranted. This may assist decision makers to develop effective and long-term plans and policies to accommodate changes in individuals' travel preferences. Therefore, based on the needs and gaps, this study contributes to the existing literature in two ways while utilizing data from the COVID-19 era: (i) develop econometric micro-behavioral models of anticipated travel behaviors after COVID-19, and identify factors affecting such behaviors, and (ii) explore behavioral differences among different types of individuals based on their characteristics. Since the data used in this study were collected during the pandemic, and individuals' daily trip frequency and usage of public transport and active modes have experienced considerable changes during COVID-19 (7, 8, 10), this study focuses on developing a trip frequency model, a transit usage model, and a bike usage model to explore individuals' anticipated changes in travel behaviors. The models are developed following a latent segmentation-based logit (LSL) modeling technique. Undertaking this modeling approach provides an opportunity to understand different types of individuals' preferential behavior (20). The LSL model estimation process follows a segmentation approach. The model develops a flexible latent segment allocation model endogenously based on individuals' characteristics to capture the unobserved heterogeneity across sample individuals within the modeling process. It is probabilistically assumed in this study that individuals' expected changes in trip frequency, transit usage, and bike usage may vary based on the socio-demographic and built environment characteristics of their home location. The models provide opportunity to test individuals' discrete latent segment-specific preference of expected travel behavior changes in activity-travel characteristics before COVID-19, expected activity attributes after COVID-19, socio-demographic characteristics, and built environment. This study develops all three travel behavior models by utilizing data from the "COVID-19 Travel Study" survey conducted in Montreal, Canada. Insights from this study will inform decision makers and planners to develop policy interventions and prioritize effective measures to accommodate changes in future travel behavior in the post-pandemic era.

Data

Data Sources

In April 2020, a survey was designed to collect data on the impacts of the COVID-19 pandemic on travel behaviors and activity systems. It had a 60% completion rate which is similar to comparable web surveys on transportation. The average duration of completing the survey was 19.5 min (excluding durations over 40 min) or 21.3 min (excluding durations over 60 min). The median duration was 20 min. The survey was designed in-house and administered online using a platform developed by the research team (21) and used for more than 15 online surveys in the last decade. A lot of attention has been paid throughout the years to the improvement of the web-based survey tool; this is why the research team did not rely on a generic tool (such as Survey Monkey) for questions as complex as travel behavior. The questionnaire was segmented in four main sections: home location and household attributes; people attributes; travel behaviors before COVID-19 and during COVID-19; and expected travel behaviors after COVID-19 (mode, frequency, etc.) including questions on teleworking, online shopping, and other changes in activities. The survey was person-based, meaning that a single respondent per household completed the questionnaire on their travel behaviors and COVID-19 impacts. However, it also collected basic information for each member of the household. The survey was launched on April 28, 2020, and distributed using social networks of partners (transit operators), sent to an in-house panel of respondents, and advertised in a newspaper. In total, 1,620 respondents completed the questionnaire.

To assess the composition of the sample, some reference indicators for the COVID-19 survey sample were estimated using the more recent large-scale "Origin-Destination" survey held in Montreal in 2018. This allows us to conclude that the sample covers the eight main zones of the region with fewer respondents from the eastern part of Montreal Island. Average age is within similar range (40.05 years for the reference value); the 25 to 44 year old age group are over-represented to the detriment of those 65 years and older but not drastically. Men are under-represented since they represent 48.77% of the population, and driving license ownership is higher in the COVID-19 survey sample than in the Montreal population (82.58% is the reference), which is partly because of lower representation of elderly people in the COVID-19 survey. Household size is within the 2.34 person average for Montreal.

Data Preparation and Variables Considered

Preparation of the dataset in this study included various processing steps. After the survey data collection, all data were cleaned carefully, and all identifiable information was replaced with anonymous codes. Respondents were asked how they anticipated changes in their travel behaviors, that is, daily trip frequency, transit usage, and bike usage after COVID-19. Four alternatives were provided for each travel behavior dimension: never used, less usage than before the pandemic (decrease), same usage as before, and more usage than before (increase). Respondents who answered "never used" were omitted during the analysis. Socio-demographic information, activity-travel characteristics before COVID-19, and expected activities after COVID-19 were extracted directly from the "COVID-19 Travel Study" database. Built environment variables were obtained from the 2016 Canadian census and 2020 Proximity Measure Database (PMD). The Canadian census database provides various types of neighborhood information at the dissemination area (DA) level, and PMD provides measures of proximity to various services and amenities at the dissemination block (DB) level. The measurements are represented as an index value ranging from zero to one, where zero indicates the least proximity and one the greatest proximity. To obtain built environment characteristics, the spatial join function in ArcGIS was utilized to join home locations with DA-level data from the census and DB-level data from the PMD.

Table 1. Summary Statistics

Distribution of Dependent Variables

	Trip frequency (n=1,580)	Transit usage (n=1,357)	Bike usage (n=1,098)
Less usage than before (decrease)	36.58%	41.60%	2.80%
Same usage as before (same)	60.06%	57.00%	65.10%
More usage than before (increase)	3.36%	1.40%	32.10%

Distribution of Independent Variables

		Trip freq.		Transit use		Bike use	
Variables	**Description**	**Mean/prop.**	**SD**	**Mean/prop.**	**SD**	**Mean/prop.**	**SD**
Socio-demographic variables							
Age	Age of the individual	42.11	14.32	40.73	13.86	41.05	13.49
Gender: male	Gender is male (dummy)	41.58%	na	41.41%	na	na	na
Gender: female	Gender is female (dummy)	na	na	na	na	55.00%	na
HH income <$120K	Annual HH income below $120K CAD (dummy)	52.28%	na	na	na	52.0%	na
HH income >$120K	Annual HH income above $120K CAD (dummy)	na	na	29.26%	na	na	na
Full-time employment	Individual is full-time employed (dummy)	64.62%	na	65.07%	na	68.00%	na
Part-time employment	Individual is part-time employed (dummy)	na	na	na	na	5.00%	na
Household size	Number of people in household	2.53	1.33	na	na	na	na
Number of cars	Number of cars in household	1.06	0.90	0.95	0.86	1.00	0.89
Carshare member: yes	Enrolled in a carsharing program (dummy)	na	na	22.70%	na	na	na
Carshare member: no	Not enrolled in a carsharing program (dummy)	70.95%	na	na	na	66.30%	na
Bikeshare member: yes	Enrolled in a bikesharing program (dummy)	na	na	na	na	19.95%	na
Bike ownership: yes	Has at least one bike in HH (dummy)	74.37%	na	na	na	88.52%	na
Transit pass: yes	Has a monthly transit pass (dummy)	na	na	66.32%	na	60.20%	na
Driving license: yes	Possesses a driver's license (dummy)	90.76%	na	89.46%	na	na	na
Activity-travel characteristics before COVID-19							
Places visited weekly	Number of places visited in a week	3.44	2.34	3.48	2.33	3.49	2.35
Visit freq. primary loc.: <1/wk	Visits primary activity loc. max once/week	na	na	4.42%	na	na	na
Primary activity: work	Primary activity type is work (dummy)	na	na	65.00%	na	66.85%	na
Primary activity: shopping	Primary activity type is shopping (dummy)	na	na	6.41%	na	na	na
Primary activity: leisure	Primary activity type is leisure (dummy)	6.14%	na	5.90%	na	na	na
Primary mode: car driving	Travel mode to primary activity is car driving	33.16%	na	24.69%	na	na	na
Primary mode: bicycle	Travel mode to primary activity is bicycle	18.23%	na	na	na	25.96%	na
Primary mode: public transport	Travel mode to primary activity is transit	36.39%	na	na	na	58.20%	na
Expected activities after COVID-19							
Plan to relocate residence	Expects to relocate residence (dummy)	32.72%	na	34.27%	na	na	na
Trip frequency: increase	Expects to increase trip frequency	na	na	na	na	2.64%	na
Car usage: increase	Expects to increase car usage	na	na	na	na	6.74%	na
Telecommute freq.: never	Expects to never telecommute	12.15%	na	11.27%	na	10.56%	na
Telecommute freq.: ≥4 days/wk	Expects to telecommute ≥4 days/week	4.75%	na	4.27%	na	na	na

Online food order: never	Expects not to order food online	26.71%	na	25.94%	na	na	na
Online groceries: never	Expects not to order groceries online	38.99%	na	39.35%	na	38.62%	na
Built environment							
Employment rate	Employment rate in the neighborhood	na	na	63.63	10.24	na	na
% rental houses	% of rental houses in neighborhood	66.19	30.78	na	na	51.70	28.41
% single-detached houses	% of single-detached houses in neighborhood	24.61	34.03	na	na	21.50	32.11
% apartments	% of apartments in neighborhood	na	na	72.15	35.48	na	na
Proximity to employment	Proximity index to employment	na	na	0.14	0.09	0.14	0.09
Proximity to transit station	Proximity index to public transport stations	na	na	0.04	0.03	na	na
Proximity to parks	Proximity index to parks	0.12	0.11	na	na	na	na
Proximity to grocery stores	Proximity index to grocery stores	0.18	0.15	0.18	0.15	0.18	0.15
Proximity to health care	Proximity index to health care facilities	0.04	0.04	na	na	na	na

Comparison Between COVID-19 Travel Survey and Montreal Origin-Destination Survey

Indicators	COVID-19 Travel Survey	Montreal OD Survey
Average age	42.32	40.05
Gender: male (%)	41.98	48.77
Driving license: yes (%)	90.68	82.58
Carshare member: yes (%)	19.57	3.29
Bikeshare member: yes (%)	14.07	2.27
Transit pass: yes (%)	56.73	25.46
One-person household (%)	22.59	34.50
Average household size	2.53	2.34
Average car ownership	1.07	1.27
HH income >$120K (%)	28.70	13.05

Note: $ = Canadian dollars (CAD); na = not applicable.

Modeling Approach

This study utilizes a random utility-based discrete choice modeling technique to estimate individuals' expected travel behavior. The multinomial logit (MNL) model is one of the suitable approaches for discrete choice modeling. However, such traditional models generally have an inherent monotonic assumption of independence from irrelevant alternatives, which overlooks the unobserved preference heterogeneity that may occur when choices are made. This may result in inconsistent and biased estimations (22). To overcome this issue, researchers have developed flexible alternative approaches such as random parameter logit (RPL) model and LSL model. The RPL model can capture heterogeneity by allowing random parameters to vary with a continuous joint parametric distribution across a population, which is required to be assumed by the analysts (23). In contrast, the LSL model provides a semiparametric specification that does not require any strong or unseemly parametric distribution about preference heterogeneity to be assumed (20); instead, it captures unobserved heterogeneity by implicitly sorting individuals into discrete latent segments.

This study develops LSL models to estimate individuals' behavior with regard to anticipated changes in trip frequency, transit usage, and bike usage after COVID-19. Individuals' probability of being included in different latent segments is determined by developing a latent segment allocation model, which is defined using individuals' observed socio-demographic and built environment characteristics. The probability of an individual *n* being allocated to latent segment *s* is given by a logit formulation based on segment membership constants, observed attributes of the individuals, and segment membership vector coefficients. One of the segments is assumed to be the reference segment for model identification. Assuming that individual *n* allocated to segment *s* chooses an alternative *j* from a set of alternatives *K*, the choice probability follows a standard logit formulation with segment-specific vector coefficients. The likelihood of an individual choosing an alternative is the expectation (over segments) of the segment-specific contributions. The LSL model estimates the parameters by maximizing the likelihood using an expectation maximization algorithm. The goodness-of-fit of each model is evaluated based on the log-likelihood value at convergence, McFadden's pseudo-R^2, AIC, and BIC.

Discussion of Results

Determination of the Number of Latent Segments

Estimation of the LSL model starts with identifying the number of latent segments, *S*. Since the number of segments is not a parameter, a hypothesis on this cannot be tested directly. This study determines the number of segments based on the AIC and BIC values (24). Results suggest that AIC and BIC values are minimum for the models with two segments. Therefore, the final models are assumed to have two latent segments. Although most parameters retained in the final models are statistically significant at least at 90% confidence level (t-stat $\geq$ 1.64), a few parameters with significance below 90% are kept for their critical insights.

Expected Changes in Trip Frequency Model Results

The latent segment allocation model is estimated considering segment 2 as the reference segment. Results exhibit a negative sign for household income below $120,000 CAD, demonstrating a lower probability of individuals in such households being allocated to segment 1. The positive parametric value of age indicates that older individuals are more likely to belong to segment 1. Built environment characteristics reveal that suburban dwellers have a higher likelihood of being allocated to segment 1. Therefore, segment 1 is probabilistically identified as "suburbanite people" and segment 2 as "urbanite people."

Several socio-demographic variables, built environment attributes, activity-travel characteristics before COVID-19, and expected online activities after COVID-19 are found to influence individuals' expected travel usages. Male individuals are more likely to decrease their trips in the suburbanite segment, while male urbanite individuals tend to increase their trip frequency. Bike ownership shows heterogeneous relationships across segments. Urbanite individuals with a bike are more likely to increase trip frequency, while suburbanite bike owners show a negative parametric value. Interesting heterogeneous outcomes are observed with driving license ownership: older and higher income suburbanite individuals tend to decrease anticipated trips, while younger lower-income urbanite people are less likely to decrease. Both segments show that public transport as primary pre-COVID mode decreases expected trip frequency. Car drivers tend to keep anticipated trip frequency the same. People expecting no online activities tend to increase trip frequency post-pandemic.

Table 2. Expected Changes in Trip Frequency Model Estimation Results

Determination of Number of Segments

Goodness-of-fit measures	2 segments	3 segments
Number of parameters	63	57
Log-likelihood at convergence	–809.78	–1156.78
McFadden's pseudo-R^2	0.3601	0.2846
AIC	1745.56	2391.56
BIC	2083.57	2600.80

Latent Segment Allocation Component

Variables	Segment 1 — Coeff. (t-stat)	Segment 2 — Coeff. (t-stat)
Segment membership probability	0.67	0.33
Constant	–8.1209 (–2.97)	Reference segment
Age	0.1327 (2.80)	
HH income below $120K	–0.8719 (–1.73)	
% rental houses in neighborhood	–0.0622 (–3.17)	
% single-detached houses in neighborhood	0.0929 (2.50)	

Random Utility Parameters in Latent Segments

Variables	Decrease Seg 1	Decrease Seg 2	Same Seg 1	Same Seg 2	Increase Seg 1	Increase Seg 2
Constant	–0.2688 (–1.95)	1.8360 (2.57)	0.8414 (1.44)	2.8731 (1.57)	Ref.	Ref.
Socio-demographic variables						
Gender: male	0.4685 (2.17)	–2.9514 (–2.06)	—	—	–0.7541 (–1.55)	0.5661 (1.84)
Household size	–0.6867 (–4.55)	–1.6812 (–1.97)	0.1268 (2.57)	1.1288 (1.66)	—	—
Number of cars	—	—	–0.1538 (–3.18)	–1.6036 (–1.71)	—	—
Carshare member: no	—	—	0.0782 (1.49)	1.7322 (2.19)	–0.1101 (–1.82)	–0.6925 (–2.44)
Bike ownership: yes	—	—	0.2645 (4.28)	–0.4395 (–3.13)	–1.3469 (–2.14)	0.1384 (3.57)
Driving license: yes	1.0456 (2.32)	–3.4874 (–1.80)	—	—	—	—
Full-time empl. × plan to relocate	0.5321 (2.50)	0.2278 (1.61)	—	—	—	—
Full-time empl. × telecommute ≥4d/wk	—	—	—	—	–0.3001 (–3.19)	–1.8551 (–2.14)
Transit pass × primary act.: work	0.3467 (1.75)	0.6671 (2.65)	—	—	–1.2103 (–4.44)	–0.1968 (–1.69)
Activity-travel before COVID-19						
Places visited weekly	—	—	—	—	–0.2915 (–1.39)	–0.1332 (–3.71)
Primary activity: leisure	0.7195 (1.92)	0.5698 (1.33)	—	—	—	—
Primary mode: car driving	—	—	0.3272 (3.37)	3.7097 (1.75)	—	—
Primary mode: bike	0.0604 (2.07)	–0.1074 (–3.00)	—	—	—	—
Primary mode: public transport	0.3497 (2.59)	3.7638 (2.20)	—	—	–0.1397 (–2.59)	–2.1824 (–1.98)
Expected activities after COVID-19						
Telecommute freq.: never	–2.0745 (–1.92)	–0.8076 (–1.99)	0.2218 (2.21)	2.1675 (1.94)	—	—
Online food order: never	–0.5250 (–2.75)	–1.2769 (–4.95)	—	—	—	—
Online groceries: never	—	—	—	—	0.1790 (3.10)	1.6233 (2.87)
Built environment						
Proximity to parks	1.0313 (2.55)	2.9752 (1.79)	—	—	—	—

Proximity to grocery stores	—	—	–2.0354 (–2.60)	–2.9937 (–2.09)	—	—
Proximity to health care	—	—	—	—	–3.9469 (–1.66)	–5.7165 (–0.64)

Marginal Effects (% points) of Five Most Impactful Determinants

	Decrease Suburb.	Decrease Urban.	Same Suburb.	Same Urban.	Increase Suburb.	Increase Urban.
Bike ownership: yes	—	—	8.17	–4.88	–2.21	24.43
Driving license: yes	2.59	–10.85	—	—	—	—
Primary mode: public transport	4.62	16.84	—	—	–13.59	–6.58
Telecommute freq.: never	–5.84	–21.71	5.73	0.92	—	—
Proximity to parks	5.76	2.99	—	—	—	—

Note: AIC = Akaike information criteria; BIC = Bayesian information criteria; $ = Canadian dollars (CAD); — = not applicable.

Expected Changes in Transit Usage Model Results

The latent segment allocation indicates that segment 1 has a higher likelihood of including urban dwellers with lower household income, no full-time workers, and younger age ("urbanite people"), while segment 2 represents "suburbanite people." Transit pass ownership increases urbanite people's probability of increased transit usage, while suburbanite people show the opposite. Driving license holders are less likely to increase transit usage. Plan to relocate residence increases the probability of reduced transit usage, especially when interacting with driving license ownership. Higher employment rate in the neighborhood reduces the probability of increased transit usage in both segments.

Table 3. Expected Changes in Transit Usage Model Estimation Results

Goodness-of-fit measures	2 segments	3 segments
Number of parameters	65	63
Log-likelihood at convergence	–730.71	–986.55
McFadden's pseudo-R^2	0.3801	0.3117
AIC	1595.42	2069.10
BIC	1944.69	2319.33

Latent Segment Allocation Component

Variables	Segment 1 — Coeff. (t-stat)	Segment 2 — Coeff. (t-stat)
Segment membership probability	0.71	0.29
Constant	–4.6933 (–1.72)	Reference segment
Age	–0.0431 (–1.82)	
Full-time employment	–0.8875 (–1.68)	
HH income above $120K	–1.7472 (–2.30)	
% apartments in neighborhood	0.0638 (2.04)	

Random Utility Parameters in Latent Segments

Variables	Decrease Seg 1	Decrease Seg 2	Same Seg 1	Same Seg 2	Increase Seg 1	Increase Seg 2
Constant	3.7625 (2.87)	–0.6204 (–1.63)	3.6586 (2.10)	0.6180 (1.66)	Ref.	Ref.
Socio-demographic variables						
Gender: male	–2.8758 (–1.87)	0.4322 (2.81)	3.3451 (1.42)	–0.9401 (–1.91)	—	—
Number of cars	—	—	–0.3156 (–2.33)	–3.4900 (–3.43)	—	—
Carshare member: yes	—	—	–1.1355 (–1.35)	–0.9107 (–2.55)	—	—
Transit pass: yes	—	—	—	—	1.0214 (1.66)	–0.5520 (–3.56)
Transit pass × primary act.: work	0.3172 (1.98)	0.4310 (1.59)	—	—	—	—
Driving license: yes	—	—	—	—	–1.7127 (–2.00)	–1.6630 (–1.76)
Activity-travel before COVID-19						
Places visited weekly	—	—	—	—	–0.9669 (–1.76)	–0.1653 (–1.65)
Visit freq. primary loc.: <1/wk	0.8315 (3.18)	0.2376 (2.49)	—	—	—	—
Primary activity: shopping	–2.9061 (–0.51)	0.4820 (3.19)	—	—	—	—
Primary activity: leisure	—	—	1.5869 (3.89)	–0.4957 (–1.91)	—	—
Primary mode: car driving	0.8716 (1.69)	0.7348 (2.93)	–1.7458 (–2.10)	–0.8537 (–1.99)	—	—
Expected activities after COVID-19						
Plan to relocate residence	1.2477 (1.54)	0.2577 (2.01)	—	—	—	—

Plan to relocate × driving license	2.1178 (2.65)	3.1898 (2.33)	—	—	—	—
Telecommute freq.: never	0.9485 (2.11)	1.0977 (2.63)	—	—	–2.2811 (–2.47)	–1.0543 (–3.81)
Telecommute freq.: ≥4 d/wk	—	—	–0.1244 (–2.28)	–0.4295 (–2.55)	—	—
Online groceries: never	–1.0350 (–3.16)	–0.5592 (–1.98)	—	—	—	—
Online food order: never	—	—	0.2922 (2.00)	0.0914 (1.63)	–2.4016 (–1.68)	–1.4349 (–2.81)
Built environment						
Employment rate	—	—	—	—	–0.1239 (–1.74)	–0.0831 (–2.59)
Proximity to employment	–1.3122 (–1.61)	5.7185 (2.24)	—	—	2.3860 (1.80)	–2.5799 (0.39)
Proximity to transit station	1.5176 (2.22)	2.6305 (3.00)	–1.8201 (–1.79)	–3.7086 (–2.93)	—	—
Proximity to grocery stores	—	—	0.5244 (1.61)	0.2635 (2.11)	–3.7469 (–2.99)	–1.6191 (–1.63)

Marginal Effects (% points) of Five Most Impactful Determinants

	Decrease Urban.	Decrease Suburb.	Same Urban.	Same Suburb.	Increase Urban.	Increase Suburb.
Transit pass: yes	—	—	—	—	2.81	–14.00
Primary mode: car driving	–9.22	2.52	–9.92	–1.56	—	—
Plan to relocate × driving license	11.50	6.18	—	—	—	—
Telecommute freq.: never	12.11	4.02	—	—	–4.29	–28.62
Proximity to transit station	9.53	19.46	–11.00	–4.68	—	—

Note: AIC = Akaike information criteria; BIC = Bayesian information criteria; $ = Canadian dollars (CAD); — = not applicable.

Expected Changes in Bike Usage Model Results

The latent segment allocation identifies segment 1 as "suburbanite people" (older, higher single-detached house percentage) and segment 2 as "urbanite people." Female individuals are less likely to increase expected bike usage in both segments. Urbanite people with more cars demonstrate higher probability to increase bike usage, while suburbanite people show the opposite. Transit pass owners tend to increase expected bike usage in both segments. Bikeshare members are less likely to decrease expected bike usage. With increased trip frequency after COVID-19, both segments show higher inclination to increase expected bike usage.

Table 4. Expected Changes in Bike Usage Model Estimation Results

Goodness-of-fit measures	2 segments	3 segments
Number of parameters	65	65
Log-likelihood at convergence	–602.06	–1006.47
McFadden's pseudo-R^2	0.3957	0.3007
AIC	1338.12	2102.94
BIC	1673.20	2328.00

Latent Segment Allocation Component

Variables	Segment 1 — Coeff. (t-stat)	Segment 2 — Coeff. (t-stat)
Segment membership probability	0.41	0.59
Constant	8.4114 (4.02)	Reference segment
Age	0.1240 (4.72)	
HH income below $120K	–1.1652 (–2.07)	
% single-detached houses in neighborhood	0.6972 (1.77)	
% rental houses in neighborhood	–0.0314 (–1.71)	

Random Utility Parameters in Latent Segments

Variables	Decrease Seg 1	Decrease Seg 2	Same Seg 1	Same Seg 2	Increase Seg 1	Increase Seg 2
Constant	–3.6646 (–1.42)	1.3531 (2.11)	Ref.	Ref.	–1.3962 (–2.67)	1.6570 (1.58)
Socio-demographic variables						
Gender: female	—	—	1.0475 (1.91)	0.6354 (1.61)	–1.2947 (–2.40)	–2.4173 (–1.65)
Number of cars	—	—	—	—	–0.1602 (–3.84)	0.6443 (2.49)
Part-time employment	—	—	0.5180 (2.88)	1.8846 (1.64)	—	—
Full-time empl. × expected car usage: increase	2.8333 (1.97)	2.7953 (2.18)	—	—	—	—
Transit pass: yes	–0.7868 (–2.98)	–2.1420 (–3.82)	—	—	0.2545 (1.69)	1.2730 (2.88)
Transit pass × primary act.: work	1.0983 (1.67)	–2.8123 (–1.89)	—	—	—	—
Bike ownership: yes	—	—	0.3408 (3.81)	–1.0156 (–2.86)	—	—
Carshare member: no	–0.0661 (–1.85)	–0.2252 (–2.00)	—	—	0.6022 (2.78)	2.3861 (1.77)
Bikeshare member: yes	–1.2733 (–1.69)	–3.9220 (–2.11)	—	—	0.2112 (4.05)	1.9805 (1.67)
Activity-travel before COVID-19						
Places visited weekly	—	—	—	—	–0.2891 (–1.50)	0.9350 (3.57)
Primary activity: work	—	—	0.7543 (2.51)	1.9420 (1.39)	—	—
Primary mode: bike	—	—	–0.2860 (–3.41)	–0.1259 (–2.37)	0.5046 (3.27)	1.2853 (2.58)
Primary mode: public transport	–1.0933 (–1.64)	–0.2881 (–1.61)	—	—	0.2205 (2.85)	1.2551 (1.59)

Expected activities after COVID-19						
Telecommute freq.: never	3.8960 (1.50)	–1.2947 (–1.75)	—	—	–0.4100 (–1.63)	0.3715 (2.03)
Online groceries: never	1.2917 (2.87)	–3.5131 (–3.15)	0.3554 (1.91)	1.8303 (1.68)	—	—
Trip frequency: increase	—	—	—	—	1.2033 (2.24)	0.5638 (2.25)
Car usage: increase	—	—	–0.7717 (–2.19)	0.6225 (1.75)	—	—
Built environment						
Proximity to employment	—	—	1.5247 (2.19)	3.4419 (1.77)	–2.4546 (–1.55)	–4.3208 (–1.76)
Proximity to grocery stores	—	—	—	—	–0.7820 (–1.99)	3.2284 (1.69)

Marginal Effects (% points) of Five Most Impactful Determinants

	Decrease Suburb.	Decrease Urban.	Same Suburb.	Same Urban.	Increase Suburb.	Increase Urban.
Bikeshare member: yes	–5.55	0.83	—	—	2.96	–6.74
Full-time empl. × car usage: increase	16.62	7.59	—	—	—	—
Primary mode: bike	—	—	–1.82	–6.05	9.82	29.08
Trip frequency: increase	—	—	—	—	4.85	11.37
Proximity to employment	—	—	8.86	14.67	–6.51	–4.88

Note: AIC = Akaike information criteria; BIC = Bayesian information criteria; $ = Canadian dollars (CAD); — = not applicable.

Conclusion

This study presents the findings of an investigation into anticipated changes in travel behaviors in the post-pandemic period using data from the time of the COVID-19 pandemic. It develops three LSL models to explore the expected changes in trip frequency, transit usage, and bike usage after COVID-19. Anticipated changes in such behaviors are estimated considering three alternatives for each dimension: less than before (decrease), same as before, and more than before (increase). The study utilizes data from the COVID-19 Travel Study survey that was administered in Montreal, Canada. Within the LSL modeling framework, the sample individuals are implicitly allocated into discrete latent segments based on their socio-demographic and built environment characteristics. The estimation process suggests that models with two latent segments are the best models to explain individuals' anticipated travel behavior. These latent segments are probabilistically identified as the segments of suburbanite people and urbanite people.

The study explores critical impacts of several socio-demographic characteristics, built environment, and activity-travel characteristics during pre- and post-pandemic times on individuals' anticipated travel behaviors after COVID-19. It discovers considerable behavioral heterogeneity across the sample individuals. Results suggest that ownership of a monthly transit pass is more likely to increase individuals' transit usage during the post-pandemic period in the urbanite segment, whereas individuals in the suburbanite segment have a lower likelihood of increase in their expected transit usage. Full-time employed people who plan to relocate their residence after COVID-19 demonstrate higher propensity to decrease their expected trip frequency. As to pre-COVID activity-travel characteristics, suburbanite people who used cycling as their primary travel mode before COVID-19 tend to decrease their expected number of trips, however, urbanite people are less likely to reduce their trip frequency. In the case of public transport, individuals who used it as a primary travel mode before the pandemic show higher likelihood to decrease their expected trip frequency in both segments. It is found that such individuals are more likely to increase their expected bike usage after COVID-19.

Expected results are found in the case of post-pandemic anticipated activities. Individuals who expect not to telecommute or order food online after the pandemic are less likely to decrease their anticipated number of trips. Plan to relocate residence after the pandemic increases the probability of reduced expected transit usage in both urbanite and suburbanite segments. Furthermore, as the proximity to employment increases, results suggest that individuals from both latent segments are less likely to increase their expected bike usage. However, heterogenous behaviors are observed in case of anticipated transit usage. Individuals belonging to the urbanite segment expect to increase their transit usage with proximity to employment; however, suburbanite people demonstrate a lower probability to increase their expected transit usage after the pandemic.

This study has certain limitations. It presents the estimation of expected changes in trip frequency, transit usage, and bike usage. However, to clearly understand the travel behaviors after COVID-19, it is important to estimate the changes in activity and travel attributes as well. One immediate future work is to estimate changes in expected activity participation, private car usage, walk mode usage, and so forth using a similar modeling framework. This study also anticipates heterogeneity across sample individuals based on their characteristics, but it is unlikely that all individuals with similar characteristics will have similar behavioral preferences. Therefore, another future work is to include random parameters in the LSL modeling framework to capture within-segment heterogeneity. In addition, data used in this study were collected during the first wave of COVID-19 in April 2020. Travelers' perspectives, attitudinal preferences, and perceived risks may have changed during subsequent waves. COVID-19 vaccine availability, increasing awareness, vaccination rates, and emergence of new variants may change individuals' travel preferences. Another limitation is not accommodating the inherent ordering in the models. Future research should develop models that capture both the ordinal nature and unobserved heterogeneity, such as latent segmentation-based ordered logit models (30) and latent segmentation-based generalized ordered logit models (31). Finally, jointly estimating the changes in trip frequency, transit usage, and bike usage with the same class membership using copula-based Bayesian modeling approaches could be an interesting future direction.

Nevertheless, this study provides important insights on expected changes in trip frequency, transit usage, and bike usage during the post-pandemic period. Models presented will be used to develop forecasting techniques to predict individual-level future travel behaviors in the Greater Montreal Area. Results can assist in the development of effective policies to support active travel and improve transit ridership. Since the results demonstrate heterogeneity across individuals, target marketing strategies could be advantageous to develop various policy interventions. The findings will assist policy makers and planners to better prepare for the post-pandemic era by developing policies to accommodate anticipated changes in travel behaviors.

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