Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Exploring the impacts of the COVID-19 pandemic on modality profiles for non-mandatory trips in the Greater Toronto Area

Patrick Loa *, Sanjana Hossain, Sk. Md. Mashrur, Yicong Liu, Kaili Wang, Felita Ong, Khandker Nurul Habib

Department of Civil and Mineral Engineering, University of Toronto, 35 St. George St., Toronto, ON, MSS 1A4, Canada

ARTICLE INFO

Keywords:
COVID-19
Pandemic
Modality
Non-mandatory activities
Latent class cluster analysis

ABSTRACT

The ongoing COVID-19 pandemic has drastically altered daily life in cities across the world. To slow the spread of COVID-19, many countries have introduced mobility restrictions, ordered the temporary closure of businesses, and encouraged social distancing. These policies have directly and indirectly influenced travel behaviour, particularly modal preferences. The purpose of this paper is to explore modality profiles for non-mandatory trips and analyze how they have changed in response to the pandemic and pandemic-related public health policies.

The data used for this study were collected from web-based surveys conducted in the Greater Toronto Area. Modality profiles were identified through the application of latent class cluster analysis, with six modality profiles being identified for both the pre-pandemic and pandemic periods. The results indicate that the importance of public transit has declined during the pandemic, while the roles of private vehicles and active modes have become more prominent. However, individuals’ changes in modal preferences vary based on their pre-pandemic modality profile. In particular, it appears that pre-pandemic transit users with access to a private vehicle have substituted public transit for travel by private vehicle, while those without private vehicle access are continuing to use public transit for non-mandatory trips. Consequently, pandemic-related transportation policies should consider those who do not have access to a private vehicle and aim to help those making non-mandatory trips using transit or active modes comply with local public health guidelines while travelling. The results highlight how the changes in modal preferences that occurred due to the pandemic differ among different segments of the population.

1. Introduction

The novel coronavirus disease (COVID-19) has fundamentally changed daily life in cities across the world. In March 2020, COVID-19 was declared a global pandemic by the World Health Organization due to its severity and the extent to which it had spread globally (World Health Organization (WHO), 2020a). In an attempt to curb the spread of COVID-19, some countries have implemented travel restrictions, locked down cities, and began to encourage social distancing (International Monetary Fund (IMF), 2020). In addition, the rapid adoption of information and communications technology (ICT) that was observed in many aspects of daily life (including remote learning, telecommuting, and online ordering) led to reduced travel in cities (The World Bank, 2020). Social distancing strategies, along with public health concerns, have directly and indirectly impacted travel behaviour and passenger transport. Besides, the implementation of telecommuting can create opportunities for individuals to spend more time with their families, as they no longer have to commute to their workplace. As a result of these factors, the activity-travel patterns of both individuals and households have transformed abruptly. Consequently, an investigation into the alterations in travel behaviour that have resulted from the pandemic is needed to understand the impacts of the pandemic on mobility and accessibility. This understanding can inform policies that are geared towards addressing the impacts of the pandemic on passenger transport.

Non-mandatory activities play an essential role in satisfying individual needs and positively contribute to physical and emotional well-being. In the literature, non-mandatory activities are grouped into one of two categories – maintenance activities and discretionary activities.
The remainder of this paper is organized into four sections. Section 2 summarizes the policies that have been implemented in the GTA in response to the COVID-19 pandemic and the impacts of the pandemic on travel behaviour. Section 3 describes the data used for this study and provides background information on the analytical methods applied in this paper. Section 4 reports the results of the study, followed by a discussion of the policy implications of these results in Section 5.

2. Background

2.1. Changes in travel behavior due to the COVID-19 pandemic

In response to the ongoing COVID-19 pandemic, varying levels of mobility restrictions have been implemented, such as the non-mandatory stay-at-home request in Japan (Parady et al., 2020), the prohibition on gatherings in Budapest (Buckşy, 2020), and the “intelligent lockdown” in the Netherlands (de Haas et al., 2020). Aside from mobility restrictions, Zhang et al. (2021) report that stay-at-home campaigns are a relatively common measure that governments have implemented. In addition to discouraging travel, some governments have encouraged residents to conduct meetings online, shift to remote working and learning, and avoid gatherings (Zhang et al., 2021). Broadly speaking, these policies have coincided with a decrease in out-of-home activity participation, and by extension, travel demand (Hanibuchi et al., 2020; Zhang, 2021). For example, Dandapat et al. (2020) found evidence of reductions in travel activity following the initial lockdown implemented in India, while Beck & Hensher (Beck and Hensher, 2020a) reported similar findings in Australia. However, the impacts of these policies on travel demand can vary based on the stringency of the policies and the infection situation (Morita et al., 2020a). Besides, perceptions towards the pandemic also appear to influence the decision to leave one’s home.

Prior studies on the topic suggest that there is a negative association between travel activity and the cumulative number of confirmed COVID-19 cases. For example, Morita et al. (2020b) found a negative correlation between the natural logarithm of cumulative case counts and mobility patterns in Japan using data from Apple Mobility Trend Reports. Besides, Maloney and Taskin (2020) found that voluntary decreases in mobility among people in the United States were influenced by the number of confirmed COVID-19 cases. Similar results are reported by Kashima and Zhang (2021), who found that the closure of schools in Japan led individuals to voluntarily cancel or postpone their plans to attend sporting events, eat at restaurants, and attend mass gatherings, even though a national state of emergency had yet to be declared. These findings reflect the potential for the fear of being infected (or the perceived risk of infection) to lead some individuals to modify their travel and activity behaviour (Oum and Wang, 2020; Zhang, 2020). Furthermore, the perception of risk, the perceived stigma associated with leaving one’s home, and the perceived degree of self-restriction of others have been found to dissuade people from spending time outside of their homes (Parady et al., 2020; Hanibuchi et al., 2020; Zhang, 2021).

Although certain non-mandatory activities can occur at home, the need (and desire) to engage in non-mandatory trips remains. For example, Parady et al. (2020) found that the pandemic has had a negligible impact on the frequency of shopping trips, while other studies have found that the share of trips made to grocery stores is greater during the pandemic than it was before the pandemic (de Haas et al., 2020; Beck and Hensher, 2020a). In addition, recreational and social activities can play an essential role in mitigating some of the negative impacts of social distancing guidelines, such as social isolation and physical inactivity (De Vos, 2020). While the demand for non-mandatory travel remains, the pandemic has coincided with a shift in modal preferences. Specifically, the pandemic has coincided with an increase in the use of active modes (i.e., walking and cycling) and a decrease in the use of public transit (Zhang, 2021). The shift in modal preferences is reflected in the relatively lower levels of transit ridership during the pandemic and the modal share of active modes approaching (and in some cases exceeding) pre-pandemic levels (Teixeira and Lopes, 2020; Buckşy, 2020; Vickerman, 2021). Evidence of these shifts have also been presented in survey-based studies such as Ozaydin and Ulenin (2020), Zhang (2021), Molloy (2020), and Marsden et al. (2021). This shift can partly be attributed to the messaging of public officials, who in some jurisdictions, have promoted walking and cycling as a means of...
staying fit (Budd and Ison, 2020), discouraged the use of public transit (Marsden et al., 2021), or encouraged the use of private vehicles (Zhou et al., 2020).

Previous studies on the topic suggest that this shift also stems from the influence of the pandemic on changes in the perceptions of travel modes. In particular, attitudes towards individual modes (such as private vehicles, walking, and cycling) appear to have either become more positive or remained unchanged. In contrast, attitudes towards shared modes (such as public transit and ride-sourcing) appear to be fairly negative (Shamshiripour et al., 2020; de Haas et al., 2020). The changes in attitudes appear to be primarily driven by the perceived risk of exposure associated with these modes (De Vos, 2020). This appears to be particularly relevant for public transit, as Holle et al. (2020) found that increases in the perceived risk of contracting influenza on public transit were associated with a greater likelihood of avoiding transit. Similarly, concerns about being infected by COVID-19 have been associated with an inclination towards using individual modes of travel (de Haas et al., 2020).

Although there is evidence that the pandemic has coincided with temporary shifts in modal preferences, many of the studies on the topic consider shifts at an aggregate level. While these results are valuable, understanding changes in modal preferences at a more disaggregated level can help inform policies that address the negative impacts of the pandemic on mobility and accessibility. This study presents and utilizes a modality profile concept to examine the shifts in the combination of modes that individuals use to make non-mandatory trips. For the purpose of this study, a modality profile is characterized by the combination of modes that individuals report using for their non-mandatory trips. Given the extent to which COVID-19 has disrupted daily life and the changes in attitudes that it has caused, the pandemic certainly has the potential to induce changes in modality profiles. Besides, the relatively unprecedented nature of the pandemic also creates the potential for new modality profiles to emerge.

2.2. Study area and policy interventions

The Greater Toronto Area, which was home to 6.4 million residents as of 2016, is composed of the City of Toronto and the four adjacent regions (Peel, York, Halton, and Durham) (Statistics Canada, 2019). The policies implemented by both the Government of Ontario and the municipalities in the GTA aimed to contain the spread of COVID-19 while minimizing the impact on the economy and social welfare. The first significant policy response came on March 17, 2020, when the provincial government declared a state of emergency. As part of this declaration, recreational facilities, schools, daycares, restaurants, and bars were ordered to close (Nielsen, 2020). Besides, residents were asked to remain in their homes unless they were travelling for “essential” purposes, such as going to work or school, visiting a doctor, or buying groceries (Government of Ontario, 2020). The closure of non-essential businesses, combined with the implementation of remote learning and telecommuting, led to a significant decline in travel demand. Roughly one month after the state of emergency was declared, the provincial government announced its three-stage plan for “reopening” Ontario, in which a phased approach would be taken to relaxing pandemic-related restrictions.

During stage 1 of the plan, only “essential” businesses (such as grocery stores and pharmacies) were allowed to operate (CBC News, 2020). In stage 2 of the plan, facilities such as shopping malls, personal care services, restaurants, bars, and recreational facilities were allowed to operate as long as they complied with specific health and safety requirements (Government of Ontario, 2020). In stage 3, all businesses were allowed to operate as long as they complied with the required health and safety measures. On June 15, 2020, most of Ontario entered stage 2, except the City of Toronto and Peel Region, who entered this stage on June 24th. Following a sustained period of declining COVID-19 cases, the provincial government gradually moved Ontario into stage three of the reopening plan. The data provided by Google through its COVID-19 Community Mobility Report suggests that people gradually began participating in non-mandatory out-of-home activities, particularly discretionary activities, as pandemic-related restrictions were lifted (see Google, 2020 for more details). As shown in Fig. 1, visits to retail and recreational facilities steadily increased from mid-April to mid-August to the point where they are approaching pre-pandemic levels. Similarly, visits to parks also displayed an upward trend (as shown in Fig. 2); the magnitude of the values presented in the figure can partly be attributed to the use of data obtained in January and February as baseline values.

In addition to the policies enacted by the provincial government, municipalities and transit agencies in the GTA also implemented their own pandemic-related policies. For example, the City of Toronto initiated the ActiveTO campaign that involved the closure of streets and the implementation of eight temporary cycling corridors spanning 23.9 km (City of Toronto, 2020). The aims of ActiveTO were to help residents “maintain physical distancing while walking, running, using mobility devices and biking” (City of Toronto, 2021). The campaign was relatively successful, as traffic count data showed that one of the more popular ActiveTO corridors was used by an average of 18,000 cyclists and approximately 4000 pedestrians each weekend (City of Toronto, 2020). In addition, each municipality and transit agency in the GTA adopted social distancing policies and required that face coverings be worn indoors, in situations where social distancing is not possible, and on-board transit vehicles.

3. Materials and methods

3.1. Survey conduct

The data for this study were obtained through web-based surveys that were conducted as part of two projects that aimed to understand the impacts of the COVID-19 pandemic on travel behaviour in the GTA. The first project is the Study into the use of Shared Travel Modes (SiSTM), which investigated the impacts of COVID-19 on the use of shared travel modes (particularly ride-sourcing); the second is the Stated Preference Experiment on Travel mode and especially Transit choice behaviour (SPETT), which investigated the impacts of the pandemic on the propensity to use public transit. The design of the two surveys were reviewed by the Office of Research Ethics at the University of Toronto (SiSTM: Human Research Protocol Number 39392; SPETT: Human Research Protocol Number 39409). The SiSTM survey and the SPETT survey collected a common set of information pertaining to socio-economic and household attributes, attitudes and perceptions towards the pandemic, and behaviour during the pandemic. The two surveys also asked respondents to provide information about their travel habits, both before and during the pandemic.

The questionnaires for the two surveys were coded into a web-based survey tool. In July 2020, links to the two surveys were sent to a market research company who sent invitations to a random sample of members of their consumer panel who live in the GTA. A residential location quota was imposed to ensure that the distribution of respondents among the five regions that comprise the GTA was consistent with the distribution of the population in the GTA. The market research company provided its panel members with non-monetary compensation based on the estimated amount of time required to complete the survey. At the time the surveys were administered, the GTA was in stage 2 of the provincial reopening framework, the daily number of new COVID-19 cases was on the decline, and restrictions were relatively relaxed compared to earlier in the pandemic. See Loa et al. (2020) for more information on the SiSTM survey and Mashru et al. (2020) for more information on the SPETT survey.
3.2. Data preparation and sample description

The SiSTM survey received 1250 responses, while the SPETT survey received 1176 responses. Incomplete responses were removed from the sample, and the postal code provided by the respondents were checked to ensure that they were in the GTA. After the data were cleaned according to these criteria, 920 responses to the SiSTM survey and 929 responses to the SPETT survey remained. Panel members who completed both surveys were identified based on their IP address, age, and gender. For these individuals, their response to the SiSTM survey was kept due to the need to modify the responses to specific questions in the SPETT survey in order to ensure that they were consistent with the response options in the SiSTM survey (discussed in further detail below). Consequently, the dataset used for the empirical investigation was comprised of 1666 responses.

Before the data could be used for empirical investigation, the responses pertaining to the travel habits of the respondents had to be slightly modified to ensure their compatibility. This issue stems from the different manner in which respondents were asked to provide the mode(s) that they used for non-mandatory trips in the two surveys. To address the issue of the two surveys providing respondents with different response options, response options in the SPETT survey were mapped to those provided in the SiSTM survey. Respondents who selected motor-cycle or other in the SPETT survey (39 total) were removed, as an analogous mode did not exist in the SiSTM survey. Aside from differences in the response options, the two surveys also took different approaches to

Fig. 1. Seven-day moving average of visits to retail and recreational facilities, compared to baseline values, from March to mid-August 2020.

Fig. 2. Seven-day moving average of visits to parks, compared to baseline values, from March to mid-August 2020.
asking respondents about their travel habits. Specifically, the SiSTM survey asked respondents to report the mode(s) they used for non-commuting trips, while the SPETT survey asked respondents to report their primary mode for shopping trips and for other non-commuting trips. This issue was addressed by creating a set of binary indicators whose value would be 1 if the respondent reported using a given mode during the specified time period (i.e., pre-pandemic or during the pandemic), and 0 otherwise. The percentage of respondents who reported using each mode pre-pandemic and during the pandemic are shown in Fig. 3.

The distributions of the socio-economic characteristics of the sample are summarized and compared to the 2016 Canadian census in Table 1. In terms of home location, the sample does a relatively good job of representing Toronto residents while overrepresenting residents of York and Peel regions and underrepresenting residents of Durham and Halton regions. In terms of gender, men are underrepresented in the sample while women are overrepresented. The share of respondents between the ages of 20 and 45 are much larger in the sample than the census, while those under the age of 20 or over the age of 65 are both under-represented in the sample. This disparity between the sample and census is expected given that the data were collected using a web-based survey that was administered to the members of consumer panel. Similarly, the share of individuals from households earning less than 40,000 CAD or over 150,000 CAD annually are both smaller in the sample than in the data from the census.

3.3. Modality profiles and latent class cluster analysis

In the literature, several approaches have been applied to segment individuals based on their modal preferences. Some studies, such as Kuhnminhof et al., 2006, 2012 and Nobis (2007), have opted to classify users are either unimodal or multimodal travellers based on whether they used more than one mode over a specific period of time. Other studies, such as Lavery et al. (2013) and Lin et al. (2019) have classified individuals based on the number modes that they reported using, however, they do not consider the combinations of modes that are used. Contemporary studies on the topic have utilized the concept of a modality style, which are defined as “behavioural dispositions towards a certain travel mode or set of travel modes that an individual habitually uses” (Vij et al., 2017). Early studies aimed to identify modality styles by applying cluster and factor analysis. These studies distinguished between segments of the population based on factors such as activity participation, trip frequency, choice of travel mode, and attitudes towards travel modes (Krizek and Waddell, 2002; Ohnmacht et al., 2009). More recent studies have conceptualized modality styles as latent classes that differ in terms as their observable travel behaviour and latent preferences.

| Table 1 | Distribution of socio-economic characteristics in the sample and the 2016 Canadian census. |
|---------|------------------------------------------------------------------------------------------------|
| Home location | Sample | 2016 Census |
| Toronto | 42.0% | 42.6% |
| York | 20.1% | 17.3% |
| Durham | 8.6% | 10.1% |
| Peel | 23.8% | 21.5% |
| Halton | 5.4% | 8.6% |
| Gender | | |
| Male | 40.1% | 48.5% |
| Female | 59.4% | 51.5% |
| Prefer not to answer | 0.5% | 0% |
| Age | | |
| 0–14 | 0.0% | 16.68% |
| 15–19 | 2.9% | 6.19% |
| 20–24 | 7.7% | 6.90% |
| 25–29 | 11.0% | 7.03% |
| 30–34 | 12.6% | 6.99% |
| 35–39 | 12.7% | 6.82% |
| 40–44 | 10.2% | 6.98% |
| 45–49 | 8.9% | 7.41% |
| 50–54 | 8.1% | 7.81% |
| 55–59 | 8.1% | 6.91% |
| 60–64 | 6.6% | 5.63% |
| 65+ | 11.2% | 14.65% |
| Household income | | |
| Prefer not to answer | 10.1% | 0.00% |
| Under $14,999 | 2.6% | 5.89% |
| $15,000 to $29,999 | 5.9% | 10.30% |
| $30,000 to 39,999 | 5.0% | 7.22% |
| $40,000 to $49,999 | 8.0% | 7.28% |
| $50,000 to $59,999 | 8.3% | 7.03% |
| $60,000 to $69,999 | 7.3% | 6.63% |
| $70,000 to $79,999 | 7.9% | 6.17% |
| $80,000 to $89,999 | 6.3% | 5.75% |
| $90,000 to $99,999 | 7.6% | 5.33% |
| $100,000 to $124,999 | 12.2% | 10.83% |
| $125,000 to $149,999 | 8.1% | 7.96% |
| $150,000 to $199,999 | 6.2% | 9.55% |
| Over $200,000 | 4.4% | 10.06% |
This study utilizes the concept of a modality profile to segment individuals based on the mode (or combination of modes) that they use to make non-mandatory trips. Specifically, latent class cluster analysis (LCCA) is applied to identify modality profiles based on the modes that respondents reported using before and during the pandemic. LCCA is similar to cluster analysis in the sense that they both involve dividing a sample into a set of relatively homogenous sub-groups. However, the distinguishing feature of LCCA is that it accounts for measurement error by taking a probabilistic approach to assigning observations to clusters (de Haas et al., 2018). In LCCA, similarity among members of the same class is assumed to stem from the values of the observed indicators being derived from the same probability distributions (Vermunt et al., 2002). LCCA is often applied to analyze a set of categorical indicator variables that are believed to be directly influenced by the value of a discrete latent variable (Molin et al., 2016). In this study, it is postulated that the values of the binary indicators for each of the two specified time periods are influenced by an unobserved latent variable that represents modality profiles (as shown in Fig. 4).

The application of latent class cluster analysis involves the estimation of two sets of parameters—the probability of belonging to each class and the class-specific probability that an individual provides a specific response to a question. Define $Y_{ijk}$ as a binary variable whose value is 1 if individual $i$ provides the $k$th response to indicator variable $j$, and 0 otherwise (where $j = 1, \ldots, J$ and $k = 1, \ldots, K$) (Linzer and Lewis, 2011). Let $\pi_{jrk}$ be the class-specific probability that an individual provides the $k$th response to indicator variable $j$, given that they belong to class $r$ ($r = 1, \ldots, R$), and $p_r$ be the probability that an individual belongs to class $r$. Assuming that local independence holds (meaning that associations between indicators can be explained by the latent variable (Molin et al., 2016)), the probability that individual $i$ in class $r$ provides a particular set of responses to the $J$ indicators ($Y_{ir}$) is then given by:

$$f(Y_{ir}) = \prod_{j=1}^{J} \prod_{k=1}^{K} (\pi_{jrk})^{Y_{ijk}}$$

(1)

where:

$$\sum_{k=1}^{K} \pi_{jrk} = 1$$

The probability that individual $i$ provides a particular response to the $J$ indicators ($Y_{ir}$) is then given by:

$$f(Y_{ir}) = \sum_{r=1}^{R} p_r * f(Y_{ir}) = \sum_{r=1}^{R} p_r \prod_{j=1}^{J} \prod_{k=1}^{K} (\pi_{jrk})^{Y_{ijk}}$$

(2)

where:

$$\sum_{r=1}^{R} p_r = 1$$

The latent class cluster analysis was conducted using the poLCA package written for the R programming language (Linzer and Lewis, 2011).

4. Results

The first step of latent class cluster analysis is to determine the appropriate number of latent classes based on the sample data. The standard approach to determining the number of latent classes involves estimating a series of models without covariates to determine the number of classes that provide the best balance of fit and parsimony while also sufficiently capturing the associations in the data. Similar to the approach applied by de Haas et al. (2018), the binary indicators corresponding to the pre-pandemic and pandemic periods were used to estimate eight models, beginning with the one-class model. The values of the Bayesian information criterion (BIC) and likelihood ratio

| R | Pre-pandemic | Pandemic |
|---|-------------|----------|
| 1 | 502 10369.27 1797.98 | 1 502 9271.08 1584.98 |
| 2 | 492 9362.26 716.80 | 2 492 8518.75 758.46 |
| 3 | 482 9281.83 562.18 | 3 482 8396.06 561.59 |
| 4 | 472 9264.79 470.95 | 4 472 8347.76 439.11 |
| 5 | 462 9231.41 363.40 | 5 462 8300.55 317.72 |
| 6 | 452 9222.66 280.46 | 6 452 8300.59 243.57 |
| 7 | 442 9244.45 228.07 | 7 442 8337.28 206.08 |
| 8 | 432 9296.81 206.25 | 8 432 8375.90 170.53 |

R: Number of latent classes.

df: Degrees of freedom.
chi-squared statistic ($G^2$) were used to compare the performance of the models (see Table 2). For the pre-pandemic period, the six-class model was chosen because the BIC values were the lowest among the tested models. The reduction in the $G^2$ value remained relatively high, even as more classes were added. The six-class model was also chosen for the pandemic period because the BIC value is virtually the same as that of the five-class model, and the $G^2$ value was lower for the former.

The class-specific probabilities that an individual reported using a specific mode for non-mandatory trips are shown in Table 3 (pre-pandemic) and Table 5 (pandemic). The expected size of each class was determined using sample enumeration, in which the class-specific membership probability of each individual was summed together. The profiles of the pre-pandemic and pandemic latent classes are shown in Table 4 and Table 6, respectively.

4.1. Pre-pandemic modality profiles

The first class, denoted as strict drivers [SD], is comprised of individuals who drive when making non-mandatory trips. The strict drivers class had the highest average age among the six latent classes (45.1) and had the largest share of males. In addition, members of this class were the least likely to live in Toronto and had the smallest share of students. This class also had the greatest share of respondents belonging to households earning over 150,000 CAD annually and had the highest level of household vehicle ownership. It is likely that individuals who display this modality profile live auto-centric lifestyles.

The second class, denoted as pedestrians/transit users [PTU], is comprised of individuals who primarily make non-mandatory trips on foot but also occasionally use public transit. Members of this class tend to be relatively older and display relatively lower levels of household vehicle ownership. Compared to the sample as a whole, members of this class are more likely to live in Toronto and were more likely to be employed on a part-time basis prior to the pandemic. In addition, this class has the greatest share of individuals who were unemployed.

The third class, denoted as transit users [TU], is comprised of individuals who primarily use public transit to make non-mandatory trips. Members of this class have the highest likelihood of owning a transit pass and are the least likely to have a driver’s license. In addition, members of this class display the lowest levels of household vehicle ownership. This class had the highest share of individuals living in Toronto and individuals who were employed on a part-time basis prior to the pandemic. Compared to the sample as a whole, members of this class were more likely to belong to households that earn less than 50,000 CAD annually and less likely to belong to households that earn more than 150,000 CAD annually.

The fourth class, denoted as private vehicle/transit users [PVT], is comprised of individuals who primarily make non-mandatory trips as the passenger or driver of a private vehicle but also use public transit on rare occasions. The members of this class display relatively high levels of household vehicle ownership but are less likely to have a driver’s license than the sample as a whole. This is somewhat expected, given that the members of this class are more likely to be driven by someone they know than they are to drive themselves. This class also has the largest share of female members.

The fifth class, denoted as mobility-on-demand users/cyclists [MDC], is comprised of individuals who appear to utilize a combination of ride-sourcing services, taxi services, and cycling to make their non-mandatory trips. This is also the only latent class where the probability of an individual reporting that they do not make non-mandatory trips was non-zero. Compared to the sample as a whole, the members of this class are younger, less likely to have a driver’s license, more likely to be male, and more likely to have been employed on a part-time basis prior to the pandemic. This class has the highest share of students and individuals from households that earn less than 50,000 CAD annually.

The sixth class, denoted as multimodals [MM], is comprised of individuals who use a variety of modes to make non-mandatory trips. Although these individuals are most likely to have reported using exclusive ride-sourcing for non-mandatory trips, they also display relatively high probabilities of reporting that they make non-mandatory trips on foot, using public transit, and using private vehicles. Members of this class display relatively high levels of both transit pass and private vehicle ownership and are more likely to be students than the sample as a whole. In addition, this class has a relatively high percentage of female members and individuals from households that earn between 50,000 CAD and 150,000 CAD annually. Compared to the other latent classes, these individuals may be more likely to base their choice of travel mode on their destination.

4.2. Pandemic modality profiles

The first class, denoted as strict drivers [SD], is comprised of individuals who primarily drive when making non-mandatory trips. Similar to the pre-pandemic class, members of this class were relatively older, more likely to be male, and more likely to belong to a household that earned over 150,000 CAD annually. These individuals were also the least likely to be students and to be living in Toronto. Interestingly, this class had the greatest share of members who were working from home on a full-time basis during the pandemic, as well as a relatively high share of members who are working at their workplace.

The second class, denoted as pedestrians/drivers [PD], is comprised of individuals who primarily walk but also occasionally drive to make non-mandatory trips. Compared to the sample as a whole, these individuals were less likely to have a driver’s license, more likely to live in Toronto, more likely to be unemployed during the pandemic, and less likely to belong to a household that earns over 150,000 CAD annually. These individuals may walk when the household vehicle(s) are being used by other household members, or they may turn to driving for trips that cannot be completed on foot.

The third class, denoted as private vehicle users [PV], is comprised of individuals who are primarily driven by someone they know when

| Table 3: Probability of using a mode for non-mandatory trip, by modality profile (pre-pandemic). |
|-----------------------------------------------|----------------|----------------|----------------|----------------|----------------|
| Mode                                         | Strict drivers | Pedestrians/transit users | Transit users | Private vehicle/transit users | MoD users/cyclists | Multimodals |
| Drive yourself                               | 1.00           | 0.37            | 0.27           | 0.45           | 0.01           | 0.67        |
| Driven by someone you know                   | 0.01           | 0.25            | 0.00           | 1.00           | 0.04           | 0.72        |
| Public transit                               | 0.01           | 0.49            | 1.00           | 0.23           | 0.00           | 0.75        |
| Exclusive ride-sourcing                       | 0.01           | 0.03            | 0.08           | 0.06           | 0.26           | 1.00        |
| Shared ride-sourcing                          | 0.00           | 0.00            | 0.12           | 0.02           | 0.21           | 0.67        |
| Taxi                                         | 0.00           | 0.07            | 0.09           | 0.03           | 0.22           | 0.40        |
| Bike                                         | 0.02           | 0.18            | 0.02           | 0.02           | 0.25           | 0.36        |
| Walk                                         | 0.04           | 1.00            | 0.14           | 0.00           | 0.00           | 0.80        |
| No trips                                     | 0.00           | 0.00            | 0.00           | 0.00           | 0.21           | 0.00        |
| Class size                                   | 906.3          | 254.2           | 208.2          | 156.7          | 91.9           | 48.7        |
| % of sample                                  | 54.4%          | 15.3%           | 12.5%          | 9.4%           | 5.5%           | 2.9%        |

MoD: Mobility-on-demand.
making non-mandatory trips but also occasionally drive themselves. Individuals who belong in this class are relatively younger than the sample as a whole, which is understandable given the relatively high share of students. This class has the highest share of female members and display relatively high levels of household vehicle ownership. These individuals appear to have a strong preference for travel by private automobile and may be accompanied by other household members on their non-mandatory trips.

The fourth class, denoted as shared mode users/cyclists [SMC], is comprised of individuals who utilize a combination of ride-sourcing, taxi, public transit, and cycling to make non-mandatory trips. The members of this class display relatively low levels of vehicle ownership and relatively high levels of transit pass ownership. This class has a relatively high share of students, individuals who are currently working at their workplace, and individuals from households who earn less than 50,000 CAD annually. Although these individuals still use public transit, they also appear to be turning to other modes to satisfy some of their mobility needs.

The fifth class, denoted as transit users/pedestrians [TP], is comprised of individuals who primarily use public transit to make non-mandatory trips but also make some of these trips on foot. This class has the lowest share of members who have driver’s licenses and the highest share of members who own a transit pass; members of this class also display the lowest household vehicle ownership levels among the six classes. Compared to the other latent classes, the members of this class are the most likely to live in Toronto and to be working at their workplace, and the least likely to be working from home. In addition, this class has the highest share of individuals from households earning less than 50,000 CAD annually.

### Table 4
Profile of the pre-pandemic latent classes compared to the survey sample.

| Sample SD | PTU | TU | PVT | MDC | MM |
|-----------|-----|----|-----|-----|----|
| Basic personal and household characteristics | | | | | |
| Average age | 43.2 | 45.1 | 43.7 | 39.1 | 40.5 | 39.2 | 37.8 |
| Has driver’s license | 87.5% | 97.3% | 74.0% | 70.6% | 82.7% | 73.8% | 88.9% |
| Owns transit pass | 38.6% | 30.7% | 38.4% | 61.4% | 45.5% | 44.3% | 55.6% |
| Has access to private vehicle | 88.6% | 99.2% | 71.7% | 67.9% | 93.7% | 70.5% | 86.5% |
| Average number of household vehicles | 1.42 | 1.64 | 1.09 | 0.94 | 1.53 | 1.23 | 1.31 |
| Gender | | | | | | | |
| Male | 40.1% | 44.4% | 35.2% | 35.9% | 29.6% | 43.6% | 31.0% |
| Female | 59.4% | 55.4% | 64.2% | 63.3% | 69.3% | 55.4% | 69.0% |
| Non-binary/prefer not to answer | 0.5% | 0.2% | 0.6% | 0.7% | 1.1% | 1.1% | 0.0% |
| Home location | | | | | | | |
| Toronto | 42.0% | 32.9% | 55.4% | 63.3% | 37.5% | 44.1% | 61.0% |
| Peel | 23.8% | 27.2% | 17.5% | 18.9% | 24.6% | 21.1% | 18.7% |
| York | 20.1% | 23.5% | 14.8% | 12.2% | 22.6% | 19.1% | 13.1% |
| Durham | 8.6% | 9.7% | 7.7% | 3.6% | 9.2% | 12.0% | 7.1% |
| Halton | 5.4% | 6.7% | 4.7% | 1.9% | 6.2% | 3.8% | 0.2% |
| Student status | | | | | | | |
| Currently a student | 16.6% | 12.1% | 14.5% | 24.6% | 25.5% | 28.1% | 27.9% |
| Non-student | 83.4% | 87.9% | 85.5% | 75.4% | 74.5% | 71.9% | 72.1% |
| Employment status | | | | | | | |
| Not employed | 18.1% | 14.6% | 27.5% | 15.9% | 24.5% | 19.9% | 18.6% |
| Part-time at home | 3.4% | 2.9% | 5.1% | 4.2% | 1.6% | 5.5% | 2.7% |
| Part-time at workplace | 10.4% | 9.1% | 10.5% | 13.9% | 12.4% | 12.1% | 8.8% |
| Part-time, home and workplace | 1.0% | 0.5% | 1.6% | 1.4% | 2.1% | 1.7% | 2.4% |
| Full-time at home | 6.6% | 6.5% | 6.7% | 5.5% | 8.8% | 8.0% | 3.3% |
| Full-time at workplace | 52.5% | 57.5% | 41.8% | 54.1% | 41.4% | 46.1% | 56.6% |
| Full-time, home and workplace | 3.2% | 3.5% | 3.0% | 2.7% | 3.3% | 1.3% | 5.6% |
| Other | 4.7% | 5.4% | 3.8% | 2.3% | 5.9% | 5.6% | 2.1% |
| Household income | | | | | | | |
| 50,000 CAD and below | 21.6% | 17.9% | 27.0% | 25.9% | 23.9% | 30.4% | 20.5% |
| 50,000 CAD to 150,000 CAD | 57.7% | 58.9% | 54.3% | 58.3% | 54.7% | 56.9% | 60.6% |
| 150,000 CAD and above | 10.6% | 12.2% | 6.3% | 7.1% | 8.4% | 3.5% | 10.7% |
| Prefer not to answer | 10.1% | 10.0% | 10.4% | 8.7% | 12.9% | 9.2% | 8.2% |

| SD: Strict drivers. 
| PTU: Pedestrians/transit users. 
| TU: Transit users. 
| PVT: Private vehicle/transit users. 
| MDC: Mobility-on-demand users/cyclists. 
| MM: Multimodals. 

### Table 5
Probability of using a mode for non-mandatory trip, by modality profile (pandemic).

| Mode | Strict drivers | Pedestrians/drivers | Private vehicle users | SM users/cyclists | Transit users/pedestrians | Non-travellers |
|------|----------------|---------------------|----------------------|------------------|--------------------------|---------------|
| Drive yourself | 1.00 | 0.59 | 0.48 | 0.15 | 0.00 | 0.00 |
| Driven by someone you know | 0.00 | 0.25 | 1.00 | 0.07 | 0.00 | 0.00 |
| Public transit | 0.02 | 0.14 | 0.00 | 0.25 | 1.00 | 0.00 |
| Exclusive ride-sourcing | 0.00 | 0.02 | 0.00 | 0.00 | 0.00 | 0.00 |
| Shared ride-sourcing | 0.00 | 0.00 | 0.00 | 0.25 | 0.00 | 0.00 |
| Taxi | 0.00 | 0.04 | 0.00 | 0.00 | 0.00 | 0.00 |
| Bike | 0.02 | 0.25 | 0.01 | 0.28 | 0.00 | 0.00 |
| Walk | 0.00 | 1.00 | 0.00 | 0.18 | 0.43 | 0.00 |
| No trips | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 |
| Class size | 911.7 | 301.2 | 171.8 | 147.9 | 89.3 | 45.0 |
| % of sample | 54.7% | 18.1% | 10.3% | 8.9% | 5.4% | 2.7% |

SM: Shared mode.
The responses to these questions across the modality profiles, the re-
nance in their modality profile. Weighted means one-factor ANOVA was used to
calculate for each profile. As shown in Table 7, the extent to which the
differences in the responses provided by the

members of each class were statistically significant. As shown in Table 7,
most of the differences in the responses across the six modality profiles
were statistically significant at the 95% confidence level, save for the
statement regarding the willingness to travel during the pandemic.
Unsurprisingly, members of the non-travellers class displayed greater
levels of agreement that there is a higher risk associated with leaving
their home, they were less willing to spend time travelling, and they
were more reliant on online orders than before the pandemic. In addi-
tion, modality profiles that include private vehicle usage tend to display
relatively high levels of agreement with statements regarding the use of
face coverings and social distancing. This may suggest that the desire to
reduce one’s risk of infection may influence the decision to travel by
private vehicle for certain individuals.

4.3. Analysis of transitions between latent classes

In order to explore potential shifts in modality profiles that have
coincided with the onset of the COVID-19 pandemic, the probability of
transitioning from each pre-pandemic class to each pandemic class was
calculated for each individual. Let the probability that person i tran-

Table 6
Profile of the pandemic latent classes compared to the survey sample.

| Basic personal and household characteristics | Sample | SD | PD | PV | SMC | TP | NT | Test stat. | p-value |
|----------------------------------------------|--------|----|----|----|-----|----|----|------------|--------|
| Average age                                  | 43.2   | 44.6| 42.6| 40.1| 37.7| 42.8| 48.9|            |        |
| Has driver’s license                          | 87.5%  | 97.1%| 80.3%| 83.8%| 71.8%| 53.0%| 75.6%|            |        |
| Owns transit pass                            | 38.6%  | 32.7%| 38.2%| 45.8%| 58.6%| 60.8%| 24.4%|            |        |
| Has access to private vehicle                | 88.6%  | 99.7%| 79.0%| 93.1%| 67.1%| 40.4%| 77.8%|            |        |
| Average number of household vehicles         | 1.42   | 1.63| 1.17| 1.58| 1.06| 0.57| 1.22|            |        |

Gender

| Male                                         | 40.1%  | 43.8%| 37.8%| 24.7%| 44.9%| 38.3%| 26.7%|            |        |
| Female                                       | 59.4%  | 56.0%| 61.9%| 74.2%| 54.7%| 59.8%| 71.1%|            |        |
| Non-binary/prefer not to answer              | 0.5%   | 0.2%| 0.3%| 1.1%| 0.4%| 1.9%| 2.2%|            |        |

Home location

| Toronto                                      | 42.0%  | 34.1%| 55.1%| 39.7%| 49.4%| 64.7%| 55.6%|            |        |
| Peel                                         | 23.8%  | 27.1%| 16.9%| 23.0%| 25.3%| 17.0%| 15.6%|            |        |
| York                                         | 20.1%  | 23.4%| 15.3%| 23.9%| 15.1%| 8.8%| 11.1%|            |        |
| Durham                                       | 8.6%   | 8.8%| 7.5%| 9.5%| 8.0%| 6.8%| 15.6%|            |        |
| Halton                                       | 5.4%   | 6.7%| 5.2%| 4.0%| 2.3%| 2.7%| 2.2%|            |        |

Student status

| Currently a student                          | 16.6%  | 13.4%| 14.6%| 26.9%| 30.1%| 16.4%| 13.3%|            |        |
| Non-student                                  | 83.4%  | 86.6%| 85.4%| 73.2%| 69.9%| 83.6%| 86.7%|            |        |

Employment status

| Not employed                                  | 26.2%  | 21.1%| 34.0%| 34.8%| 20.4%| 34.3%| 46.7%|            |        |
| Part-time at home                            | 5.7%   | 4.5%| 9.1%| 4.6%| 9.7%| 2.8%| 4.4%|            |        |
| Part-time at workplace                       | 6.1%   | 7.1%| 3.4%| 4.8%| 8.0%| 7.2%| 2.2%|            |        |
| Part-time, home and workplace                | 0.7%   | 0.8%| 0.6%| 0.6%| 0.9%| 1.1%| 0.0%|            |        |
| Full-time at home                           | 24.5%  | 26.9%| 24.0%| 22.7%| 20.4%| 15.6%| 20.0%|            |        |
| Full-time at workplace                      | 26.5%  | 29.5%| 18.8%| 18.7%| 31.9%| 32.7%| 17.8%|            |        |
| Full-time, home and workplace               | 5.4%   | 5.5%| 5.8%| 6.2%| 5.9%| 2.8%| 2.2%|            |        |
| Other                                       | 4.8%   | 4.8%| 4.3%| 7.5%| 2.9%| 3.6%| 6.7%|            |        |

Household income

| 50,000 CAD and below                        | 21.6%  | 18.1%| 22.5%| 21.4%| 26.0%| 44.6%| 26.7%|            |        |
| 50,000 CAD to 150,000 CAD                  | 57.7%  | 60.0%| 57.6%| 55.5%| 56.0%| 46.5%| 48.9%|            |        |
| 150,000 CAD and above                      | 10.6%  | 12.4%| 8.7%| 10.7%| 11.0%| 3.5%| 0.0%|            |        |
| Prefer not to answer                        | 10.1%  | 9.5%| 11.3%| 12.4%| 7.0%| 5.4%| 24.4%|            |        |

SD: Strict drivers.
PD: Pedestrians/drivers.
PV: Private vehicle users.
SMC: Shared mode users/cyclists.
TP: Transit users/pedestrians.
NT: Non-travellers.

CAD annually. These individuals may be using public transit out of ne-
cessity and make shorter trips on foot.

The sixth class, denoted as non-travellers [NT], is comprised of indi-
viduals who have not left their homes to participate in non-mandatory
activities during the pandemic. The non-travellers class has the highest
average age among the six latent classes and the highest share of indi-
viduals who were not employed at the time of the survey. Despite
having relatively high levels of automobile ownership, these individuals
appear to be refraining from participating in non-mandatory activities
outside of their homes.

To help understand the attitudes and perceptions towards the
pandemic, respondents were asked to indicate their level of agreement
with a series of statements using a five-point Likert scale. To compare
the responses to these questions across the modality profiles, the re-
sponses were assigned numerical values (1: strongly disagree, 3: neither
agree nor disagree, 5: strongly agree), and the average response was
calculated for each profile. As shown in Table 7, the extent to which the
respondents agreed (or disagreed) with the statements varied based on
their modality profile. Weighted means one-factor ANOVA was used to
determine whether the differences in the responses provided by the
tions from pre-pandemic class \( j \) to pandemic class \( k \) be denoted by \( P(j,k) \). As shown in Equation (3), for any pair of pre-pandemic and pandemic classes, \( P(j,k) \) is given by the product of the probability that an individual belongs to pre-pandemic class \( j \) and pandemic class \( k \).

\[
P(j,k) = P(j)P(k)
\]

where:

\( j \) Represents a pre-pandemic latent class \( j \in \{SD,\ PD,\ PV,\ SM,\ TP,\ OT,\ MM\} \)

\( k \) Represents a pandemic latent class \( k \in \{SD,\ PD,\ PV,\ SMC,\ TP,\ NT\} \)

\( P(j) \) Represents the probability that person \( i \) belongs to pre-pandemic class \( j \)

\( P(k) \) Represents the probability that person \( i \) belongs to pandemic class \( k \)

The transition probabilities were calculated for all 36 combinations of pre-pandemic and pandemic classes for each individual. Sample enumeration was then used to determine the number of individuals who transition between each pair of classes (summarized in Fig. 5). This information was used to calculate the probability of an individual belonging to a pandemic class conditional on their pre-pandemic class (the results are summarized in Table A1 and Figure A1).

As expected, individuals belonging to the strict drivers class pre-pandemic primarily remain in the strict drivers class during the pandemic. Among those who did transition to a different modality profile, the majority transitioned to modality profiles where private vehicles played a prominent role. Among members of the pedestrians/transit users class, slightly under two-thirds (65.2%) transitioned to the pedestrians/drivers class, while another 12.1% became either strict drivers or private vehicle users. In terms of the members of the transit users class, 26.5% transitioned to the strict drivers class while another 18.7% and 22.1% became members of the pedestrians/drivers and private vehicle users classes, respectively. Roughly 22% of these individuals transitioned to the transit users/pedestrians class. Finally, 58.7% of the members of the private vehicle/transit users class transitioned to the private vehicle users class, while another 26.1% transitioned to a class where private vehicles play a prominent role. These results suggest that, among pre-pandemic transit users, those with alternative options for making non-mandatory trips are primarily turning to private vehicles and walking for their non-mandatory trips.

5. Discussion

As the results suggest, the modality profiles for non-mandatory trips in the GTA have changed in response to the pandemic and the related policies. Broadly speaking, the changes in modality profiles suggest that private vehicles are now playing a more prominent role in mobility for non-mandatory trips than they did before the pandemic. In contrast, the role of public transit has diminished. This is consistent with the work of Beck and Hensher (2020b), who found that modal shares for private vehicles and active modes rebounded more strongly than transit modal shares in Australia, and de Haas et al. (2020), who found that the decline in transit trips was greater than that of private vehicle trips in the Netherlands. Aside from highlighting the shifts in aggregate modal shares that have coincided with the onset of the pandemic, this study also provides insights into the manner in which individuals’ modality profiles have changed in response to the pandemic. The results presented in this paper show that the percentage of the sample that belongs to a modality profile where private vehicles play a prominent role has increased from 63.8% to 83.1%. Conversely, the percentage of the sample that belongs to a modality profile where transit plays a prominent role has decreased from 30.7% to 14.2%. Besides, it appears that the pandemic has coincided with the emergence of three new modality profiles—pedestrians/drivers, private vehicle users, and non-travellers.

5.1. Short-term policy implications

The analysis of the transition between modality profiles sheds light on the approaches that pre-pandemic transit users are taking to make non-mandatory trips during the pandemic. The shifts of individuals from modality profiles where public transit plays a prominent role to modality profiles where private vehicles play a prominent role suggest that individuals with access to a private vehicle are turning to private vehicles (and avoiding using public transit) for non-mandatory trips during the pandemic. Correspondingly, this would suggest that, for members of the transit users/pedestrians class, the use of public transit to make non-mandatory trips during the pandemic is at least partly influenced by a lack of access to a private vehicle. The majority (84.5%) of the members of this class were members of either the transit user (51.5%) or the pedestrian/transit user (33.0%) classes prior to the pandemic. Given that the members of these classes displayed relatively low rates of driver’s license ownership, private vehicle access, and household vehicle ownership, it is likely that members of the transit user/pedestrian class have limited modal options when it comes to longer-distance trips. In addition, the members of the transit users/pedestrians class display substantially lower rates of household vehicle ownership than the other modality profiles (0.57 vehicles per household compared to between 1.06 and 1.63 vehicles per household). Although these individuals can turn to ride-sourcing or taxi services as an alternative to public transit, the cost of these services can limit the feasibility of using these services on a frequent basis.

Aside from private vehicle access, members of the transit user/pedestrians class are significantly more likely to belong to households earning less than 50,000 CAD annually. This is consistent with previous studies that have found that individuals from lower-income households, the elderly, and individuals with mobility impairments are more likely to be dependent on public transit for their mobility (Krizek and El-Geneidy, 2007; Brown et al., 2018). Based on guidance from the World Health Organization, which states that physical distancing measures can help limit the risk of the interpersonal transmission of COVID-19 (World Health Organization (WHO), 2020b), transit agencies should aim to provide service at a frequency that helps to ensure that
local physical distancing guidelines can be met (if applicable) over the duration of the pandemic. As outlined by Qu et al. (2020), transit agencies should utilize all of the data at their disposal (such as smart fare cards and automated passenger counter data) to monitor route-level ridership and plan service accordingly. This information can also be used to inform public information campaigns that encourage people to use public transit at times where demand is lower. By managing crowding on public transit vehicles and platforms, transit agencies can help mitigate the risk of infection experienced by individuals who rely on public transit for their mobility. This can also have a positive impact on transportation equity by helping to ensure that these individuals are able to maintain a sufficient level of mobility and accessibility. Besides, having sufficient mobility and accessibility can help mitigate the negative impacts of social distancing measures and lockdowns, including isolation and depression, particularly among the elderly (Morita et al., 2020b).

Given the decline in ridership (and as a result, farebox revenues), transit agencies may need financial support from state/provincial and local governments to provide the aforementioned level of service (Vuchic, 2005). Aside from mitigating the risk of infection, managing crowding on transit vehicles can help to mitigate the negative impacts that the pandemic has had on the perception of public transit services (Bucksy, 2020), which could help increase ridership as restrictions are relaxed and accelerate the return to pre-pandemic ridership levels once the pandemic is over. Given that fares help fund operational costs, it is important that state/provincial and local governments continue to support transit agencies even after the pandemic is over; this will help agencies avoid a downward spiral where lower fare revenues lead to “additional service cuts that in turn lead to even lower ridership” (Polzin et al., 2018). Evidence from the 2003 severe acute respiratory syndrome (SARS) outbreak in Taiwan suggests that public confidence is a key component to ridership returning to pre-pandemic levels (Wang, 2014), which may be difficult to build if agencies are unable to provide sufficient levels of service due to budgetary constraints.

Transit agencies could also partner with transportation network companies (TNCs), such as Uber and Lyft, to supplement or expand their paratransit services. This type of partnership could help address declines in the operating capacity of these services that stem from the decision to limit the number of passengers transported during each trip (Cochran, 2020) or expand paratransit service to serve more customers. Although the per-mile cost of paratransit service tends to be relatively high, partnerships with TNCs for paratransit have the potential to reduce the cost of the service (Polzin et al., 2018). This would provide older individuals and individuals with mobility impairments with door-to-door service without the need for access to a private vehicle. This would also allow these individuals to limit their exposure to other passengers while they are travelling (Mah, 2015).

Aside from the reduced prominence of public transit and increased prominence of private vehicles, the transition analysis suggests that active modes are playing a more prominent role in pandemic modality profiles than they did prior to the pandemic. Specifically, the percentage of the sample that belongs to a modality profile where walking plays a prominent role increased from 15.3% to 23.5%, and the percentage of the sample belonging to a modality profile where cycling plays a prominent role increased from 5.5% to 8.9%. These increases can partially be attributed to members of the transit users class transitioning to modality profiles where active modes play a prominent role in mobility post-pandemic than they did pre-pandemic. This could be mitigated by replacing certain trips with online activities which may be difficult to build if agencies are unable to provide sufficient levels of service due to budgetary constraints. Similar to data collected through stated preference surveys, it is certainly possible that the actual behaviour of the respondents differs from their anticipated behaviours.

If these anticipated changes in modal preferences were to be fully realized post-pandemic, it is likely that private vehicles would play a more prominent role in mobility post-pandemic than they did pre-pandemic. If this is the case, there is the potential for post-pandemic congestion levels to be greater than pre-pandemic levels. However, this could be mitigated by replacing certain trips with online activities (Marsden et al., 2021). It will be important to monitor travel demand and modal shares post-pandemic to determine whether the pandemic has influenced long-term changes in travel behaviour and travel demand and to determine whether further policy interventions are necessary. Depending on the extent to which public transit ridership rebounds post-pandemic, agencies may need to consider developing ridership growth strategies, given the relationship between ridership and operating budgets.

6. Conclusion

This paper presented the results of an investigation into the impacts of the COVID-19 pandemic on modality profiles for non-mandatory trips among residents of the GTA. Despite the ongoing pandemic and stay-at-home orders, non-mandatory activities play an essential role in ensuring that physiological and psychological needs are met. Using data obtained from two web-based surveys of GTA residents, this study aimed to identify modality profiles for non-mandatory trips that existed prior to the pandemic and during the pandemic and to understand how modality profiles have changed as a result of the pandemic. Six pre-pandemic
state/provincial governments prepare for future public health emergencies. This approach allowed heterogeneity in the transitions between pre-pandemic and pandemic modality profiles to be captured. The identification of modality profiles helped to provide insights into the impacts of the pandemic on the mobility and accessibility of different segments of the population, and to determine the aggregate socio-economic characteristics of the segments. The findings presented in this study can be used to help inform the development of emergency plans that can help local and state/provincial governments prepare for future public health emergencies.

One of the key limitations of the study is that the results are obtained using data that were collected during a period of time where daily number of new COVID-19 cases was relatively low. Since the surveys were conducted, Ontario has experienced both a second wave and third wave of the pandemic, in which case counts have exceeded the values observed during the first wave. Consequently, the approaches that people currently take to completing non-mandatory trips may have evolved over time, meaning that they may differ from the approaches that were taken at the time that the surveys were conducted. Subsequent data collection efforts should aim to understand how modality profiles have changed over the course of the pandemic, as this may provide insights into the nature of post-pandemic modal preferences. The other key limitation of this study is that the data for the study were collected through a web-based survey that was administered to a market research panel. This method of data collection introduces the potential that the survey respondents are, on average, younger and more likely to belong to middle-income households than the population of the study area. Given the influence of age and income on modal preferences, this discrepancy could affect the modes that the respondents used for non-mandatory trips.

Future work should incorporate a structural model into the application of the latent class cluster analysis to investigate the influence of socio-economic and household attributes on the probability that an individual belongs to a particular latent class (as done by Molin et al. (2016)). This approach can help reduce the impacts of measurement errors by modelling the probability of class membership as a function of observed characteristics. Similarly, heterogeneity in the shifts in modality profiles that have coincided with the pandemic can be captured in a more detailed manner by modelling the transition probability as a function of socio-economic and household attributes (as done by de Haas et al. (2018)). Additionally, future work could define latent classes of individuals based on the attitudes and perceptions rather than the modes they used to make non-mandatory trips (this is referred to as the sociographic approach to measuring an individual’s lifestyle in Van Acker (2015)). This would provide valuable insights into the impacts of perceptions towards the pandemic on modal preferences. Future data collection efforts should ask respondents to indicate the frequency with which they used each mode to make non-mandatory trips, rather than asking them whether each mode was used. This would facilitate the identification of modality styles, which are believed to influence both long-term (such as housing location and vehicle ownership) and short-term (such as travel mode choice and activity participation) decisions (Vij et al., 2017).

CRediT author statement

Patrick Loa: Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. Sanjana Hossain: Methodology, Writing – original draft, Writing – review & editing. Sk. Md. Mashrur: Writing – original draft, Writing – review & editing. Yicong Liu: Formal analysis, Visualization, Writing – review & editing. Kaili Wang: Writing – original draft, Writing – review & editing. Felita Ong: Writing – original draft, Writing – review & editing. Khandker Nurul Habib: Conceptualization, Writing – review & editing, Supervision.

Declaration of competing interest

The authors have no conflicts of interest to report.

Acknowledgments

This study was funded through an NSERC discovery grant and the Percy Edward Hart professorship fund. The authors would like to thank the editor and the two anonymous reviewers, whose comments helped improve the quality of the manuscript.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tranpol.2021.05.028.

Appendix A. Class-specific Transition Probabilities
Fig. A1. Probability of belonging to a pandemic modality profile, given an individual’s pre-pandemic profile (Note: SD: strict drivers; PD: Pedestrians/d. drivers; PV: Private vehicle users; SMC: Shared mode users/cyclists; TP: Transit users/ pedestrians; NT: Non-travellers)

Table A1

Probability of belonging to a pandemic modality profile, given the individual’s pre-pandemic profile

| Pandemic Modality Profile | Pre-pandemic Modality Profile | Strict drivers | Pedestrians/drivers | Private vehicle users | Shared mode users/cyclists | Transit users/pedestrians | Non-travellers |
|---------------------------|-------------------------------|----------------|---------------------|-----------------------|---------------------------|--------------------------|---------------|
| Strict drivers            | SD                            | 87.1%          | 5.4%                | 4.2%                  | 2.2%                      | 0.3%                     | 0.8%          |
| Pedestrians/transit users | PD                            | 7.2%           | 65.2%               | 4.8%                  | 7.9%                      | 11.6%                    | 3.2%          |
| Transit users             | PV                            | 26.3%          | 18.7%               | 7.3%                  | 19.9%                     | 22.1%                    | 5.5%          |
| Private vehicle/transit users | SMC                      | 15.8%          | 10.4%               | 58.7%                 | 9.5%                      | 2.2%                     | 3.4%          |
| Mobility-on-Demand users/cyclists | TP                    | 20.7%          | 6.4%                | 7.8%                  | 43.3%                     | 7.6%                     | 14.2%         |
| Multimodals               | SD                            | 10.9%          | 51.4%               | 11.8%                 | 24.4%                     | 1.5%                     | 0.0%          |
Vermunt, J.K., Magidson, J., 2002. Latent class cluster Analysis [Internet]. In: Hagenaars, J.A., McCutcheon, A.L. (Eds.), Applied Latent Class Analysis, first ed. Cambridge University Press, Cambridge, pp. 89–106. Available from. https://www.cambridge.org/core/product/identifier/9780511499531/type/book.

Vickerman, R., 2021. Will Covid-19 put the public back in public transport? A UK perspective [Internet] Transport Pol. 103, 95–102. https://doi.org/10.1016/j.tranpol.2021.01.005.

Vij, A., Gorripaty, S., Walker, J.L., 2017. From trend spotting to trend ‘splaining: understanding modal preference shifts in the San Francisco Bay Area [Internet] Transport. Res. Part A Policy Pract 95, 238–258. https://doi.org/10.1016/j.tra.2016.11.014.

De Vos, J., 2020. The effect of COVID-19 and subsequent social distancing on travel behavior [Internet] Transp Res Interdiscip Perspect 5, 100121. https://doi.org/10.1016/j.trip.2020.100121.

Vuchic, V.R., 2005. Urban Transit: Operations, Planning, and Economics. John Wiley & Sons, Inc., Hoboken.

Wang, K.-Y., 2014. How change of public transportation usage reveals fear of the SARS virus in a city. PloS One 9 (3).

World Health Organization (WHO), 2020a. WHO Director-General’s opening remarks at the media briefing on COVID-19 - 11 March 2020 [Internet] [cited 2020 Nov 6]. Available from. https://www.who.int/dg/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19---11-march-2020.

World Health Organization (WHO), 2020b. Overview of Public Health and Social Measures in the Context of COVID-19 [Internet] [cited 2021 Apr 4]. Available from. https://www.who.int/publications/i/item/overview-of-public-health-and-social-measures-in-the-context-of-covid-19.

Zhang, J., 2020. Transport policymaking that accounts for COVID-19 and future public health threats: a PASS approach [Internet] Transport Pol. 99, 405–418. https://doi.org/10.1016/j.tranpol.2020.09.009.

Zhang, J., 2021. People’s responses to the COVID-19 pandemic during its early stages and factors affecting those responses [Internet] Humaitst Soc Sci Commun 8 (1), 1–13. https://doi.org/10.1057/s41599-021-00720-1.

Zhang, J., Hayashi, Y., Frank, L.D., 2021. COVID-19 and transport: findings from a world-wide expert survey [Internet] Transport Pol. 103, 68–85. https://doi.org/10.1016/j.tranpol.2021.01.011.

Zhou, H., Wang, Y., Huscroft, J.R., 2020. Impacts of COVID-19 on the transportation sector: a report on China [Internet] SSRN Electron J 1–20. Available from. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3679662.

Zhu, J., Fan, Y., 2018. Daily travel behavior and emotional well-being: effects of trip mode, duration, purpose, and companionship [Internet] Transport. Res. Part A Policy Pract 118, 360–373. https://doi.org/10.1016/j.trapa.2018.09.019.