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How will individuals travel post-COVID? A statistical framework to identify the determinants of different travel behaviors

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Abstract

The outbreak of the pandemic in 2020 has caused an unforeseen situation that significantly changed individuals' travel patterns around the globe. The transmission prevention measures that were put in place have had both short- and long-term effects on people's activity systems and their daily travel patterns. In order to investigate the pandemic's effects on travel patterns and activity systems, a web-based questionnaire was developed and distributed in Montreal, Canada, in April and May of 2020. In addition to questions about activities before and during COVID-19, a section on how people anticipated travelling in the post-pandemic era was also included in the questionnaire. This research presents insights into how people are planning to travel in the post-COVID period utilizing K-means clustering and Multinomial Logit (MNL) models. the data gathered from the survey resulted into 1620 completed questionnaires, out of which 1597 were valid. This investigation offers crucial insights on anticipated changes in travel frequency, use of public transportation, and use of bicycles throughout the post-pandemic era. The findings of this study will help planners and policymakers create plans that will better prepare the cities for the post-pandemic era by taking into account the projected changes in people's travel patterns.

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Keywords: COVID-19; anticipated travel behavior; trip frequency; K-means clustering; MNL model

1. Introduction

Coronavirus disease of 2019 or in short COVID-19 is the name given by World Health Organization (WHO) to a respiratory disease caused by SARS-CoV-2 (Severe Acute Respiratory Syndrome Coronavirus 2). Reported for the first time in Wuhan, China in December 2019, SARS-CoV-2 is the novel coronavirus and the successor of SARS-

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CoV, a virus that caused a pandemic from late 2002 to mid-2003 (Centers for Disease Control and Prevention). SARS-CoV had a higher fatality rate than SARS-CoV-2, however SARS-CoV-2 is more easily transmitted as its viral load is at a high level even in the early stages of infection. On the contrary, the viral load of a SARS-CoV infection peaks much later in the illness (Healthline). Although SARS-CoV posed a higher fatality rate, the outbreak lasted for a short period and had resulted into 8098 cases and 774 deaths globally (News Medical). On the other hand, as of 24th of August, 2022, there were about 601 million confirmed cases of COVID-19 and 6.48 million deaths globally (World Health Organization). Due to the higher transmissibility level of SARS-CoV-2, the pandemic has lasted for a significantly longer period affecting numerous aspects of human life on the planet. Although COVID-19 is fundamentally a health threat to people's lives, its impacts are not limited to the health domain and goes way beyond into numerous dimensions such as environment, economy, transportation, education, tourism, etc.

Among all the sectors, the pandemic has significantly affected the transportation sector in numerous ways. For example it has resulted into: declination in the usage of public transportation and air transport, increase in the usage of private cars and active modes of transportation (walking and cycling), substantial reduction in trips to and from work and school, reduction in the level of activities which has led to decrease in the number of trips and trip distances, growth of online shopping and teleworking activities, significant decrease in the frequency of all kinds of trips specially eating out and leisure trips, rise of traveling speeds, significant reduction in accidents particularly among those that happened in the early morning, reduced rate of deaths caused by accidents (Kim, 2021), and rise in the number of people who have a negative attitude towards public transit and inclination towards private modes of transportation (Sharifi & Khavarian-Garmsir, 2020).

The COVID-19 pandemic has had various short-term and long-term effects on many aspects of human life and his surrounding environment. Now, after more than two years from the beginning of the pandemic, even though many countries have relieved social distancing rules and mandatory use of masks, these effects have not disappeared and are tangible. In other words, not only some of the effects of the pandemic have not disappeared, but also they have been accepted and remained as a "new normal" in the form of somewhat stable and long-term effects.

The focus of this research is on the impacts of COVID-19 on mobility patterns and travel behaviors of people in Montreal, Canada. During the COVID-19 pandemic, Montreal has experienced five primary lockdown periods in which the majority of non-essential businesses and services were shut down. The national institute of public health (INSPQ) has compiled a comprehensive online record of all activities and actions associated with the COVID-19 pandemic in Quebec. From the beginning of the pandemic and during the lockdowns, access to certain areas was restricted, the Canadian border remained closed, and there was a considerable decline in international travel to Montreal. For the majority of the time, daycare facilities remained open; however, until September 2021, universities and colleges remained closed. Between March 2020 to September 2020, primary and secondary schools were closed (while being switched to online learning), however, they have since reopened. Moreover, teleworking was widely used by many companies and organisations in Montreal and return to office work was limited (Deschaintres et al., 2022; INSPQ, 2022).

In this study, our objective is to identify the determinants of anticipated travel behaviors of individuals in the post-COVID era in two steps. In the first step, we intend to categorize individuals using K-means clustering based on their levels of anticipated travel frequency in the post-COVID phase. Then, in the second step, we will identify the determinants of belonging to each of the resulting categories of the first step by employing a Multinomial Logit (MNL) model. This study will provide insights on individuals' travel behavior in the post-COVID era and implies that cities should anticipate and prepare for a new normal. It also enables us to develop prospective travel behavior scenarios and to predict the travel demand in the post pandemic world. Although only time will be able to accurately assess the pandemic's effects, this investigation represents our expectations for what the future will hold and offers crucial information for future planning.

2. Literature review

The outbreak of the pandemic in 2020 has significantly affected daily travel behaviors of individuals around the globe. As the COVID-19 is a highly contagious respiratory disease, it was declared as a global pandemic by World Health Organization on March 11th, 2020 (World Health Organization, 2022). Declaration of this disease as a worldwide pandemic resulted in extreme lockdowns, social distancing rules, self-isolation measures, and travel restrictions in order to prevent its distribution and to protect people's lives (Altmann et al., 2020). The preventive measures that are conducted to hinder the distribution of the virus, in the end resulted into lower levels of mobility and affected people's routine travel behaviors. Therefore, in order to unmask the COVID-induced travel behaviors and to discover the changes that have been made in the way people do their daily activities, investigating the relationships between the COVID-19 outbreak and transportation is of great importance.

The transportation network of a city is one of its core components that connects the origin and destination of individual's different activities. This connecting role of the transportation networks makes them as one of the highly ranked areas with regard to probability of spreading and getting infected by contagious diseases, especially COVID-19 (Thometz, 2020). In this sense, people reduced their out of home activities during the pandemic in order to minimize the probability of getting infected by COVID-19. This reduction in the level of out of home activities affected the general travel behavior of people in different areas (Choi et al., 2014). As an example, the number of daily trips has drastically reduced because of the pandemic (Fatmi, 2020; Zhang & Lee, 2021) which has consequently resulted into reduced peak hour congestion and lower network traffic (Bucsky, 2020). Moreover, even though the distance travelled initially decreased during the outbreak, it began to rise during the reopening phases, primarily through active modes like cycling and walking (Dingil & Esztergár-Kiss, 2021). During the pandemic, people have considerably moved towards more bicycle usage (Molloy et al., 2020) and they also grew a preference for using their private car as it provided lower levels of interaction and contact with other individuals (Troko et al., 2011). Regarding the impacts of virtualisations on travel behavior during COVID-19, an investigation on the relationship between teleworking and online shopping with the amount of time spent travelling has found that teleworking is linked to shorter travel times for cars and public transportation, whereas online shopping is linked to longer travel times for walking and cycling (Ozbilen et al., 2021).

From all the different modes of transportation, public transit and active modes of transportation have been more affected. In fact, according to Bucsky (2020), public transit sector has experienced a significant reduction in ridership (Bucsky, 2020). In another study conducted by De Vos (2020) on the effect of COVID-19 and social distancing on travel behavior, it has been found that COVID-induced measures have generally reduced travel demand while specifically reducing the demand of public transit (De Vos, 2020). There are numerous similar studies on the impacts of COVID-19 on public transportation use. For example, in a study conducted in Hanover, Germany, it has been found that bus and local light rail are being replaced by bicycles, cars, and teleworking (Schaefer et al., 2021). As another instant, Zhang and Lee (2021) observed that usage of active modes (walking and cycling) has taken the place of public transportation usage in many cases (Zhang & Lee, 2021). Fuller et al. (2019), Li et al. (2021), and Saberi et al. (2018) have also reported similar results stating that a significant increase in cycling usage may happen in a situation where people avoid public transportation (Fuller et al., 2019; Li et al., 2021; Saberi et al., 2018).

With regard to taxis and ridehailing services, the results of a study which is conducted on impacts of COVID-19 on activity behaviors of individuals in Chicago, implies that because of higher probability of getting infected by COVID-19 the usage of public transit, taxi, and ridehailing services reduced substantially (Shamshiripour et al., 2020). In another investigation which has focused on lower public transit ridership and reduced share of ridehailing services, similar results were obtained (Nian et al., 2020). Fear of catching the virus from another person was the main factor behind these changes in the routine travel pattern of individuals during COVID-19, which ultimately resulted in an increase in telecommuting and e-learning as well as a decrease in involvement in public activities and occasions throughout the pandemic (De Vos, 2020; Zhang & Lee, 2021).

As we delve into the research examining how the pandemic has influenced individuals' travel behavior, we come to the realization that the majority of these studies primarily concentrate on the current state of people's travel patterns. What is missing and not sufficiently investigated in the existing literature is how people anticipate travelling in the post-COVID world. One might contemplate that after a period of more than two years since the beginning of the COVID-19 epidemic, all of its effects have completely disappeared and it is meaningless to examine them. However, it should be noted that not only the evidence indicate that the travel behavior of people has not returned to its previous state, but also we are facing a phenomenon called stickiness of behavior. Moreover, psychological studies related to formation of habits in the behavior of people also confirm the existence of a new normal. According to findings of Lally (Lally et al., 2010), it takes an average of 66 days for a habit to form with a range of 18 to 254 days. Today, we have passed the upper bound value of this threshold and there are mobility behaviors that have formed because of COVID-19. These behaviors seem to persist and have a permanent impact on the way people travel. The other thing besides all those mentioned, is the increasing trend in the number of vaccinated people as the time goes on. Therefore, on one hand, since the number of people that are vaccinated increases as the time goes on, and on the other hand, as there are behaviors that seem to persist and have a permanent impact on the way that people travel, it is crucial to investigate individuals' anticipated travel behaviors and to be prepared for the post-COVID world.

Only a few studies have examined how individuals anticipate travelling after the pandemic. It has been discovered that because of the fear of viral infection, people may travel less even after the pandemic, use of public transportation may remain lower than what it was prior to COVID-19, and a large decline in shared modes of transportation may happen (De Vos, 2020; Hensher, 2020). On the contrary, walking and cycling can become quite important (Schwedhelm et al., 2020). In a study that has used the Netherlands Mobility Panel survey, de Haas et al. (2020) conducted a descriptive analysis of anticipated travel behavior of individuals (De Haas et al., 2020). In their investigations, the majority of the respondents were found to expect to use all modes of transportation equally as much as they did prior to COVID-19; however, the attitude of travelers toward choosing private cars is anticipated to improve whereas public transit would become noticeably less desirable after the pandemic. Regarding the reduction in desirability of public transportation, Currie et al. (2021) also highlight the significance of the infection fear for the users of this mode (Currie et al., 2021). With an anticipated 20% decrease in public transportation use, they have found that public transport ridership would not entirely recover. Additionally, they found that sustained work from home levels, higher than pre-pandemic rates, are anticipated (Currie et al., 2021). In another effort in 2020, Conway et al. launched a survey on highly educated individuals in the United States. They discovered that while post-pandemic travel by public transportation may not entirely return to pre-COVID usage levels, individuals are more inclined towards walking and cycling than they were previously (Conway et al., 2020).

Long story short, the majority of the related studies up to this point have concentrated on the descriptive study of COVID-19's effects on prospective travel behavior of individuals. Understanding the behavioral observations in the post-COVID period is lacking and it is unclear if individuals' travel patterns will return to normal or alter significantly in terms of trip frequency and mode preferences to become a new normal. Therefore, it is necessary to conduct behavioral analyses based on statistical modelling techniques to explore the key factors that influence different types of people's anticipated travel behaviors. These analyses will help decision-makers create effective, long-term policies and strategies to take into account transitions in people's travel preferences.

3. Data

To gather information on how the COVID-19 pandemic has affected travel patterns and activity systems, the 2020 COVID Travel Survey was designed in April 2020 in Montreal, Canada. The survey was conducted online using the platform that is developed by our research team (Bourbonnais & Morency, 2013). This platform has contributed to the implementation of more than 15 other online surveys during the last several years. The 2020 COVID Travel Survey was divided into four main sections: home location and household attributes, person attributes, travel behaviors prior to and during COVID-19, and anticipated travel behaviors in post-COVID (mode, frequency, etc.). In the section related to post-COVID travel behaviors, respondents were questioned about anticipated changes in their travel behaviors, such as daily trip frequencies, use of public transportation, and use of bicycles after COVID-19. For each mode of transportation, in this section, there were four frequency options: never used, used less than before, used in the same way as before, and used more than before the epidemic.

On April 28th, 2020, the survey went live. It was also promoted in a newspaper, delivered to an in-house panel of responders, and spread via social media. The survey was completed by 1620 people. This sample cannot be regarded as representative of the population due to the manner it was created. Out of the 1620 records, 23 records were removed due to the lack of information and incompleteness of the responses. In this way, this survey resulted into 1597 observations. Table 1 presents the descriptive statistics of the 2020 COVID Travel Survey data.

Table 1. Summary statistics of the 2020 COVID Travel Survey data (number of observations = 1597)

Variables	Number of observations (%)	% in census*
Age (Min = 4, Median = 40, Max = 105, Mean ± sd = 42 ± 14)		
Age < 25	153 (10%)	28.1%
Age [25, 40)	620 (39%)	20.5%
Age [40, 65)	698 (44%)	33.2%
Age ≥ 65	126 (8%)	18.0%
Gender: man	671 (42%)	49.0%
Gender: woman	926 (58%)	51.0%
Household size (Min = 1, Median = 2, Max = 12, Mean ± sd = 2.53 ± 1.33)		
Household size = 1	358 (22%)	34.4%
Household size = 2	610 (38%)	31.9%
Household size = 3	234 (15%)	14.1%
Household size = 4	262 (16%)	12.8%
Household size ≥ 5	133 (8%)	6.9%
Household income < 60k $	341 (21%)	38.7%
Household income [60k $, 120k $)	493 (31%)	36.8%
Household income ≥ 120k $	460 (29%)	24.5%
Household plan to move: yes ("Does the pandemic and the different confinement periods make you think about your home location and your type of residence?")	520 (33%)	
Transit pass ownership: yes	912 (57%)	
Environmental importance ("Has the pandemic changed the importance you attach to environmental issues and climate change?")		
No, not important ("No, these are not important issues")	15 (1%)	
No, same ("No, these issues have always been important")	1038 (65%)	
Yes, other issues ("Yes, but other issues are now more important")	136 (9%)	
Yes, more ("Yes, it is even more important")	408 (26%)	
Residence ownership: yes	939 (59%)	
Carsharing membership: yes	315 (20%)	
Bicycle ownership: yes	1186 (74%)	
Household number of cars (Min = 0, Median = 1, Max = 7, Mean ± sd = 1.07 ± 0.91)		
Household number of cars = 0	445 (28%)	
Household number of cars = 1	712 (45%)	
Household number of cars = 2	355 (22%)	
Household number of cars ≥ 3	85 (5.3%)	
Cellphone ownership: no	94 (6%)	

* 2021 Canadian Census of Population

4. Methodology

4.1. K-means clustering

Clustering is the process of grouping a given set of data points so that they are more similar to one another within their own group than they are to those in other groups. In other words, the goal is to separate groups of data with similar characteristics and place them in specific clusters. Finding these groups in the data is the objective of the K-means clustering method, with the variable K representing the number of groups. Based on the given features of the data, this method iteratively assigns each data point to one of the K groups. Results of applying K-means algorithm to a dataset include centroids for each of the K clusters found in the dataset (or K centroids) as well as a label indicating the number of the cluster that each point in the dataset belongs to.

Assume that we have a dataset, D, which contains n points in the Euclidean space. K-means clustering method distributes the points in D into K clusters, $(C_1, \dots, C_K)$, in a manner that $C_i \subset D$ and $C_i \cap C_j = \emptyset$. In order for the objects inside a cluster to be similar to one another yet different from objects in other clusters, the distribution quality is evaluated using an objective function. In other words, a high intracluster similarity and a low intercluster similarity are the goals of this objective function. The centroid of a cluster, c_i, is used as a representation of that cluster in the K-means clustering method. In this method of clustering, the centroid is equal to the mean of the points in each cluster. Now we can calculate the difference between each point, $p \in C_i$, and its respective cluster center, c_i. Then, the within-cluster variation, which is the sum of squared error between all objects in C_i and the centroid c_i, can be used to assess the quality of clustering. Thus, the equation for the sum of squared error of all the objects in the dataset is equal to (Han et al., 2012):

$$E = \sum_{i=1}^{k} \sum_{p \in c_i} \left| p - c_i \right|^2 \tag{1}$$

In Equation (1), the distance from each point to its cluster center is squared and then all the distances are summed. The goal of this objective function is to produce K clusters that are as compact and as distinct as possible. Finding the optimum point of this objective function is an NP-hard problem even for a general value of K in two-dimensional Euclidean space. However, with a fixed number of clusters (K) and a fixed dimensionality of the space, the problem can be solved (Han et al., 2012).

In this research, we have used five variables to create our clusters. In fact, we asked the respondents whether they would travel in post-COVID less frequently, more frequently, or with the same frequency as they did pre-COVID. In addition to the question related to the general change in the frequency of travelling, we have also asked respondents about their anticipated travel frequency by walking, cycling, public transportation, and car.

4.2. Multinomial Logit model

In this research, probability of belonging to a cluster is modelled using the MNL models. Within the framework of our MNL model, the probability of belonging to a particular cluster depends on the utility derived from that specific cluster for the individual. The individual's utilities can potentially be affected by different attributes and theoretically, the determinants of belonging to a certain cluster are identified by the differences between the utilities of available alternatives (here, clusters).

Assuming that each individual has a set of feasible choices shown by C_n, the number of feasible choices can be defined as $J_n \leq J$. In this way, the probability of alternative i in C_n being chosen by individual n can be stated as (Ben-Akiva et al., 1985):

$$P_n(i) = Pr\left(U_{in} \geq U_{jn}, \forall j \in C_n \right) \tag{2}$$

Derivation of the MNL model formula is explained in detail by (Ben-Akiva et al., 1985). In short, in the MNL models, the final formula for calculating the probability of alternative i being chosen by individual n is expressed as Equation 3 (Ben-Akiva et al., 1985):

$$P_n(i) = \frac{e^{V_{in}}}{\sum_{j \in C_n} e^{V_{jn}}} \tag{3}$$

where the nominator is the exponential of the utility of the alternative i, and the denominator is the sum of the exponentials of the utilities of all the alternatives.

By using the MNL models in this research, we have investigated the role of age, gender, household size and income, household number of cars, having a bicycle, having the plan to move the household location, having a transit pass, environmental issues, ownership of the residence, having carsharing membership, and having a cellphone on belonging to each of the travel frequency clusters.

5. Results and discussion

5.1. K-means clustering

In this research we have employed K-means clustering method to categorize the anticipated travel behavior of individuals after the COVID-19. In fact, we have asked the respondents whether they will travel post-COVID with a frequency less than the frequency they used to travel pre-COVID, same as the frequency they used to travel pre-COVID, or more than the frequency they used to travel pre-COVID. In addition to the general change in the frequency of trips, we have also asked individuals about their anticipated travel frequency by walk, bicycle, public transportation, and car. Note that in the mode specific questions, there is also a fourth alternative that respondents can choose. This alternative indicates that the respondent never uses the specific mode.

For the purpose of clustering, we have assigned a value to each of the individual's responses regarding their level of anticipated travel frequency after COVID-19. For the individuals who will travel less frequently than pre-COVID, we have assigned -1. For those who will travel more frequently than before, we have assigned +1. For those who indicated that they will travel with the same frequency as before or that they never use a specific mode, we have assigned 0. In this way, for each respondent there is a string consisted of five consecutive numbers that describes the frequency of travel in the post-COVID era. For example, a string of (0, 1, 1, -1, 0) indicates that the person will travel as frequent as before the pandemic, while using more walking and cycling, less public transportation, and same level of car. Using these five stated travel frequencies, we have clustered the individuals using the K-means clustering method.

The first step in the K-means clustering method is choosing the number of clusters, K. For this purpose, we have used the elbow method. Elbow method is a method which is usually used to select the appropriate number of clusters. It calculates the Within Cluster Sum of Squares (WCSS) which is basically the sum of squared distance between each point and its cluster centroid. By plotting the WCSS for different K values, we observe that as the K increases the WCSS decreases. The resulting graph has a high negative slope at the beginning (i.e., small K values), however, as the K increases the slope is reduced and the graph becomes almost parallel to the x-axis. By observing the plot, we can determine a specific K in which the slope of the graph suddenly reduces. This point is called the elbow point and is used as the optimum number of clusters that we can consider in the K-means clustering method. Figure 1 shows the different values of WCSS corresponding to different K values for the 2020 COVID Travel Survey data.

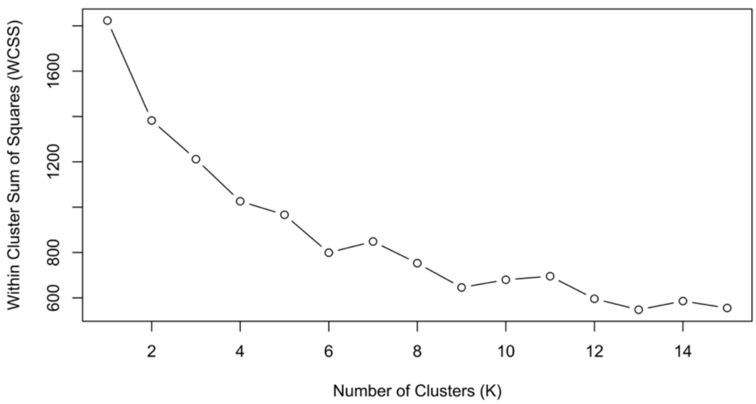

Figure 1. WCSS of different K values for 2020 COVID Travel Survey data

According to Figure 1, the optimal number of clusters – or the elbow point – for the 2020 COVID Travel Survey data is equal to four. Although one can propose that six can also be the optimal number of clusters, it is not an appropriate choice for two reasons: Firstly, the difference of WCSS values for k = 4 and k = 6 is not significant and secondly, considering six clusters for our data results into groups of individuals that are highly similar to each other thus making it hard to differentiate their corresponding travel behaviors. Table 2 presents the profile of the clusters as well as the number of cases in each cluster with K = 4 for 2020 COVID Travel Survey data.

Table 2. Cluster centers of 2020 COVID Travel Survey (K = 4, number of observations = 1597)

Frequencies	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Travel frequency	-0.24	-0.64	-0.60	0.34
Walk frequency	0.09	0.52	-0.03	0.24
Bicycle frequency	-0.01	0.80	-0.06	0.75
Transit frequency	0.02	-0.85	-1.00	-0.01
Car frequency	-0.11	-0.17	0.13	-0.18
Age < 25	8.9%	10.7%	5.9%	18.6%
Age [25, 40)	34.9%	45.8%	40.1%	44.3%
Age [40, 65)	45.1%	42.0%	47.7%	30.7%
Age ≥ 65	11.0%	1.6%	6.3%	6.4%
Gender: man	44.2%	39.2%	39.0%	41.4%
Gender: woman	55.8%	60.8%	61.0%	58.6%
Number of cases (%)	851 (53%)	319 (20%)	287 (18%)	140 (9%)

According to Table 2, the first cluster represents those respondents who stated that they will travel in the same way that they did before the outbreak of the pandemic. The second and third clusters belong to those individuals who mentioned that they will travel less frequently in the post-COVID period than they used to do before it. They also stated that they are going to use less public transit after the COVID. The only difference between these two clusters is in their anticipated level of active modes usage. Those in cluster 2 are more inclined towards active modes of transportation (walking and cycling) with higher levels of usage in comparison to pre-COVID, while the members of cluster 3 will use active modes in a similar manner that they did before the pandemic. Finally, the fourth cluster is the representative of the people who anticipated that they will travel more frequently in the post-COVID in comparison to pre-COVID situations. Moreover, they will also use active modes of transportation with a higher frequency after the pandemic. In order to better understand the most important characteristic of each cluster and for the ease of referencing them throughout the rest of the paper, we decided to assign a name to each of the clusters. The assigned names are as follows:

- Cluster 1: Status quo
- Cluster 2: Active modes users with lower trip frequency and transit use
- Cluster 3: Lower trip frequency and transit use
- Cluster 4: Active modes users with higher trip frequency

5.2. Multinomial Logit model

Table 3 provides the results of estimating the coefficients of the MNL model as well as their student t-test and p-value statistics. For avoiding the collinearity and endogeneity problems in the model, the relation between the variables have been investigated and the input variables of the model selected based on the results of the investigation. Since our database includes both continuous and categorical variables, different types of measures and tests were used according to the characteristics of the data. For the relation between two continuous variables, Pearson's correlation coefficient has been used while for the relation between two categorical variables, Chi-square test of independence has been used. For the relation between a continuous and a categorical variable, ANOVA test has been used. Maximum Likelihood Estimation (MLE) method is used to fit the MNL model, meaning that the parameter estimates are those that maximise the likelihood of the observed data. One of the goodness of fit measures that is reported for MNL models is McFadden's R squared. This measure is defined as:

$$R^2_{McFadden} = 1 - \frac{LogLikelihood_{Fitted\ model}}{LogLikelihood_{Null\ model}} \tag{4}$$

In Equation (4), the nominator of the fraction is the LogLikelihood value for the fitted model while the denominator is the LogLikelihood value that corresponds to the null model. Null model is referred to a model with only one intercept and no other variables. As the range of the LogLikelihood function is (-∞, 0], the range of the McFadden's R^2 is between zero and one, exactly similar to the R^2 value for a linear regression. However, logistic regression is used for modeling discrete dependent variables. Two of the other model selection criteria are Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). AIC (Akaike, 1974) uses in-sample fit to calculate the likelihood that a model will accurately predict or estimate future values. The model with the lowest AIC among all other models is a good model. BIC assesses the trade-off between model fit and complexity (Stone, 1979). Similar to AIC, an improved fit is indicated by a lower BIC value. Moreover, it is worth to note that in the estimation process of the MNL model, the constant for the utility function of the first cluster is normalized to zero in order for it to be identifiable (Bierlaire, 2020).

According to the results presented in Table 3, the estimated coefficient related to age ≥ 65 in the first cluster has a significant positive value of 0.487 with a 0.031 p-value. It means that those with age ≥ 65 are more inclined to travel in the post-COVID in the same manner as they did pre-COVID. This age group (age ≥ 65) is also negatively significant for the second cluster with an estimated value of -0.956 and a p-value of 0.016. It indicates that being in this age group decreases the probability of belonging to cohort that anticipate travelling with a lower frequency and a lower usage of public transit while using more active modes of transportation after the pandemic. In the third cluster, all three age groups are statistically significant with p-values less than 0.01. Moreover, the estimated coefficients for all the three age groups in the third cluster are positive, with the [25, 40) age group having the lowest effect and age group ≥ 65 having the highest effect. This confirms the findings of Ergin (2022) who found that as the age increases the level of public transportation usage is reduced (Ergin, 2022). It is also in line with the findings of Kopsidas et al. (2021) who reported that travelers with an age between 46 and 65 years are less probable to use public transportation (Kopsidas et al., 2021).

With regard to results of age in the fourth cluster, the model shows that being in the [25, 40) and [40, 65) age groups reduce the probability of belonging to this cluster and therefore being a user who is going to travel with a higher frequency than pre-COVID and with a higher level of active modes usage.

The dummy variable of gender has been observed to have no significant impact on belonging to any behavioral cohort. In a similar study, Ergin (2022) found that women prefer using public transportation more than men (Ergin, 2022), however, our study does not provide any insights on the effect of gender in belonging to the clusters, since all the estimated coefficients for gender variable does not meet the statistical significance criterion.

Households consisting of two or more individuals exhibit a reduced tendency to be associated with the first cluster. In fact, households with the size ≥ 2 are less probable to travel the same as before COVID. We can interpret this result in a reverse way. We can say that being in a one-person household increases the probability to keep the status quo of travelling pre-COVID in the post-COVID era.

Household income has been categorized in three groups: less than 60k $, between 60k $ and 120k $, and more than 120k $. In our model, having a household income of less than 60k $ is shown to have a statistically significant and negative impact on the probability of belonging to the second cluster. In other words, being in a household with an annual income < 60k $, reduces the probability of being in the cohort that travels less frequently and uses less public transit, while using a higher level of active modes after the pandemic. In this regard, Ergin (2022) reported that having a low level of income increases the tendency to use public transportation (Ergin, 2022). His finding is in contrast to our results; however, our finding might be attributed to the usage of active modes which is a part of the characteristics of the second cluster.

The dummy variable of a household that plan to move in the near future is also included in the model and has been found to be significant for the first three clusters. For the first cluster it has the value of -0.421 which indicates that having the plan to move the residential location decreases the probability of being in the status quo users group. In the second cluster, the estimated coefficient is equal to 0.234 with a p-value of 0.031 expressing that those households that plan to move are more probable to travel and use public transit less than before the pandemic while using more active modes after the pandemic. With regard to the third cluster that belongs to those who anticipated to have a lower trip frequency and public transportation use, the estimated coefficient is also statistically significant with a value of 0.191 and a p-value of 0.088. This indicates that it is more probable that those who plan to move, belong to the group that travel less frequently and use less transit in the post-COVID in comparison to the pre-COVID. The dummy variable of planning to move is not statistically significant for the fourth cluster.

Having a public transit pass has been observed to be statistically significant in all the four clusters with a p-value of less than 0.01. In the first and fourth clusters the estimated coefficient is negative while in the second and third clusters it is positive. It means that having a transit pass decreases both the probability of belonging to the cohort that keeps the status quo post-COVID and the probability of belonging to the cohort that will travel more frequently with a higher level of active modes usage. On the other hand, having a transit pass increases the probability of belonging to the cluster of active modes users with lower trip frequency and transit use (cluster 2), and the cluster of those with lower trip frequency and transit use (cluster 3).

The effect of COVD-19 pandemic on the importance of environmental issues and climate change for individuals is also studied in our research. In the survey, we have asked the respondents: “Has the pandemic changed the importance you attach to environmental issues and climate change?”. There are four responses for this question in our survey: 1) “Yes, it is even more important”, 2) “Yes, but other issues are now more important”, 3) “No, these issues have always been important”, and 4) “No, these are not important issues”.

We have tried all the four variables as dummy in our modelling process, however, only the dummy variable that is related to those who responded “Yes, it is even more important” has turned out to be statistically significant. In fact, it is statistically significant for all the four clusters. Interestingly, those who stated that the pandemic has caused them to attach a higher level of importance to environmental issues and climate change are more probable to use active modes of transportation. In more detail, this variable has a negative value for the first and third clusters while having a positive value for the second and fourth clusters.

Ownership of the dwelling is also significant for all the clusters except for the second cluster. Those who are the owner of their dwelling are more inclined to belong to the first cluster, which are status quo users, and the third cluster, which are those who are going to have a lower trip frequency and transit use in the post-COVID world. On the contrary, being the owner of the dwelling is associated with lower probability of travelling more frequently and using active modes of transportation more (i.e., the fourth cluster).

The dummy variable of having a carsharing service membership is found to be statistically significant only for the second cluster. The estimated coefficient of this variable is 0.233 with a p-value of 0.067 which indicates that those with a carsharing membership are more probable to be in the cohort of the active modes users with lower trip frequency and transit use.

Owning a bicycle is another dummy variable in our model that is statistically significant for the first three clusters. According to the model estimation results, owning a bicycle translates into lower probability of belonging to the first cluster (status quo users) and the third cluster (users with lower trip frequency and transit use) while it translates into higher probability of belonging to the group that will travel less frequently, use less public transit, and more importantly higher level of active modes usage in the post-COVID (the second cluster).

Our model estimation results implies that the dummy variable of having two or more cars in the household is statistically significant only for the second cluster, with an estimated coefficient of -0.363 and a p-value of 0.009. This indicates that those households with two or more cars are less likely to be a member of the group that includes active modes users with lower trip frequency and public transit use.

Last variable but not least, it has been found that individuals who do not own a cellphone are more inclined to keep their pre-COVID travel habits after the pandemic as the estimated coefficient of the related variable (Having no cellphone) is statistically significant only for the first cluster with a parameter value of 0.346 and a 0.066 p-value.

The value of Null LogLikelihood in our model is equal to -2213.912. In the course of the modelling process, we were able to increase the LogLikelihood value from -2213.912 to -1750.693. Using these values, McFadden’s pseudo-R^2 is equal to 0.209. According to McFadden (1977) “values of 0.2 to 0.4 for ρ^2 represent an excellent fit” (McFadden, 1977). Thus, the pseudo- R^2 of our model is considered to be excellent.

Table 3. Results of the logistic regression model of 2020 COVID Travel Survey data

Variables	Cluster 1: Status quo			Cluster 2: Active modes users with lower trip frequency & transit use			Cluster 3: Lower trip frequency & transit use			Cluster 4: Active modes users with higher trip frequency		
	Value	t-test	p-value	Value	t-test	p-value	Value	t-test	p-value	Value	t-test	p-value
Alternative-specific constant	0.000	NA	NA	-2.34	-6.26	0.000***	-2.78	-6.68	0.000***	-1.32	-2.97	0.003***
Age [25, 40)	-0.067	-0.46	0.649	-0.074	-0.40	0.689	0.661	2.93	0.003***	-0.520	-2.36	0.018**
Age [40, 65)	-0.003	-0.02	0.985	-0.022	-0.11	0.909	0.833	3.65	0.000***	-0.808	-3.46	0.001***
Age ≥ 65	0.487	2.16	0.031**	-0.956	-2.41	0.016**	0.991	3.04	0.002***	-0.522	-1.44	0.149
Gender: man	0.113	1.36	0.173	-0.067	-0.62	0.534	-0.103	-0.95	0.342	0.057	0.40	0.687
Household size ≥ 2	-0.218	-1.99	0.047**	0.063	0.44	0.662	0.217	1.45	0.148	-0.063	-0.34	0.734
Household income < 60k $	0.055	0.50	0.615	-0.320	-2.16	0.031**	0.022	0.15	0.882	0.244	1.36	0.175
Household plan to move: yes	-0.421	-4.76	0.000***	0.234	2.16	0.031**	0.191	1.70	0.088*	-0.005	-0.03	0.975
Transit pass ownership: yes	-0.382	-4.38	0.000***	0.476	4.09	0.000***	0.451	3.57	0.000***	-0.544	-3.76	0.000***
Environmental importance – Yes, more	-0.340	-3.65	0.000***	0.313	2.81	0.005***	-0.334	-2.74	0.006***	0.360	2.43	0.015**
Residence ownership: yes	0.164	1.66	0.097*	-0.121	-0.98	0.327	0.327	2.56	0.010**	-0.370	-2.22	0.026**
Carsharing membership: yes	-0.152	-1.38	0.168	0.233	1.83	0.067*	0.021	0.15	0.881	-0.103	-0.56	0.579
Bicycle ownership: yes	-0.170	-1.78	0.076*	0.660	4.77	0.000***	-0.299	-2.41	0.016**	-0.191	-1.20	0.228
Household number of cars ≥ 2	0.071	0.67	0.506	-0.363	-2.61	0.009***	0.192	1.41	0.159	0.101	0.54	0.591
Cellphone ownership: no	0.346	1.84	0.066*	-0.393	-1.24	0.216	0.081	0.33	0.744	-0.034	-0.09	0.925
Null LogLikelihood	-2213.912											
Initial LogLikelihood	-2213.912											
Final LogLikelihood	-1750.693											
McFadden's pseudo-R^2	0.209											
Akaike Information Criterion (AIC)	3619.386											
Bayesian Information Criterion (BIC)	3936.563											
Number of observations	1597											

*** p-value < 0.01 ** 0.01 < p-value < 0.05 * 0.05 < p-value < 0.10

6. Conclusion

This investigation presents the findings of analysing individuals' anticipated travel behaviors in the post-COVID period. This study adds to the body of knowledge in two ways: 1) it examines travel behavior differences among people based on their trip characteristics and then categorizes them accordingly; 2) it utilizes an econometric micro-behavioral model within the framework of Discrete Choice Models (DCM) to identify the factors that influence the anticipated post-COIVD travel behavior of individuals. In the first step, we have categorized individuals based on their anticipated level of usage of each mode of transportation in the post-covid era using K-means clustering method. Then, we have modelled their anticipated choices and identified the determinants of belonging to each category by employing Multinomial Logit (MNL) models. In this way were able to find out the travel mode preferences of each group regarding the way they plan to do their daily activities.

The resulting four clusters in this investigation are 1) status quo users, 2) active modes users with lower trip frequency and transit use, 3) users with lower trip frequency and transit use, and 4) active modes users with higher trip frequency. According to the results of the multinomial logit model, having an age ≥ 65, being the owner of the dwelling, and having no cellphone increase the probability of belonging to the first cluster who are the status quo travelers. On the other hand, being in a household with two or more members, having a plan to move in the near future, ownership of a transit pass, importance of environmental issues, and bicycle ownership decrease the probability of belonging to the first cluster. Having a plan to move in the near future, transit pass ownership, importance of environmental issues, carsharing membership, and owning a bicycle increase the probability of belonging to the second cluster that include those individuals who stated that, in comparison to the pre-COVID, they will travel with a lower frequency and use less transit while using more active modes after the COVID-19. Being in the age ≥ 65 group, having an annual income lower than 60k $, and presence of two or more cars in the household decrease the probability of being in the second cluster. The variables that increase the probability of belonging to the third cluster are having a plan to move in the near future, transit pass ownership, and being the owner of the dwelling as well as all the three age groups. Moreover, importance of environmental issues and owning a bicycle decrease the probability of being in the cohort of individuals with lower trip frequency and transit use. Importance of environmental issues increases the probability of belonging to the last cluster which includes those who are going to travel with a higher frequency and higher level of active modes usage than pre-COVID. Additionally, being in the [25, 40) and [40, 65) age groups, owning a transit pass, and ownership of the dwelling reduce the probability of being in this cluster.

This study can be employed to develop forecasting methods to anticipate people's prospective travel patterns in the Greater Montreal Area. It offers crucial insights on determinants of anticipated changes in travel frequency, walking, cycling, use of public transportation, and use of cars throughout the post-pandemic era. The results of this study enable us to develop prospective travel behavior scenarios and to predict the total travel demand as well as demand for walking, cycling, public transportation, and car in the post-COVID world. In fact, by segmenting the population based on the clusters of this study, we can estimate projected travel behaviors of each classification for different time horizons in the future. The findings of this study can help designing efficient policies that encourage active travel and enhance the transit user experience as well as estimating the futuristic travel demand of people. In conclusion, the study's findings will help planners and politicians create plans that will better prepare for the post-pandemic era by taking into account the projected changes in people's travel patterns.

7. Future works

One of the avenues for further research on this topic is utilising a longitudinal survey that will monitor respondents throughout the time instead of a cross-sectional survey. In addition to the variables that have been investigated in this study, considering individuals' perceptions and attitudes toward using each of the transportation modes in a post-pandemic setting is also another step that can be taken to further understand people's travel behaviors and mode preferences. Moreover, the data used in this study was gathered during COVID-19's initial wave. Due to the development of COVID-19 vaccinations and growing awareness of virus transmission, it is possible that people's perspectives throughout the subsequent pandemic waves have altered. Another wave of the COVID-19 Survey is presently being conducted in order to record these preferred changes, and the results will be utilised to re-estimate the travel behavior models.

References

Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control, 19*(6), 716-723.

Altmann, D. M., Douek, D. C., & Boyton, R. J. (2020). What policy makers need to know about COVID-19 protective immunity. *The Lancet, 395*(10236), 1527-1529.

Ben-Akiva, M. E., Lerman, S. R., & Lerman, S. R. (1985). *Discrete choice analysis: theory and application to travel demand* (Vol. 9). MIT press.

Bierlaire, M. (2020). A short introduction to PandasBiogeme. *A short introduction to PandasBiogeme*.

Bourbonnais, P.-L., & Morency, C. (2013). Web-based travel survey: a demo. In *Transport survey methods: best practice for decision making*. Emerald Group Publishing Limited.

Bucsky, P. (2020). Modal share changes due to COVID-19: The case of Budapest. *Transportation Research Interdisciplinary Perspectives, 8*, 100141.

Centers for Disease Control and Prevention. *CDC Museum COVID-19 Timeline*. Retrieved 2 September 2022 from https://www.cdc.gov/museum/timeline/covid19.html

Choi, J., Do Lee, W., Park, W. H., Kim, C., Choi, K., & Joh, C.-H. (2014). Analyzing changes in travel behavior in time and space using household travel surveys in Seoul Metropolitan Area over eight years. *Travel Behaviour and Society, 1*(1), 3-14.

Conway, M. W., Salon, D., da Silva, D. C., & Mirtich, L. (2020). How will the COVID-19 pandemic affect the future of urban life? Early evidence from highly-educated respondents in the United States. *Urban Science, 4*(4), 50.

Currie, G., Jain, T., & Aston, L. (2021). Evidence of a post-COVID change in travel behaviour–Self-reported expectations of commuting in Melbourne. *Transportation Research Part A: Policy and Practice, 153*, 218-234.

De Haas, M., Faber, R., & Hamersma, M. (2020). How COVID-19 and the Dutch 'intelligent lockdown'change activities, work and travel behaviour: Evidence from longitudinal data in the Netherlands. *Transportation Research Interdisciplinary Perspectives, 6*, 100150.

De Vos, J. (2020). The effect of COVID-19 and subsequent social distancing on travel behavior. *Transportation Research Interdisciplinary Perspectives, 5*, 100121.

Deschaintres, E., Morency, C., & Trépanier, M. (2022). Assessing the Impacts of the COVID-19 Pandemic on Subway Ridership and on the Interactions with other Transportation Modes. https://doi.org/https://doi.org/10.21203/rs.3.rs-2315989/v1

Dingil, A. E., & Esztergár-Kiss, D. (2021). The influence of the Covid-19 pandemic on mobility patterns: The first Wave's results. *Transportation Letters, 13*(5-6), 434-446.

Ergin, M. E. (2022). Evaluation of Different Phases of Covid-19 Pandemic using by Hybrid Approach Modeling. https://doi.org/https://doi.org/10.21203/rs.3.rs-2195767/v1

Fatmi, M. R. (2020). COVID-19 impact on urban mobility. *Journal of Urban Management, 9*(3), 270-275.

Fuller, D., Luan, H., Buote, R., & Auchincloss, A. H. (2019). Impact of a public transit strike on public bicycle share use: An interrupted time series natural experiment study. *Journal of Transport & Health, 13*, 137-142.

Han, J., Kamber, M., & Pei, J. (2012). *Data Mining: Concepts and Techniques*. Morgan Kaufmann.

Healthline. *COVID-19 vs. SARS: How Do They Differ?* Retrieved 3 September 2022 from https://www.healthline.com/health/coronavirus-vs-sars#severity

Hensher, D. A. (2020). What might Covid-19 mean for mobility as a service (MaaS)? *Transport Reviews, 40*(5), 551-556.

INSPQ. (2022). *Ligne du temps COVID-19 au Québec*. Retrieved 29 May 2023 from https://www.inspq.qc.ca/covid-19/donnees/ligne-du-temps?fbclid=IwAR03hqhQlvE1m4iaIYQ-r0ilMerd5BJ-PPN1XM05XHMk-Ow3zWZCNcTWUxU

Kim, K. (2021). Impacts of COVID-19 on transportation: Summary and synthesis of interdisciplinary research. *Transportation research interdisciplinary perspectives, 9*, 100305.

Kopsidas, A., Milioti, C., Kepaptsoglou, K., & Vlachogianni, E. I. (2021). How did the COVID-19 pandemic impact traveler behavior toward public transport? The case of Athens, Greece. *Transportation Letters, 13*(5-6), 344-352.

Lally, P., Van Jaarsveld, C. H., Potts, H. W., & Wardle, J. (2010). How are habits formed: Modelling habit formation

in the real world. *European Journal of Social Psychology, 40*(6), 998-1009.
Li, H., Zhang, Y., Zhu, M., & Ren, G. (2021). Impacts of COVID-19 on the usage of public bicycle share in London. *Transportation Research Part A: Policy and Practice, 150*, 140-155.
McFadden, D. (1977). *Quantitative Methods for Analyzing Travel Behaviour of Individuals: Some Recent Developments*.
Molloy, J., Tchervenkov, C., Hintermann, B., & Axhausen, K. W. (2020). Tracing the Sars-CoV-2 Impact: The First Month in Switzerland–March to April 2020. *Arbeitsberichte Verkehrs-und Raumplanung, 1503*.
News Medical. *How does SARS-CoV-2 Compare to SARS-CoV?* Retrieved 3 September 2022 from https://www.news-medical.net/health/How-does-SARS-CoV-2-Compare-to-SARS-CoV.aspx
Nian, G., Peng, B., Sun, D., Ma, W., Peng, B., & Huang, T. (2020). Impact of COVID-19 on urban mobility during post-epidemic period in megacities: from the perspectives of taxi travel and social vitality. *Sustainability, 12*(19), 7954.
Ozbilen, B., Wang, K., & Akar, G. (2021). Revisiting the impacts of virtual mobility on travel behavior: An exploration of daily travel time expenditures. *Transportation Research Part A: Policy and Practice, 145*, 49-62.
Saberi, M., Ghamami, M., Gu, Y., Shojaei, M. H. S., & Fishman, E. (2018). Understanding the impacts of a public transit disruption on bicycle sharing mobility patterns: A case of Tube strike in London. *Journal of Transport Geography, 66*, 154-166.
Schaefer, K. J., Tuitjer, L., & Levin-Keitel, M. (2021). Transport disrupted–Substituting public transport by bike or car under Covid 19. *Transportation Research Part A: Policy and Practice, 153*, 202-217.
Schwedhelm, A., Li, W., Harms, L., & Adriazola-Steil, C. (2020). *Biking provides a critical lifeline during the coronavirus crisis*. Retrieved 2 September 2022 from https://www.wri.org/insights/biking-provides-critical-lifeline-during-coronavirus-crisis
Shamshiripour, A., Rahimi, E., Shabanpour, R., & Mohammadian, A. K. (2020). How is COVID-19 reshaping activity-travel behavior? Evidence from a comprehensive survey in Chicago. *Transportation Research Interdisciplinary Perspectives, 7*, 100216.
Sharifi, A., & Khavarian-Garmsir, A. R. (2020). The COVID-19 pandemic: Impacts on cities and major lessons for urban planning, design, and management. *Science of the Total Environment, 749*, 142391.
Stone, M. (1979). Comments on model selection criteria of Akaike and Schwarz. *Journal of the Royal Statistical Society. Series B (Methodological)*, 276-278.
Thometz, K. (2020). *UIC Study Analyzes How COVID-19 Has Changed Travel Behavior, Lifestyles*. Retrieved 27 October 2022 from https://news.wttw.com/2020/06/14/uic-study-analyzes-how-covid-19-has-changed-travel-behavior-lifestyles
Troko, J., Myles, P., Gibson, J., Hashim, A., Enstone, J., Kingdon, S., Packham, C., Amin, S., Hayward, A., & Van-Tam, J. N. (2011). Is public transport a risk factor for acute respiratory infection? *BMC Infectious Diseases, 11*(1), 1-6.
World Health Organization. *WHO Coronavirus (COVID-19) Dashboard*. Retrieved 3 September 2022 from https://covid19.who.int/
World Health Organization. (2022). *Two years of COVID-19: new report highlights the 100 weeks of WHO/Europe's efforts to protect lives and livelihoods during the pandemic*. Retrieved 26 Ocotber 2022 from https://www.who.int/europe/news/item/11-03-2022-two-years-of-covid-19-new-report-highlights-the-100-weeks-of-who-europe-s-efforts-to-protect-lives-and-livelihoods-during-the-pandemic
Zhang, J., & Lee, J. (2021). Interactive effects between travel behaviour and COVID-19: a questionnaire study. *Transportation Safety and Environment, 3*(2), 166-177.