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Will COVID-19 be the end for the public transit? Investigating the impacts of public health crisis on transit mode choice

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ABSTRACT

COVID-19 had an unprecedented impact on transit demand and usage. Stiff and vigilant hygiene safety requirements changed travellers' mode choice preferences during the COVID-19 pandemic. Specifically, transit modal share is radically impacted. Therefore, quantitative measurements on transit demand impact are urgently needed to facilitate evidence-based policy responses to COVID-19. Thus, we collected 1000 random samples through a web-based survey in the Greater Toronto Area (GTA), Canada, on traveler's modal choices behavior during the COIVD-19 pandemic. The paper presents an analysis with this firsthand dataset to understand transit users' behavioral adaptation resulting from the spreading of COVID-19 in 2020. We found that the transit frequency dropped by 21% to 71% for various socioeconomic groups in the GTA during the pandemic. The transit modal share dipped for all trip purposes. For private vehicle owners, around 70% of transit users switched to their private vehicles. More than 60% of those without cars switched to active transport for all travel purposes. Also, ride-hailing services are the second most popular substitution of transit for them. More than 80% of the respondents agreed with all transit safety policies, such as mandatory face-covering listed in the survey. Moreover, a similar proportion of the respondents agreed to return to public transit in the future. Multinomial, nested, and mixed logit models are estimated to capture relationships between modal choices and various factors. We found that the daily number of new COVID-19 cases impacts the choice of transit negatively. However, vaccine availability and mandatory face-covering onboard positively affect travellers' choices of riding transit during the pandemic.

1. Introduction

The outbreak of novel coronavirus disease, COVID-19, in December 2019 continued to circulate globally in an unprecedented manner causing irretrievable casualties worldwide (Lipsitch et al., 2020; De Vos, 2020). In early March 2020, the World Health Organization (WHO) declared COVID-19 a global pandemic due to its widespread severity (WHO Director-General's opening remarks at the media briefing on COVID-19 - 11, March 2020). By July 15, 2020, the virus is spreading worldwide with a spiking death toll. There were over 13 million confirmed cases, with more than half a million reported death (WHO Coronavirus Disease (COVID-19)). In response to the pandemic, countries worldwide closed international borders for non-essential travel, imposing travel restrictions and

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locking cities to enforce social distancing, all of which grinding their economy to a halt (Sweden is taking a very different approach to Covid-19 — Quartz). In addition, elementary and high schools were shut down for an unknown period, and colleges and universities shifted to remote learning. Furthermore, most employers adopted telecommuting policies and strictly maintained sector-specific safety guidelines in case of compulsory work-at-office (School closures caused by Coronavirus (Covid-19); Big tech firms ramp up remote working orders to prevent coronavirus spread - CNN). Consequently, the daily mobility of bustling urban life has come to a halt. Furthermore, social distancing strategies have abruptly altered the travel behaviors of urban residents. It not only affected the operation of urban transit systems but also has the potential to shift peoples' mode choice decisions, which is yet to be examined thoroughly.

Amongst all travel modes available for metropolitan residents, transit suffered the most. Contradicting the principle of social distancing, transit systems are designed to transport the mass amount of people effectively. It is suspected that the subway system accelerated the transmission of viruses across New York City, which operates one of the busiest transit systems in North America (Harris et al., 2020). Besides passengers, transit operators are also at considerable risk. During the outbreak in New York City, 123 COVID-related death was reported by Metropolitan Transportation Authority employees (Guse, 2020). Consequently, public transit ridership has dropped drastically within a noticeably short period upon the onset of the COVID-19 outbreak. In the City of Toronto, Canada, where more than 1.6 million transit trips were conducted before the pandemic, the transit ridership plummeted to 15 % of its original volume since Ontario announced the state of emergency (ES-1 Fast Cities; Coronavirus impact: Could Canadians end up using cars more, taking transit less | CTV News). With exceptionally low ridership, transit authorities are currently challenged to cope with unrecoverable expenses due to a radical fall in farebox revenue. In addition, they are constantly stressed to develop effective recovery strategies to reinstate the lost demand and, at the same time, ensure health and safety for its employees and transit riders in the post-pandemic period. Conversely, such dramatic events might affect habitual transit riders' travel behavior and lead to a permanent travel mode switch. Hence, understanding the transformed mode choice behavior has become a pressing issue for researchers and policy-makers. Thus, the economic reopening and restructuring of the existing urban transportation system can be effectively outlined during the post-COVID era.

This study conducted an empirical analysis on public transit usage behavior in the Greater Toronto Area (GTA), Canada, to examine the impact of the pandemic on urban residents' travel modal choice behavior. The primary objective is to report firsthand status quo of urban residents' transit usage during the pandemic and empirically examine travellers' modal choices after the first wave of the pandemic in Canada. In addition, the study also investigated travellers' acceptance of various health and safety policies implemented in public transit systems with econometric modelling techniques. Findings from this study can facilitate transit service planning during and post the COVID-19 pandemic.

The remainder of this paper is organized into six sections. Section 2 summarizes relevant preceding studies, followed by Section 3, outlining the data collection methodology. Section 4 reports data analysis, followed by Section 5, presenting an econometric investigation. Section 6 presents a discussion on possible policy implications of the results of the empirical investigation. Finally, section 7 reviews the policy implications based on the findings and concludes the study.

2. Literature review

Respiratory infections like coronavirus are transmitted through the eyes, nose, or throat via liquid droplets, aerosol generated by coughing, or sneezing. The transmission can either occur directly, being close to someone with respiratory symptoms or indirectly by contacting the infected surfaces or objects (La Rosa et al., 2020). Therefore, WHO issued guidelines to practice social distancing, avoiding shared or crowded spaces, and taking other self-protective hygienic measures to slow the dissemination of the infectious disease (Advice for the public). Moreover, early studies during the pandemic concluded that taking actions such as restricting mobility, social distancing, and self-isolation directly decelerated the propagation of the virus (Fang et al., 2020; Wells et al., 2019; Muller et al., 2020; Cartenì et al., 2020).

The practicing social distancing for prolonged periods and the continuous fear of travelling due to the pandemic have already started to reform urban mobility. Consequently, travellers' mode choices are affected. Shifting to work from home (WFH), remote learning in conjunction with reduced participation in social activities and events during the pandemic has radically curtailed travel demand and altered travel behaviors. Early studies suggested that WFH would plummet the overall number of trips made by individuals significantly (Shaz and Corpuz, 2012). In addition, people might be accustomed to shop groceries and buying clothes online, resulting in fewer shopping trips (Shi et al., 2019). The collective impact of these disaggregated behavioral changes should be thoroughly investigated to understand how the transportation system will be reshaped in the "new normal" post the pandemic.

Among all travel modes, transit and shared transport turned out to be crucial for public health and safety concerns during the pandemic. Studies on COVID-19 asserted that the virus remains transmissive on the surface, such as plastics, and stainless steel, for several hours (Van Doremalen et al., 2020). Therefore, public transport poses the highest risk of such infectious diseases as transit riders have to share space with each other (Troko et al., 2011). For instance, subways were suspected to be one of the prominent media to accelerate the spread of COVID-19 in New York (Harris et al., 2020). Prior studies also addressed regional bus (Piso et al., 2009), rail transport (Zhang et al., 2011. 2011.; Cui et al., 2011; Palmer et al., 2007), water transport (Palmer et al., 2007), and air transportation (Brownstein et al., 2006; Grais et al., 2004; Epstein et al., 2007) to play a vital role in mass spreading during previous influenza pandemics such as the Spanish flu in 1918, A(H1N1) influenza pandemic in 2009. However, literature revealed that a gradual increase in public confidence tended to restore the lost public transport ridership over time during public health crises (Wang, 2014). Besides transit, ride-hailing services also lost significant demand during the pandemic. However, the risk is lower than public transport if services are used exclusively (Uber is doing 70 percent fewer trips in cities hit hard by coronavirus - The Verge).

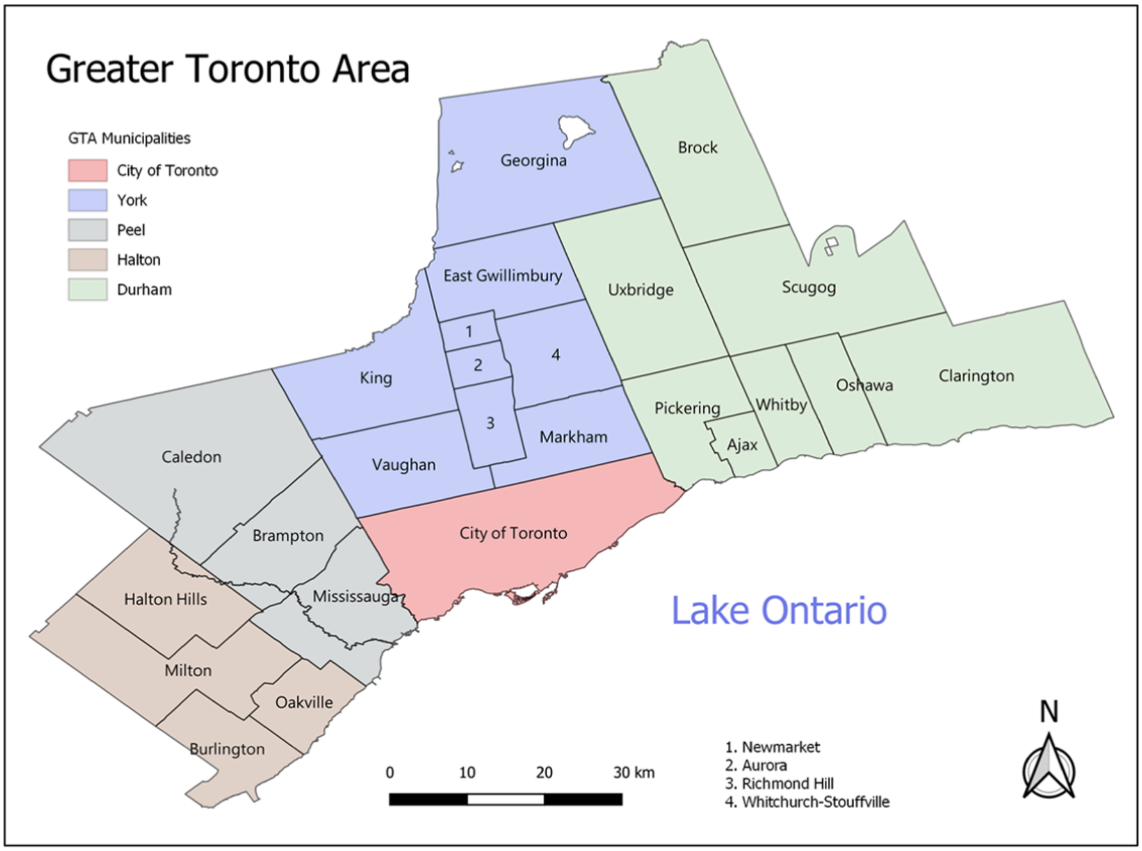

Fig. 1. Map the Greater Toronto Area (GTA) with the number of samples collected from each region.

While avoiding transit, people having access to private cars will be more prone to drive themselves. Also, several reports on mobility during the COVID-19 indicated that biking and walking (active transportation) had become popular travel mode choices for short journeys during the pandemic. Thus, people can travel while maintaining social distancing (De Vos, 2020; MOBIS Covid19 Mobility Report; Teixeira and Miguel, 2020). However, literature highlighting the role of cycling during previous pandemics was rare to find. Nevertheless, this limited studies remarked that biking demand increased in the post-pandemic era of the 2002–2004 SARS outbreak (Weinert et al., 2007). This suggests the possibility of travel mode preferences changes due to the pandemic. Therefore, in-depth analyses are required to capture possible shifts in traveller's modal choice preferences during the pandemic.

Public transit is vital for the collective effort to cut greenhouse gas emissions. Studies observed air quality improvements worldwide during the COVID-19 pandemic brought by a reduction in out-of-home activities (Li et al., 2020; T - Federal Transit Administration DO). Such trend may not continue in post-COVID era. Thus, promoting public transport will be one key aspect of meeting the emission target during that period. Therefore, transit authorities and planners should take proactive actions to retain transit demands immediately as city dwellers might shift to other modes or purchase personal mobility tools, resulting in the loss of permanent transit demand. There are few guidelines regarding public transportation pandemic planning and responses after the 2004 SARS and 2009 H1N1 outbreak (Fletcher et al., 2014; Toronto Public Health; Gupta and Abramson, 2007), suggesting transit policies, such as frequent disinfection and face coverings while commuting to adopt at distinct stages of the pandemic. However, empirical research on effectiveness and travellers' acceptance of policies mentioned in the guidelines is limited. This study will contribute to the literature in this regard.

Earlier research on mode choices discovered several factors that may encourage consumers to use public transportation for their commute trips. These influential factors include subsidized transit pass, better access to transit services, increased parking cost, decreased travel time and public transit cost, and higher transit service frequency (Zhou, 2016; Zhou, 2014; Zhou, 2012; Danaf et al., 2014; Boyd et al., 2002). In addition, some researchers observed that safety concerns and commuting distance are the key factors that influence commuters. For example, females might select active transportation modes such as walking and bike and avoid transit if they feel unsafe (Akar et al., 2013; Khattak et al.).

Regarding the COVID-19 pandemic, some studies conducted descriptive statistical analysis on the impact of COVID-19 on the modal share (Bucsky, 2020; Beck and Hensher, 2020). They found sanitization, social distancing, crowd management, and infection concerns to affect travellers' decision to take transit (Abdullah et al., 2021; Elias and Zatmeh-Kanj, 2021; Aaditya and Rahul, 2021). Pandemic awareness, exposure to the infections, and perceptions of lockdown were also found to affect mode choice behavior (Hotle

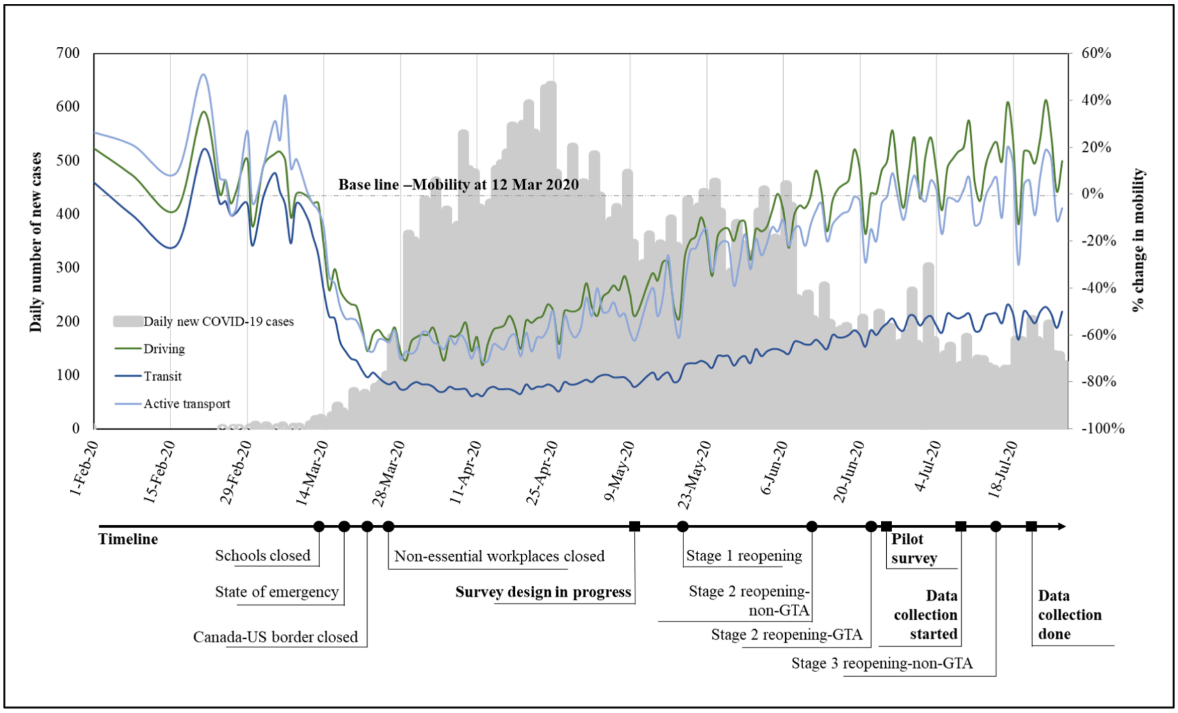

Fig. 2. The daily number of new cases in Ontario and the Apple Mobility trends in Toronto, Ontario (COVID-19 - Mobility Trends Reports - Apple; Timeline: Emergency orders impacting Toronto and Ontario amid the COVID-19 pandemic | CTV News).

et al., 2020; Rahimi et al., 2021). However, to the authors' best knowledge, a handful of studies designed and tested stated preference experiments to investigate the impact of daily new cases, vaccination availability, and feasible transit safety policies on transit choice decisions. The paper contributes to filling that research gap.

3. The survey

The study area for this investigation is the Greater Toronto Area (GTA), the largest Canadian urban region in Ontario, Canada. The GTA has five regional municipalities: the city of Toronto, Region of Peel, York, Durham, and Halton, as illustrated in Fig. 1. According to the recent Canadian Census, almost 24.3 % of the residents of the GTA use public transit as a primary mode of commuting trips (Statistics Canada. Census in Brief: Commuters using sustainable transportation in census metropolitan areas). The municipalities and regions in the GTA operate 12 integrated local public transit systems administered by corresponding regional governments. Amongst the local transit agencies, the Toronto Transit Commission (TTC) is the largest transit agency in Canada, handling the largest share of the transit ridership in the GTA (City of Toronto. Toronto Transit Commission). In addition, a regional transit system named GO transit operates both bus and train services that offer inter-regional connectivity. However, transit ridership dropped by almost 80 % since the declaration of a state emergency in Ontario on Mar 17, 2020, as shown in Fig. 2. (COVID-19 - Mobility Trends Reports - Apple; Timeline: Emergency orders impacting Toronto and Ontario amid the COVID-19 pandemic | CTV News). However, with the declination of new covid cases from the mid of June 2020, the GTA started to reopen gradually, and thus, mobility tends to increase. Critical dates regarding the pandemic in Ontario and the survey design are also highlighted in the figure.

Given the study's objective, an online survey was conducted in the GTA. The questionnaire was designed using the survey platform alchemer.com. The primary focus was to capture participants' attitudes towards transit and its usage before and during the pandemic when the daily new cases were at the declining phase of the first wave. The GTA was preparing for reopening gradually at the time of the survey. The term "before the pandemic" in the study is defined as the time frame before the declaration of a state emergency in Ontario. As the pandemic was at the recovery stage from the first wave is considered as the period "during the pandemic" in the study. Prior to the field, a pilot survey was conducted among the research team working on multiple COVID-19 related studies (Habib et al., 2021) and professionals in local transit agencies to improve that survey for better quality. The data were collected for two weeks starting from Jul 10, 2020, through an online research panel. In total, 905 completed data out of 1176 responses (after cleaning for incomplete information) were used for the empirical investigations of this paper.

3.1. The questioannire design

The survey questions started with participants' socio-demographic characteristics, employment status, and household attributes

Table 1
Modal alternatives considered in the SP experiments.

Modal alternatives	Intra-regional trips	Inter-regional trips	Remarks
Auto drive (drive yourself)	✓	✓	Available to the respondent has access to a private car
Auto passenger (driven by the household member(s))	✓	✓	Available to the respondent has access to a private car
Taxi/Ride-hailing	✓	✓	Available to everybody
Carpool (shared ride with unknown)	✓	✓	Available to everybody
Cycle	✓	–	Maximum trip distance is no greater than 10 km
Walk	✓	–	Maximum trip distance is no greater than 3 km
Local transit with walk access	✓	–	Available to everybody
Local transit with transfer	✓	–	Available to everybody
Regional transit with walk access	–	✓	The regional transit station is within 1 km
Regional transit with local transit access	–	✓	Available to everybody
Local transit with local transit access	–	✓	Available to everybody; Connected local transit from different regions
Park & ride	✓	✓	Available to the respondent has access to a private car
Kiss & ride	✓	✓	Available to the respondent has access to a private car
Transit with taxi/ride-hailing access	✓	✓	Available to everybody
Carpool & ride	✓	✓	Available to everybody
Cycle & ride	✓	✓	Available to everybody

Notes: 1. (✓) indicates that the alternative is considered in the study context.
2. (−) indicates that the alternative is not considered in the study context.

such as residence location, size, number of dependent children, private vehicles, and adult bikes. The following survey section captured respondents' pandemic concerns, subsequent measures practiced during the pandemic, and the impact of COVID-19 on their daily life. Next, the survey collected respondents' typical modes for commuting and non-commuting trips and how frequently they used transit before and during the pandemic. Respondents who shifted from public transit to other modes during the pandemic were asked additional questions regarding their reasons for the modal shift. Furthermore, an attitudinal section was designed to account for the respondent's latent preferences. The descriptive statistic will be presented and discussed in Section 4. Besides descriptive parts, the survey also conducted stated choice experiments on respondents' modal choices. Details of the experimental design will be presented in the following section.

3.2. Stated choice experiment design

The stated preference (SP) experiment investigates the impact of pandemic-related factors and transit safety policies on mode choice. The SP experiment accounted for two travel contexts: intra- and inter-regional trips. The former consists of trips within the municipalities within a local transit system. In contrast, the latter accounts for trips between regions. These trips involve multiple regional transit systems. 48 SP scenarios, 24 per context, were designed using D-efficient designs. Such practice is common in exploring the effects of novel factors on mode choice (ChoiceMetrics, 2018; Lin, 2017). However, each respondent was provided with 6 SP scenarios, randomly pooled from the 24 context-specific SP scenarios.

3.3. Alternative selection

Table 1 illustrates the alternatives considered in each SP context. A comprehensive modal alternative set was established for the corresponding context. Each context will have its own sets of mode choice alternatives considering their feasibility. Thus, mode choice model parameters can be estimated consistently. Active transportation modes were considered only in intra-regional contexts only, which are primarily short-distant trips.

3.4. Attributes consideration

Three groups of attributes were presented in each SP scenario: level of service (LOS) variables, pandemic characteristics, and transit safety policies specific to transit alternatives. LOS variables such as in-vehicle travel time (IVTT), out-of-vehicle travel time (OVTT), and travel cost were considered (Zhou, 2016; Zhou, 2014; Zhou, 2012; Danaf et al., 2014; Boyd et al., 2002). The travel time was pivoted around the mode-specific travel time required for traversing the average travel distance in the respective travel contexts. The distances for both contexts were retrieved from the 2016 Transportation Tomorrow Survey (TTS) (Ashby, 2016). The TTS is a regional household travel survey conducted every-five years in the GTA area since 1986. The average speed and levels were selected based on the travel time and buffer time indices in the Toronto context, along with previous mode choice studies using SP experiments (University of Toronto, 2020; TomTom; Sweet et al., 2011; Frei et al., 2017; Idris et al., 2014; Danaf et al., 2019; Arentze and Molin, 2013; El-geneidy et al., 2007; RW B, 1997). The baseline travel time for each mode was calculated based on the travel speed of the respective mode in an urban context. The average speed for vehicular modes was found to be 45 km/hr, whereas the speed was 40 km/hr for public transit. The average travel time for bicycle and walking was quantified as 8 km/hr and 4 km/hr, respectively. In addition, four attribute levels, varying from −25 % to 50 %, were considered for travel time.

Likewise, the travel cost for the alternatives was calculated based on the average trip distance and mode-specific per-kilometer cost.

Table 2
Attribute levels for pandemic characteristics and transit safety policies in the SP experiment.

Attribute Level	Pandemic characteristics		Transit safety policies
	last 14 -day average of new cases	Vaccination status	
1	0 to 10 cases	Vaccines are not discovered yet	Mandatory face covering
2	10 to 100 cases	You are vaccinated, but no mass vaccination	Installation of hand sanitizers at stations and transit vehicles
3	100 to 300 cases	Mass vaccination (herd immunity achieved)	Boarding and alighting at the different doors
4	More than 300 cases.	–	Contactless payment
5	–	–	Enforcing strict passenger limits on vehicles
6	–	–	Temperature scan before boarding

Table 3
Summary Statistics of the collected data.

	Samples				2016 Census
	Mean	Standard Deviation	Min	Max	
Age	44.90	15.68	17.00	88.00	39.7 (average)
Household size	2.91	1.57	1.00	16.00	2.7 (average)
Number of household vehicle(s)	1.43	0.93	0.00	7.00	–
Number of household adult bicycle	1.13	1.25	0.00	10.00	–
Number of household member(s) aged below 18	0.60	0.93	0.00	4.00	–
Number of household member(s) aged above 60	0.55	0.81	0.00	4.00	–
Regions (%)					
Toronto	47.40				42.60
Peel	22.30				21.50
York	18.80				17.30
Halton	3.50				8.50
Durham	8.00				10.10
Gender (%)					
Female	58.10				51.48
Male	40.90				48.52
Possess driving license (%)	86.30				–
Having access to the private vehicle (%)	86.50				–
Having transit pass (%)	35.80				–
Student status (%)					
Full-time student	9.40				–
Part-time student	5.00				–
Current employment status (%)					
Full-time at workplace	28.20				–
Full-time at home	21.50				–
Full-time, hybrid workplace (home and workplace)	5.10				–
Part-time at workplace	6.60				–
Part-time at home	6.00				–
Part-time, hybrid workplace (home and workplace)	1.20				–
Not employed	25.40				–
Level of education (%)					
Less than high school	2.20				16.30
High school diploma or equivalent	15.60				25.90
Trades certificate or diploma	4.90				2.40
College or non-university certificate or diploma	19.40				17.30
University certificate or diploma below bachelor’s level	8.50				5.00
Bachelor’s degree	33.10				22.00
Advanced degree (Master, Ph.D., M.D.)	16.20				9.10
Household Income (%)					
below $ 14,999	2.46				4.84
$ 15,000 - $ 49,999	22.48				28.47
$ 50,000 -$ 99,999	39.93				43.68
$ 100,000 -$ 149,999	22.93				13.67
above $ 150,000	12.19				9.33
Primary travel modes for commuting trips before COVID-19 (%)					
Private vehicle	62.46				62.42
Public transit	22.46				24.29
Walk	7.10				5.25
Bicycle	4.35				1.43
Other	3.62				6.61

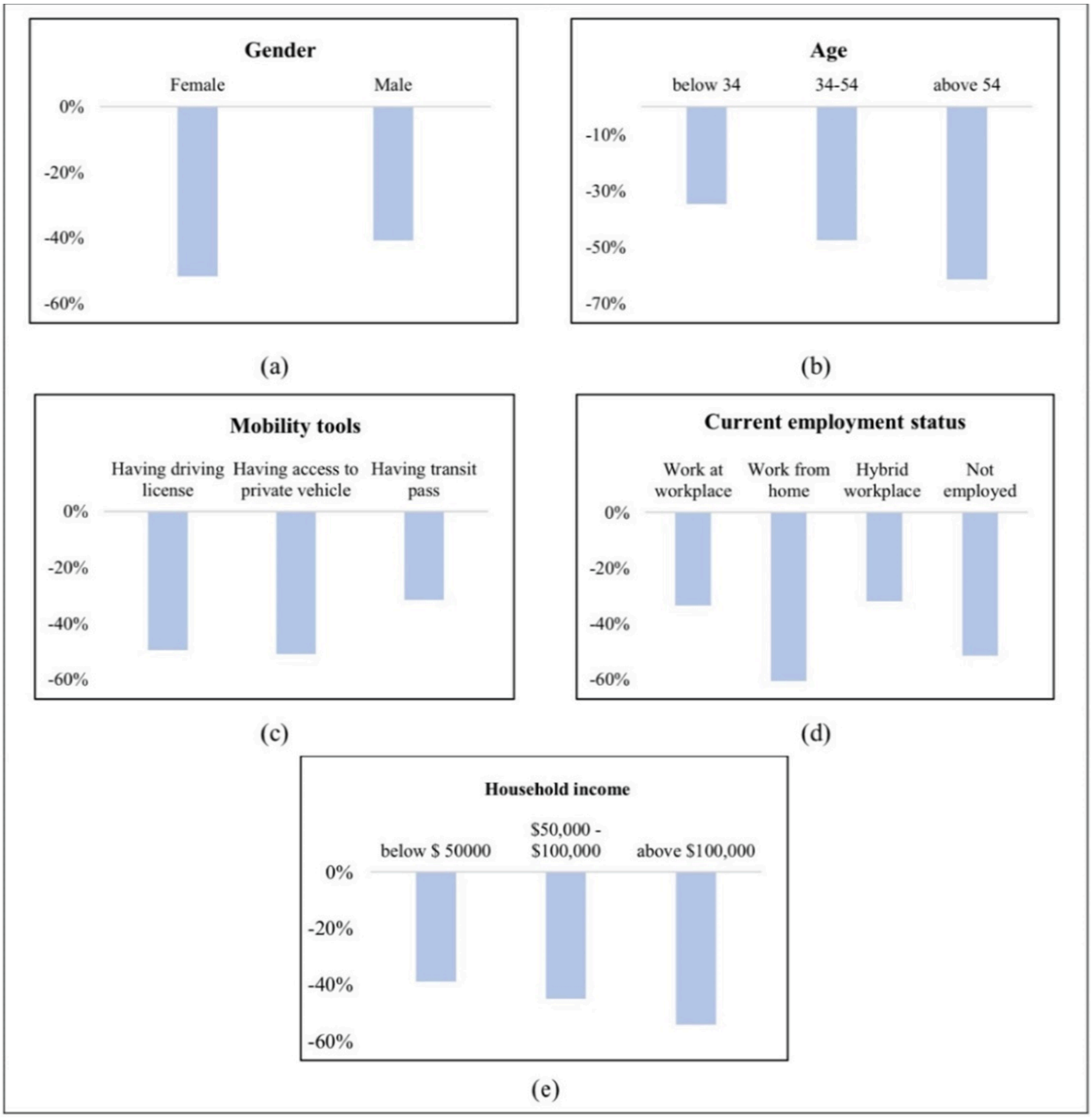

Fig. 3. Percent change in public transit usage during the pandemic.

The attribute levels of cost were depicted from earlier studies and ranged from −50 % to 50 % of the base value (Frei et al., 2017). The base travel cost of driving alone consists of fuel and parking costs (Canadian Automobile Association (CAA)). Besides, the baseline value for travel cost for auto passengers was considered half of the baseline fuel cost value while driving alone since the cost might be split by drivers and passengers onboard (Bhat and Sardesai, 2006) Conversely, the fares of on-demand travel alternatives like exclusive taxi/ride-hailing services were calculated based on the pricing scheme used by the service provider at the time of data collection (Uber; Co-opCabs). In the case of shared riding with strangers, the base fare was considered two-thirds of the exclusive riding base fare. At the same time, a fixed fare of $3.25 was considered for local transit alternatives in the intra-regional context. On the contrary, the transit fare for the inter-regional travel context was calculated based on average travel distance, as the regional transit in the GTA used a distance-based fare system. Like travel time attributes, the travel cost also had four levels for all alternatives, except for local transit alternatives in the intra-regional SP experiments, which have fixed fares.

The pandemic characteristics in the SP scenarios were indicated by the daily number of new cases in the last two weeks and vaccine availability. WHO continuously updated these facts to track the development of the pandemic (WHO Coronavirus Disease (COVID-19)). The attribute levels for the daily number of cases were set as the COVID-19 cases reported in the study area (as illustrated in Fig. 2). As described in Table 2, four levels were set for this attribute. Three levels were defined to characterize the vaccination status in the SP scenarios. In addition to these attributes, the choice experiment also accounted for various transit safety policies that might be

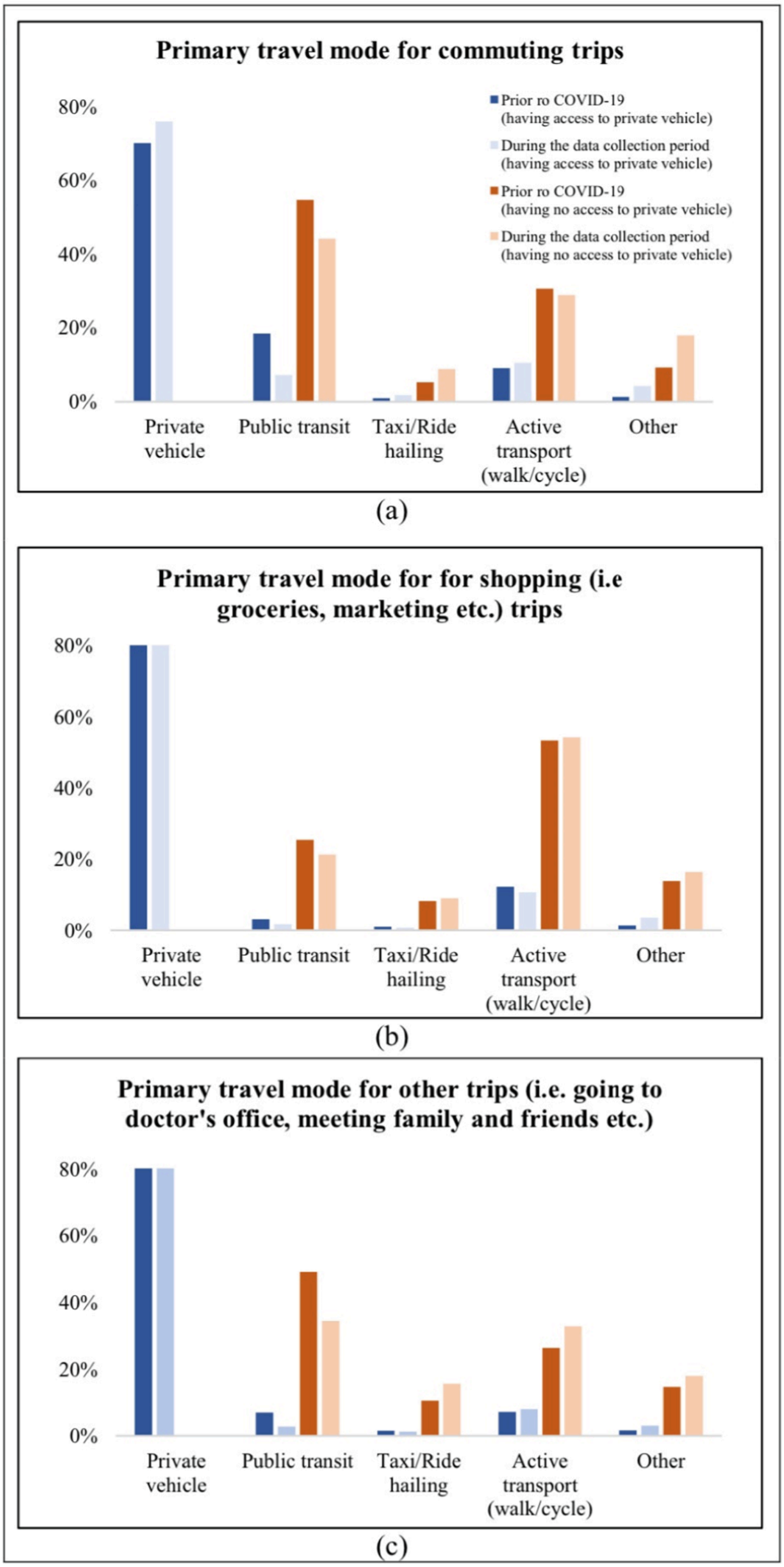

Fig. 4. COVID impacts on primary travel modes by trip purposes.

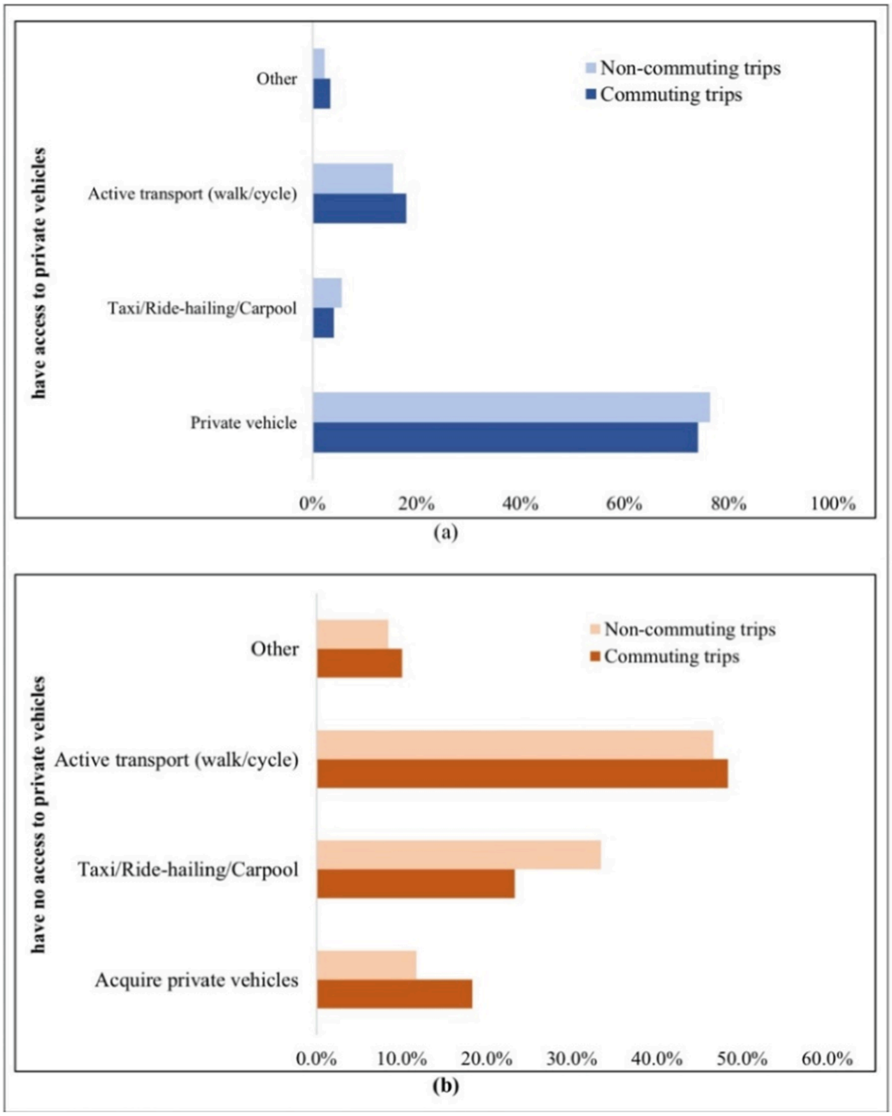

Fig. 5. COVID impacts on primary travel modes by trip purposes.

implemented to protect transit riders as well as operators. The transit policies incorporated in the scenarios were selected based on TTC's report on feasible transit policies during the COVID-19 pandemic published in July 2020 (Toronto Transit Commission, 2020). In total, six safety policies were tested in the experiment. All policies are described in Table 2.

Moreover, some constraints are enforced to ensure choice situations' feasibility while designing the SP options using a D-efficient design. For example, in the case of mass vaccination, the daily number of cases was kept below the highest level. More waiting time was also added when a strict passenger limit on transit alternatives was enforced due to reduced transit capacity. Similar trade-offs were considered where necessary to replicate realistic representations of the scenarios.

4. Descriptive analysis

As shown in Table 3, the sample's overall distribution of key socioeconomic attributes matched closely with the 2016 Canadian Census (Statistics Canada, 2020). However, the sample over-represents female residents, individuals having an undergraduate degree, and individuals with income ranging from $50,000 to $100,000. This might be attributed to the demographic composition of the commercial survey panel used by the study compared to the comprehensive coverage of the census.

4.1. The shift of transit usage frequency by socioeconomic factors

Respondents' transit usage frequency dropped significantly for COVID-19. We compared changes in the number of respondents

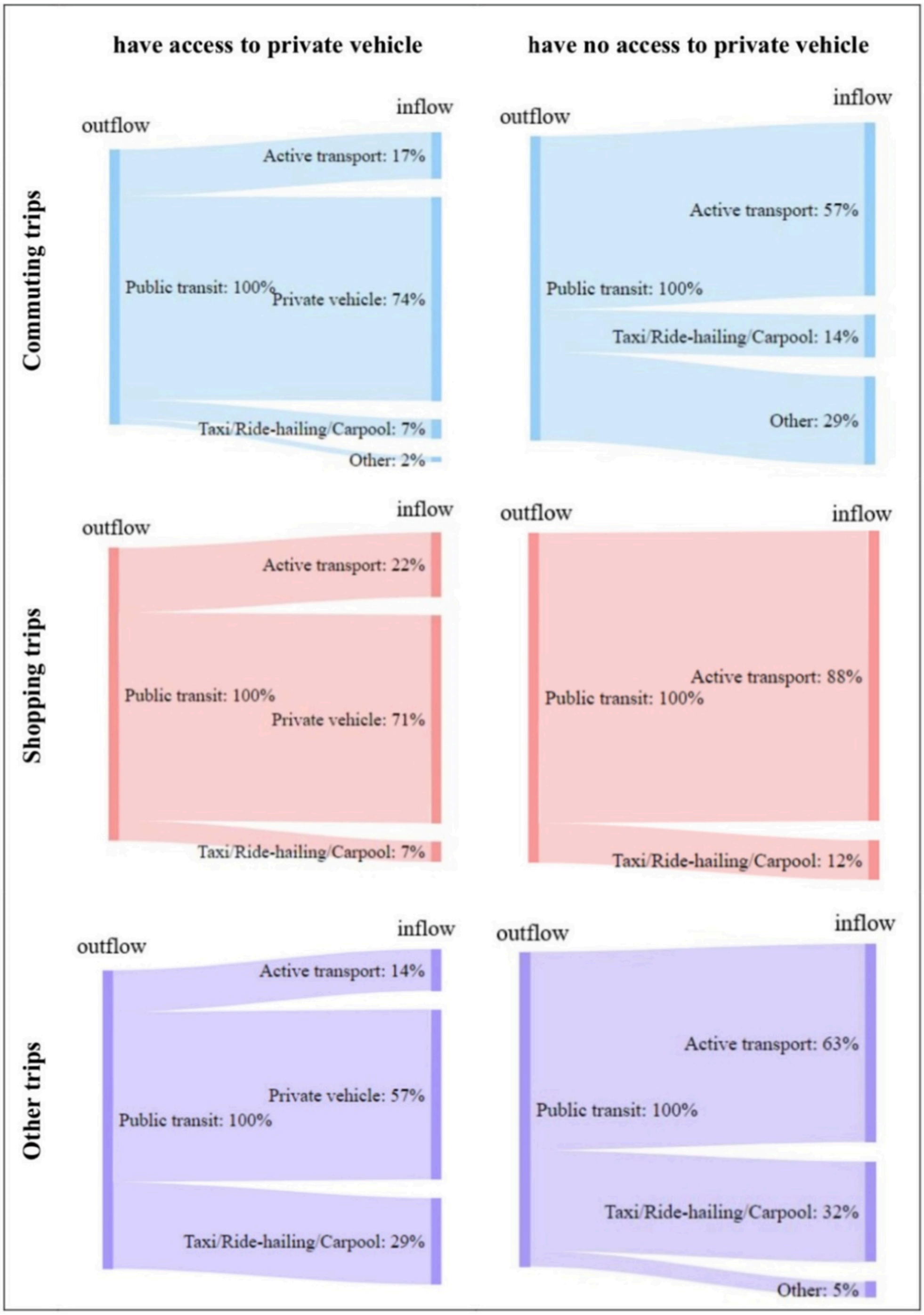

Fig. 6. Substitutions for transit for COVID by trip purposes.

who reported they took transit at least once a month before and after COVID-19. Variations are composed based on various socio-demographic variables. The results are presented in Fig. 3. Transit frequency dips from 21 % to 70 % for different socioeconomic groups. The results are consistent with the aggregate mobility report provided by Apple and other credible sources (COVID-19 - Mobility Trends Reports - Apple; Timeline: Emergency orders impacting Toronto and Ontario amid the COVID-19 pandemic | CTV News). Females used less transit than males. For different age groups, the drop in transit frequency increased as respondents' age increased. As vulnerable groups to COVID-19, senior citizens avoid transit. Thus, their mobility during the pandemic would be further restricted. For motility tools, driver's license holders and car owners have relatively high transit frequency drops. The findings are consistent with the previous observation that private vehicles are the most popular substitutions for transit. However, employees who

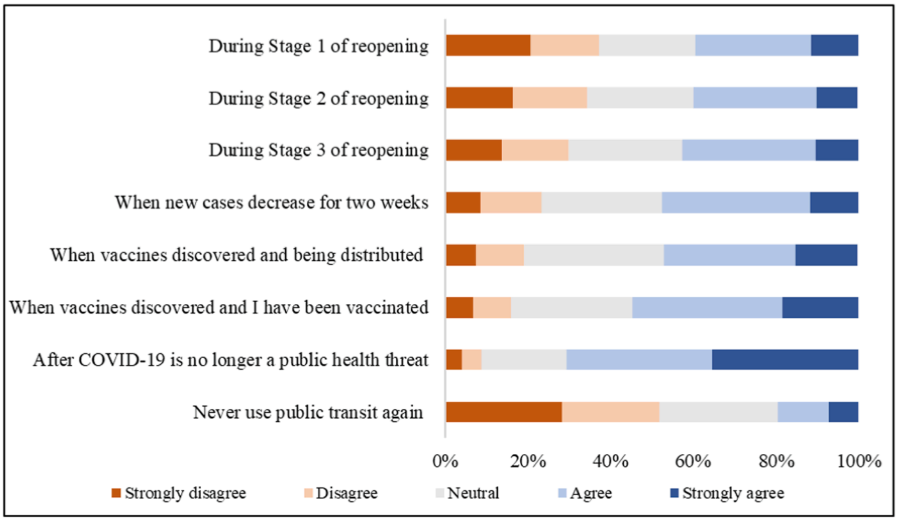

Fig. 7. Stated timing of returning to normal usage of public transit.

work remotely from home during the pandemic reduced their transit frequency significantly. It proves the effectiveness of "working from home" as a health and safety policy to limit contact between people. Transit frequency also decreased monotonically as household income increased. It reflects that lower-income groups are the most transit-dependent despite the risk of COVID-19. So adequate policy attention should be given to them. The distribution of the transit usage based on socioeconomic attributes is presented in Appendix A1.

4.2. The shift of primary travel modes by trip purposes

Respondents avoided transit for COVID-19. We collected respondents' primary travel modes for commuting, shopping, and other trips before and after the spread of COVID-19. Mode shares collected are categorized into two groups by respondents' private vehicle availability. We found that transit modal share dropped for the groups (with/without vehicles), as presented in Fig. 4. The group without vehicle access is still heavily dependent on transit for all travel purposes. For those who have private cars, around 18.5 % of them commuted by public transits in typical conditions. However, this number drops to 7.3 % due to COVID-19. However, transit demands for respondents without vehicle access are relatively inelastic. 54.7 % of them commuted by transit before, and 44.2 % are still using transit despite COVID-19. People with private vehicle access rarely used transit for their shopping trips before COVID-19. Only 3.1 % of them took transit. Currently, only 1.7 % of them still take transit for shopping.

For people without vehicle access, a quarter of them used transit for shopping transit. 21.3 % still rely on transit to conduct shopping, especially grocery shopping, which maintains their necessities. Other purposes of travel reveal a similar trend. 7 % of people with vehicle access used transit in typical conditions. However, only 2.8 % still use transit now. For the no vehicle group, 49.2 % of them used transit before for other purpose trips. 34.4 % of them still travel by transit. It is evident that transit still provides vital services for people without vehicles during the pandemic. Indeed, people without private vehicles have limited alternatives when they try to avoid transit.

4.3. Alternative mode choices to transit

With people trying to avoid public transit for COVID-19, respondents were asked about their substitutions for transit (see Fig. 5). Again, results indicate personal vehicle popularity is strengthened because of COVID-19. Around 80 % of respondents with vehicle access stated they would use cars instead of avoiding transit. For residents who currently have no access to vehicles, 18.3 % considered acquiring private vehicles for commuting. Around 50 % of them would consider active transportation for both commuting and non-commuting trips. As proposed by Hensher et al., encouragement of using active transportation, especially for short trips, will be urgently needed from policymakers (Beck and Hensher, 2020). Without proactive policy actions, vehicle popularity will inevitability be strengthened. As a result, subsequent issues such as congestion, air pollutions, emissions will persist.

Despite respondent's stated opinions, we also tracked respondents' choices of substitutions for transit if they were transit users before but avoid it for COVID-19. Fig. 6 shows the flows of respondents' choices by each trip purpose. Overall, their stated opinion and behaviors match closely. Private vehicles are the most popular choice if people have access to cars. For car owners, 74 %, 71 %, and 57 % of transit avoiders switched to cars for commuting, shopping, and other purposes trips, respectively. Around 20 % of them shifted to active transport for all purposes. Also, approximately 30 % of them used taxi/ride-hailing/carpool instead of transit for other purposes. Most respondents with no vehicle access choose active transport (walk & bike) instead. 88 % of them either walked or cycled to shop during COVID-19, whereas 32 % used taxi/ride-hailing/carpool for other trips. Transportation planners should pay attention to the

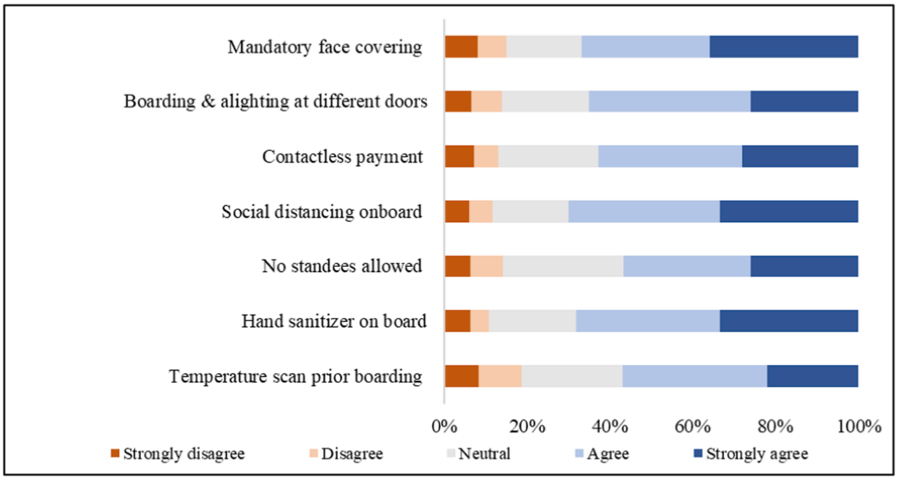

Fig. 8. Willingness to use transit followed by implantation of health & safety policies.

substitution patterns for transit during the pandemic. Returning of auto-dependency was found during the pandemic. This would be a pressing issue if such a trend continued in the future. As a result of ridership loss, congestion costs might increase immensely due to the high presence of single-occupancy vehicles in the transportation network.

4.4. *Timing of returning to normal public transit usage*

Ontario governments planned to open the economy in three stages: all three stages having social distancing as a continued measure (Ryan R. Coronavirus).Therefore, respondents' opinions on the timing of returning to their normal transit usage are collected. Results are presented in Fig. 7. 80 % of respondents believed that they would come back to transit at some point. The trend is clear that people will gradually return to transit as a threat of COVID-19 diminishing. More respondents agreed to use transit as staged economy reopening progressed. Also, 77 % of them agreed to return to transit as the number of new cases steadily dropped. Moreover, the successful discovery of vaccines will boost people's confidence in transit. Once the vaccine is discovered and distributed, 80 % of respondents agreed to return to transit even without being vaccinated (see Fig. 7).

4.5. *Health & safety implemented on public transit*

Respondents' opinions on the implementations of various health and safety measures on transit are collected. Feasible policies investigated in this study are selected with direct consultancy from Toronto Transit Commission (TTC) employees and their public reports (Toronto Transit Commission, 2020). Respondents' attitudes toward all policies are presented in Fig. 8. All policies are well received with an approved rate (attitudes neutral or higher) 85 % or higher. The only exception is offering a temperature scan before boarding transit vehicles. However, this policy still has an 81.3 % approval rate. In addition, on July 2, 2020, one of the policies, mandatory face covering, has been required on all Toronto Transit Commission (TTC) vehicles. Since implementation, 90 % of policy compliance rates without rigid enforcement are reported (Spurr, 2020). It also suggests the potential of successful implementation of other policies investigated in this study, if necessary.

5. Econometric modelling framework

The study developed multinomial logit (MNL), nested logit (NL), and mixed logit (ML) mode choice models for the inter-and intra-regional contexts. Let the random utility for an individual, i, in an SP scenario, s, with j alternatives can be expressed as:

$$U_{ijs} = V_{ijs} + \varepsilon_{ijs} = asc_j + \beta_j X_{ijs} + \varepsilon_{ijs} \quad [1]$$

where, V_{ijs} refers systematic utility of each alternative and ε_m denotes a random error component with a zero mean. V_{ijs} can further be specified as a function of alternative specific constants, $asc_{j,}$ and set of attributes, X_{ijs} regarding alternatives, individuals, and scenarios presented. In (Lipsitch et al., 2020); β_j is the vector of estimated parameters.

Thus, the choice probabilities for the MNL mode choice model with j alternatives are given by:

$$P_{ijs} = \frac{e^{\mu V_{ijs}}}{\sum_{m=1}^{j} e^{\mu V_{ims}}} \quad [2]$$

where μ is the scale parameter and assume to be 1 in this case.

Table 4
The goodness-of-fit indices of the estimated models.

Intra-regional trip context (C1)			
	MNL	**NL**	**MMNL**
Loglikelihood of equiprobable model	−13446.810	−13446.810	−13446.810
Loglikelihood of the full model	− 8535.085	− 8527.737	−8193.210
Rho-Square value of the equiprobable model	0.365	0.366	0.391
Adjusted Rho-Square value of the equiprobable model	0.360	0.361	0.385
Akaike Information Criterion (AIC)	17204.170	17197.470	16534.430
Bayesian information criterion (BIC)	17653.100	17673.210	17030.270
Inter-regional trip context (C2)			
	MNL	**NL**	**Mixed-NL**
Loglikelihood of equiprobable model	−14341.51	−14341.51	−14341.510
Loglikelihood of the full model	−8706.52	−8693.28	−6538.560
Rho-Square value of the equiprobable model	0.393	0.394	0.544
Adjusted Rho-Square value of the equiprobable model	0.390	0.390	0.540
Akaike Information Criterion (AIC)	17509.04	17490.56	13185.130
Bayesian information criterion (BIC)	17830.67	17838.98	13546.960

Conversely, the NL model overcomes the independence of irrelevant alternatives (IIA) assumptions in the MNL structure by nesting alternatives, and the unconditional probability of choosing an alternative j within the nest, T, can be written as follows:

$$P_{ijs|T} = \frac{e^{\mu_T V_{ijs}}}{\sum_{m=1}^{k} e^{\mu_T V_{ims}}} * \frac{e^{\frac{\mu_R}{\mu_T} ln\left(\sum_{m=1}^{k} e^{\mu_T V_{ims}}\right)}}{\sum_{T'=1}^{T} e^{\frac{\mu_R}{\mu_{T'}} ln\left(\sum_{m'=1}^{k'} e^{\mu_{T'} V_{im's}}\right)} + \sum_{l=1}^{r} e^{\mu_R V_l}} \quad [3]$$

where μ_R, μ_T denotes the upper-level scale (assume to be 1) and scale for nest T. $\frac{\mu_R}{\mu_{T'}}$ is the logsum parameter for each nest, which should be between 0 and 1.

For an alternative (l), out of any nest, the probability of choosing that alternative is:

$$P_{ils} = \frac{e^{\mu_R V_{ils}}}{\sum_{T'=1}^{T} e^{\frac{\mu_R}{\mu_{T'}} \ln\left(\sum_{m'=1}^{k'} e^{\mu_{T'} V_{im's}}\right)} + \sum_{l=1}^{r} e^{\mu_R V_l}} \quad [4]$$

Each respondent in the study had 6 SP scenarios observations six(s) with respective j alternatives for each travel context explained in Section 3.

If the variable y_{ijs} denotes whether alternative j is chosen in the SP context, s, by the individual, i, the log-likelihood function of the MNL and NL mode choice model is given by:

$$LL(\beta_j) = \sum_{i=1}^{i} ln\left(\prod_{s=1}^{6} \prod_{j \in C} P_{ijs}^{y_{ijs}}\right) \quad [5]$$

The study developed a random parameter mixed logit (ML) model that can capture more realistic choices behaviors (Hensher and Greene, 2003). Therefore, a mixing density is introduced $f(\xi_j)$ to the parameters for which preference heterogeneity will be captured across the individuals. The density is specified by hyperparameters, θ, (i.e., zero mean and the standard variance, σ_j^2), which are to be estimated. The paper considered temporal and cost parameters to follow a log-normal distribution, so that the corresponding parameters are bound to have their intuitive sign and positive value of travel time (VOT) can be approximated (Stephane et al., 2004). The mixed models were also estimated considering panel effects.

In the ML model, the MNL model specification in (De Vos, 2020) is extended to:

$$P_{ijs|\xi_j} = \frac{e^{\mu V_{ijs|\xi_j}}}{\sum_{m=1}^{j} e^{\mu V_{ims|\xi_j}}} \quad [6]$$

The unconditional choice model for any alternative after mixing distribution can be written as:

$$P_{ijs} = \int P_{ijs|\xi_j} f(\xi_j) d\xi_j \quad [7]$$

As $f(\xi_j)$ is not a closed form, it was estimated using simulation in a Maximum Likelihood Estimator. Earlier studies concluded such estimators to be consistent, asymptotically efficient, and asymptotically normal (Mcfadden and Train). Using Monte-Carlo simulation, (How countries are using edtech (including online learning, radio, television, texting) to support access to remote learning during the COVID-19 pandemic) can be estimated with the log-likelihood function shown in (Big tech firms ramp up remote working orders to

Table 5
Model estimates for intra-regional trips context (C1).

Modal alternatives	Auto drive	Auto passenger	Taxi/RH	Carpool	Transit with walk access	Transit with transfer(s)	Park & ride	Kiss & ride	Transit with taxi/RH access	Carpool & ride	Cycle & ride	Cycle	Walk
Attributes						**Estimate (*t*-stat)**							
Alternative specific constants	*as ref*	0.311 (1.02)	**−0.936 (−2.54)**	**−1.33 (−2.71)**	**−1.395 (−3.06)**	**−1.564 (−3.29)**	**−3.057 (−3.29)**	**−3.111 (−3.98)**	**−1.860 (−2.07)**	**−1.704 (−2.11)**	−2.026 (−1.61)	−0.145 (−0.37)	**−0.762 (−2.15)**
Level of service													
In-vehicle travel time (mean)		**−3.982 (−28.42)**						**−5.484 (−9.89)**				**−3.982 (−28.43)**	
In-vehicle travel time (S.D.)		**1.670 (15.17)**						0.400 (1.92)				**1.670 (15.17)**	
Out-of-vehicle travel time	—	—					−0.008 (−1.418)					—	—
Travel cost						**−0.015 (−3.78)**						—	—
Trip Characteristics													
Commuting trip[1]	—	—	—	—	—	—	—	—	—	—	—	**0.288 (2.66)**	
Pandemic Characteristics													
Avg. daily new cases in last two weeks: (Ref. *Zero case*)													
10–100[1]	—	—	−0.222 (−1.42)		—	—	—	—	—	—	—	—	—
Vaccine or treatment availability: (Ref. *No vaccination*)													
You are vaccinated but no mass vaacination[1]	—	—	**0.328 (2.84)**		—	—	—	—	—	—	—	**0.294 (2.96)**	
Mass vaccination (Herd immunity achieved)[1]	—	—	**0.488 (2.79)**					**0.544 (3.97)**				**0.383 (2.50)**	
Transit safety policies													
Mandatory face covering[1]	—	—	—	—				0.123 (1.61)				—	—
Enforcing strict passenger limits on vehicles[1]	—	—	—	—				**0.177 (2.55)**				—	—
Installation of hand-sanitizers[1]	—	—	—	—				0.132 (1.73)				—	—
Temperature scan prior to boarding[1]	—	—	—	—				**−0.147 (−2.10)**				—	—
Socio-demographic variables													
Age	*as ref*	**−0.018 (−3.54)**	**−0.030 (−3.84)**	**−0.048 (−4.18)**	**−0.024 (−3.12)**	**−0.025 (−2.88)**	**−0.035 (−2.26)**	**−0.028 (−2.75)**	**−0.069 (−3.25)**	**−0.086 (−3.64)**	**−0.057 (−2.40)**	**−0.035 (−4.47)**	—
Gender: Female[1]	*as ref*	**0.344 (2.47)**	—	**−0.552 (-2.10)**	—	—	—	—	—	—	−0.760 (-1.39)	**−0.703 (-3.47)**	—
Currently have a transit pass[1]	*as ref*	—	—	—	**0.456 (2.18)**	0.324 (1.44)	**1.731 (3.60)**	**0.848 (2.13)**	—	0.828 (1.35)	0.886 (1.45)	—	—
Vehicle per household members[1]	*as ref*	**−1.320 (−5.39)**	**−1.539 (−3.94)**	—	**−2.077 (−5.75)**	**−2.129 (−5.09)**	**−2.408 (−2.70)**	−1.380 (−1.59)	**−1.592 (−1.97)**	**−2.009 (−2.87)**	**−3.829 (−3.44)**	**−1.566 (−4.18)**	**−1.110 (−3.41)**
Identify household members as high risk of getting infected[1]	*as ref*	—	—	—	—	—	—	—	—	**−1.625 (−2.04)**	—	**−0.492 (−2.21)**	—
Current workplace: Home[1]	*as ref*	—	—	—	—	—	—	—	—	—	—	0.370 (1.71)	0.324 (1.59)
Lost employment during the pandemic[1]	*as ref*	0.487 (1.94)	—	—	—	—	—	—	—	—	—	—	—

Notes: estimates having $p < 0.05$ are in boldface; RH = Ride-hailing.
1. The variables are dummy.

Table 6
Model estimates for inter-regional trips contexts (C2).

	Auto drive	Auto passenger	Taxi/ RH	Carpool	LT with LT access	RT with walk access	RT with LT access	Park & ride	Kiss & ride	RT with taxi/ RH access	Carpool & ride	Cycle & ride
Attributes							**Estimate (*t*-stat)**					
Alternative specific constants	as ref	0.232 (1.043)	0.848 (1.457)	−0.653 (−1.082)	0.446 (0.65)	1.051 (1.682)	0.591 (0.972)	−0.413 (−0.62)	0.396 (0.607)	0.155 (0.249)	0.727 (1.15)	**1.478 (1.978)**
Level of service attributes												
Travel time (Mean)		**−5.893 (−75.65)**						**−3.799 (−14.62)**				
Travel time (S.D.)		**2.797 (38.67)**						**2.365 (7.04)**				
Travel cost (Mean)						**−4.214 (−28.20)**						
Travel cost (S.D.)						**2.489 (19.79)**						
Coefficient of expected maximum utility	**0.371 (20.69)**		—	—	—	—	—			**0.553 (3.72)**		
Pandemic Characteristics												
Avg. daily new cases in last two weeks: (Ref. *Zero case*)												
100–300[1]	—	—	—	—				−0.26 (−1.65)				
more than 300[1]	—	—	—	—				**−0.715 (−4.53)**				
Vaccine or treatment availability (Ref. *No vaccination*)												
You are vaccinated but no mass vaccination[1]	—	—	—	—				**0.427 (2.933)**				
Mass vaccination (Herd immunity achieved) [1]	—	—	—	—				**1.030 (5.526)**				
Transit safety policies												
Mandatory face covering[1]	—	—	—	—	—				0.092 (1.806)			
Boarding and alighting at different door[1]	—	—	—	—	—				**0.151 (2.526)**			
Socio-demographic variables												
Age[1]	*as ref*	**−0.027 (−5.01)**	**−0.06 (−4.55)**	**−0.061 (−4.32)**	**−0.054 (−3.56)**	**−0.039 (−2.95)**	**−0.042 (−3.33)**	**−0.029 (−2.12)**	**−0.045 (−3.56)**	**−0.049 (−3.68)**	**−0.074 (−4.92)**	**−0.079 (−4.64)**
Gender: Female[1]	*as ref*	—	**−0.604 (−2.14)**	—	—	—	—	—	—	—	—	—
Currently have a transit pass[1]	*as ref*	—	—	—	—	—	**0.524 (2.72)**	—	—	—	—	—
Vehicle per household members[1]	*as ref*	**−0.995 (−3.95)**	**−2.132 (−3.41)**	−0.875 (−1.78)	**−2.8 (−4.13)**	**−3.304 (−5.28)**	**−3.527 (−5.64)**	**−2.322 (−3.9)**	**−3.256 (−4.68)**	**−3.033 (−4.84)**	**−3.101 (−4.46)**	**−3.84 (−4.72)**
Income: below $40,000[1]	*as ref*	—	—	—	0.366 (1.26)	—	—	—	—	—	—	—
Identify household members as high risk of getting infected[1]	*as ref*	—	—	—	—	—	—	—	—	—	−0.289 (−1.18)	−0.41 (−1.48)
Current workplace: Home[1]	*as ref*	—	—	—	—	—	—	—	—	−0.437 (−1.48)	—	—

Notes: estimates having $p < 0.05$ are in boldface; RH = Ride-hailing.
1. The variables are dummy.

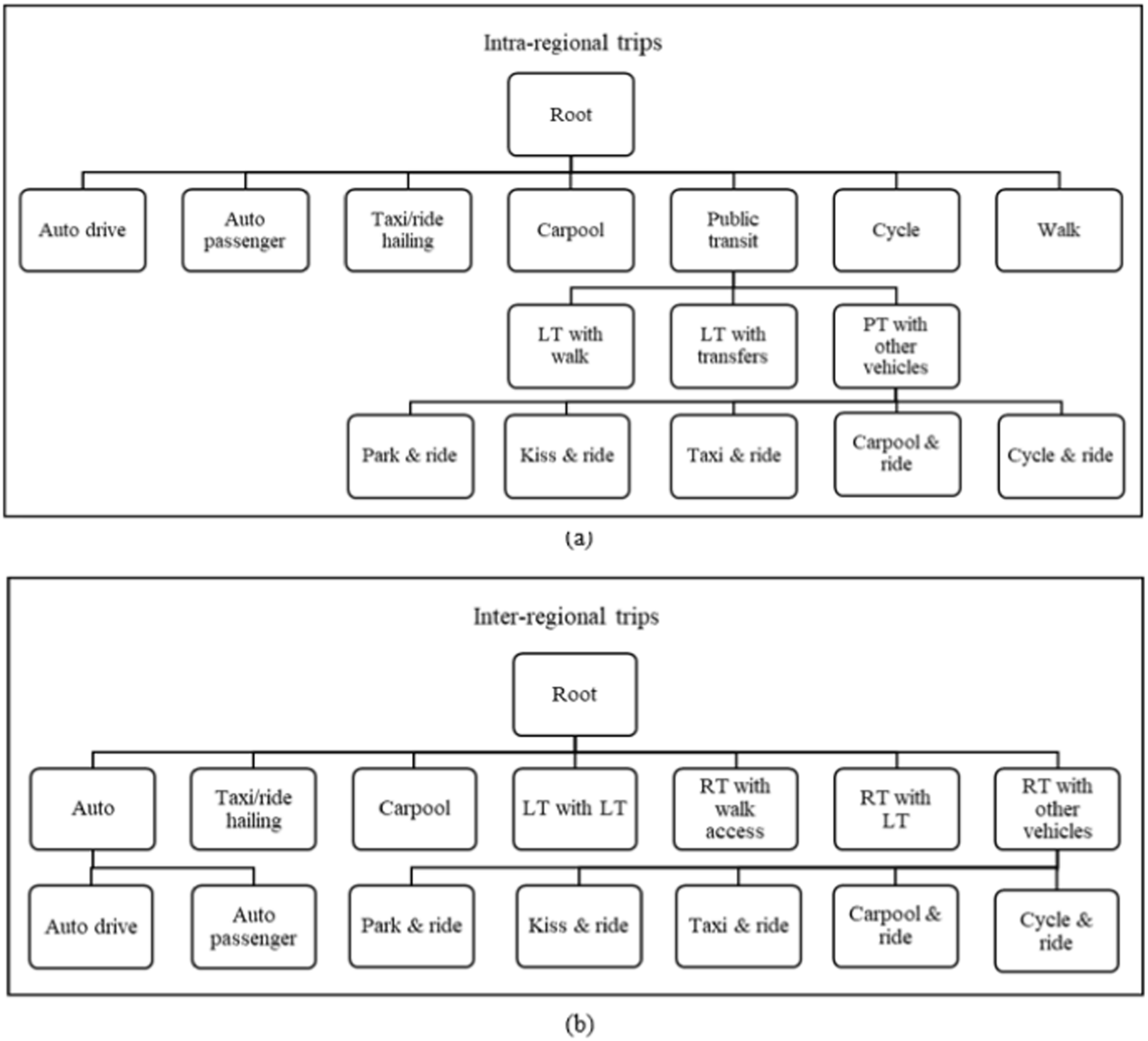

Fig. 9. Final nesting structure in NL models.

prevent coronavirus spread - CNN).

$$LL(\beta_j) = \sum_{i=1}^{i} ln\left(\frac{1}{R}\sum_{\xi_j^R}\left(\prod_{s=1}^{6}\prod_{j\in C}P_{ijs}^{y_{ijsR}}\right)\right) \quad [8]$$

where R indicated the number of simulations, in this study, 500 Halton sequence draws were used to simulate the log-likelihood.

The models were estimated using the "Apollo" package in open-sourced software RStudio (Hess and Palma, 2021). The estimation procedure, statistical test, and goodness of fit were well explained in prior literature (Train, 2009).

In case of further analysis involving interaction with random parameters, the study followed the simulation approach (Hensher and Greene, 2003). Therefore, for each of the significant random parameters in the ML model, 2000 simulation draws from their respective distributions were made for each associated parameter. Later, interactive estimates (i.e., the value of travel time) were estimated for each draw, and median values from the respective distributions were considered for the discussions. The use of median values instead of mean was informed by prior literature arguing that the long-tail of the log-normal distribution tends to increase the mean value to an irrational level, making the model interpretation unreasonable (Erik and Jan, 2006).

6. Modelling results

Six mode choice models were developed for intra-regional trip context (C1) and inter-regional trip context (C2). Tables 4, 5, and 6 summarize the estimation result. The explanatory variables were selected based on the corresponding parameter's appropriate sign and significant *t*-statistic (95 % confidence interval). However, some parameters were retained in the models despite having insignificant *t*-stat because of their explanatory importance regarding mode choice behaviors. As for the model developments, several nesting structures were tested for the NL models. The final NL model was selected based on the required range of the coefficient of logsum parameters for each nest. The final nests are illustrated in Fig. 9.

Multiple model specifications were tested, and the final model selected had the best goodness of fit. It was found that the mixed multinomial logit (MMNL) model fits the best for the C1 context. Similarly, in the C2 context, the mixed nested logit (Mixed-NL) model had the best fit. The goodness-of-fits indicators for all models are presented in Table 4. Overall, all models had acceptable goodness-of-fit (Train, 2009), while the ML models yielded the best goodness-of-fits in both contexts. This indicates the necessity to consider heterogeneity in the modelling process for better understanding of the mode choice behaviour. Thus, the results from the ML model are discussed for the intra-and inter-regional contexts and presented in Tables 5 and 6, respectively. However, the corresponding MNL and NL models are also provided in Appendix A2 and A3.

6.1. Intra-regional trips

Most of the alternative specific constants (ASC) were significant, indicating that some key variables are excluded in the final model specification. Conversely, the estimates of LOS variables were significant and had their expected signs. It denotes the rational behavior of adding disutility towards additional IVTT, OVTT, and cost to alternatives. Moreover, the model depicted higher sensitivity towards access/egress and waiting time than the OVTT. The approximated value of IVTT savings from the model was found to be CA $16.07 per hour for the transit alternatives, which were slightly higher than the minimum wage rate of CA $14.35 in the study area (Ontario.ca). Conversely, the value of IVTT for non-transit alternatives was roughly-four and half times higher than in the case of transit alternatives (CA $72.19 per hour), which echoed the results of the prior literature (Nam et al., 2005). On the other hand, as the cost parameter's mean and standard deviation were insignificant, no error mixing was done for the corresponding variable. However, the mean and standard deviation of the mode-specific (i.e., transit and non-transit modes) IVTT estimates were found to be highly significant, validating the existence of heterogeneous preference amongst the individuals.

Regarding pandemic characteristics, all but the ML model concluded that the daily number of cases significantly affects the transit mode choices. It was observed that increases in the daily infection cases escalate aversion towards transit alternatives. In opposition, all three models validated that mass vaccination achievement would significantly induce the transit mode choice in the said context. The finding implies the importance of the rapid rollout of the vaccination to recover the lost transit demand. Moreover, similar propensities concerning vaccination were also found for other alternatives such as taxi/ride-hailing, carpool, and active transport. This again highlights the importance of mass vaccination in returning to a normal lifestyle.

Amongst the transit safety policies, all models suggested that the enforcement of strict passenger limit in the transit vehicles were significant. The result indicates that trip makers' inclination towards a policy that ensures social distancing while taking transit. The finding is intuitive, as the ability for riders to practice social distancing will lead to lesser health and safety risks onboard transit vehicles. In addition, mandatory face-covering and availability of the hand-sanitizer induced transit mode choice with a lower confidence level. The finding echoed previous studies regarding passengers' positive attitude towards transit safety policies such as crowd management and mask mandate (Abdullah et al., 2021; Elias and Zatmeh-Kanj, 2021; Aaditya and Rahul, 2021). Interestingly, all the models concluded that checking the temperature for riders before boarding transit vehicles negatively influenced the transit mode choice. This can be explained by the riders' skeptical view toward the temperature scanners to detect COVID accurately (Whelan, 2020; Tipton and Mekjavic, 2021). Furthermore, scanning riders might incur additional waiting time at the stops or stations, leading to the aversion toward the policy.

Several attributes regarding socioeconomic and mobility tools ownership at the household level were also investigated in the study. Among many socioeconomic attributes tested, age and gender significantly affected mode choice for intra-regional trips. It was noted that individuals of higher age were more inclined to use personal vehicles. On the contrary, female travellers are more into being driven by household members than sharing rides with strangers and alternatives associated with cycling. These findings aligned with previous studies (Hasnine et al., 2018). Individuals' current employment status and alteration of employment arrangements during the pandemic also influenced their mode choice behaviors. The study found that individuals currently working from home had more preference towards active transport whenever feasible. Similar preferences were observed if the trips were for commuting purposes, such as going to work or school. On the contrary, those who had lost a job during the pandemic tend to be an auto passenger if they have private vehicle access. Furthermore, considering the household structure, the model revealed that individuals having household members at high risk of getting infected during the pandemic were more motivated to avoid using transit and other shared modal alternatives like carpooling and ride-hailing. This is instinctive considering the adoption of social distancing and self-isolation measures during the pandemic to avoid the risk of infection until medical interventions such as vaccination are available.

Regarding the mobility tools, vehicle ownership in the household played a very influential role when selecting travel modes. Higher vehicles per household were noted to trigger a higher propensity to drive alone and avoid other alternatives. Conversely, individuals having transit pass at the time of data collection were more inclined toward the transit alternatives. The outcomes are reasonable, considering that continuing to purchase transit passes during the pandemic might indicate that travellers heavily relied on transit to fulfill their mobility needs despite the risk of COVID-19.

6.2. Inter-regional trips

Like in the C1 context, the LOS variables were also significant with expected signs. However, for parsimony, the models for C2

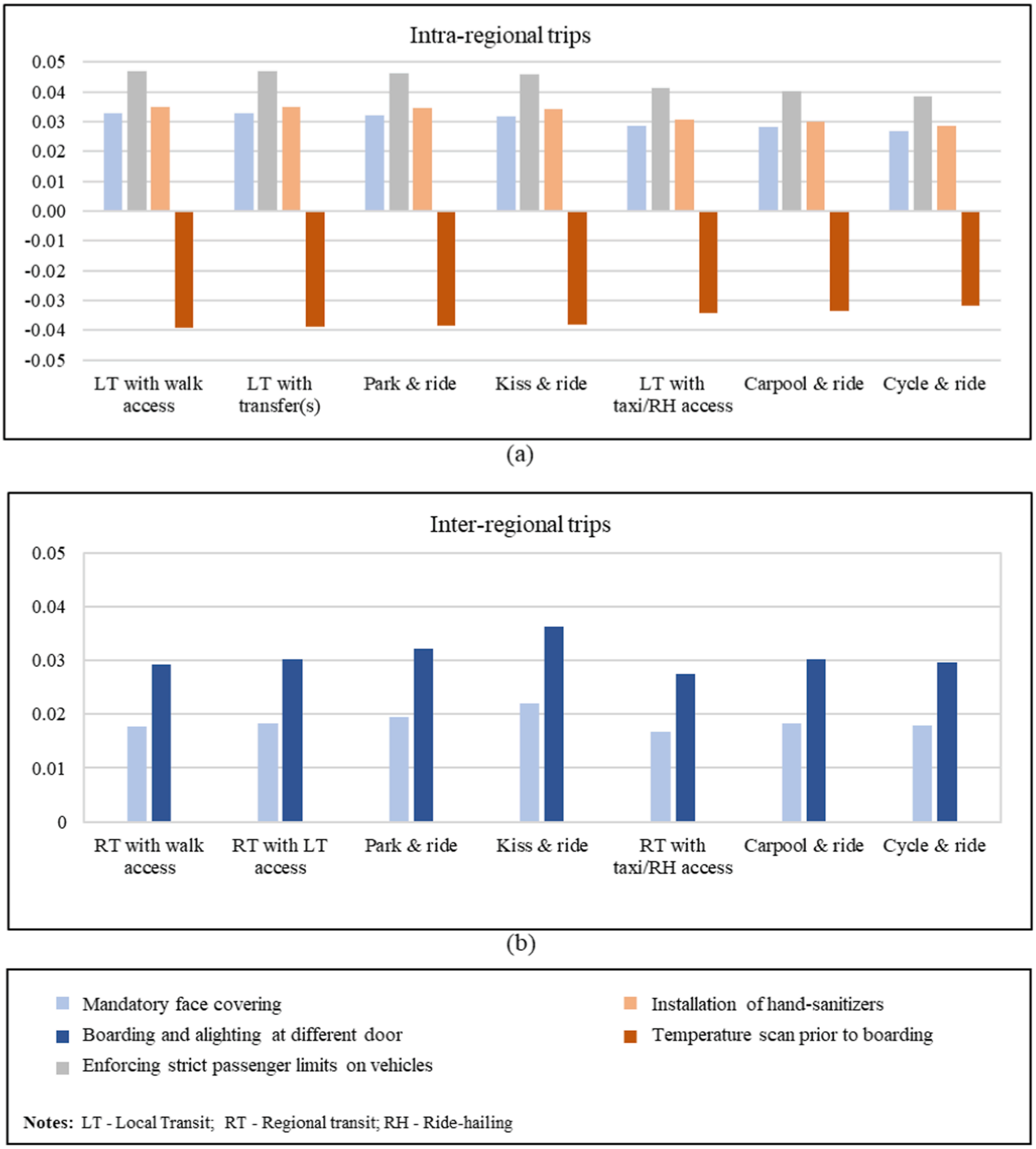

Fig. 10. Change in transit modal share due to the implementation of transit safety policies.

context accounted for total travel time instead of IVTT and OVTT separately since regional transit trips might have multiple transfers. Moreover, the statistically significant mean and standard deviation coefficients of the cost and travel time attributes in the Mixed-NL model validated the existence of diverse sensitivity towards these variables across the respondents.

The model approximated the value of travel time (VOT) for transit alternatives to be CA $60.35 per hour, while the estimated VOT for non-transit modes was CA $7.43 per hour. Unlike the VOTs for the C1 context, the VOT for transit was found to be higher than the non-transit alternatives in C2. This might be due to distinct trip characteristics in the regional transit context. Unlike intra-regional trips, which are shorter and for various purposes, inter-regional trips are mostly long-distance commuting trips with average travel distances ranging around 30 km (University of Toronto). In addition, regional transit services in the GTA usually enjoyed exclusive right-of-way for commuter trains and express buses (City of Toronto). Thus, travellers using such transit services were expected to commute to work without uncertainties like traffic congestion and the additional stress of driving. Therefore, higher VOT demonstrated for transit riders in context C2 fit the study context well, confirming the validity of the models established in this study.

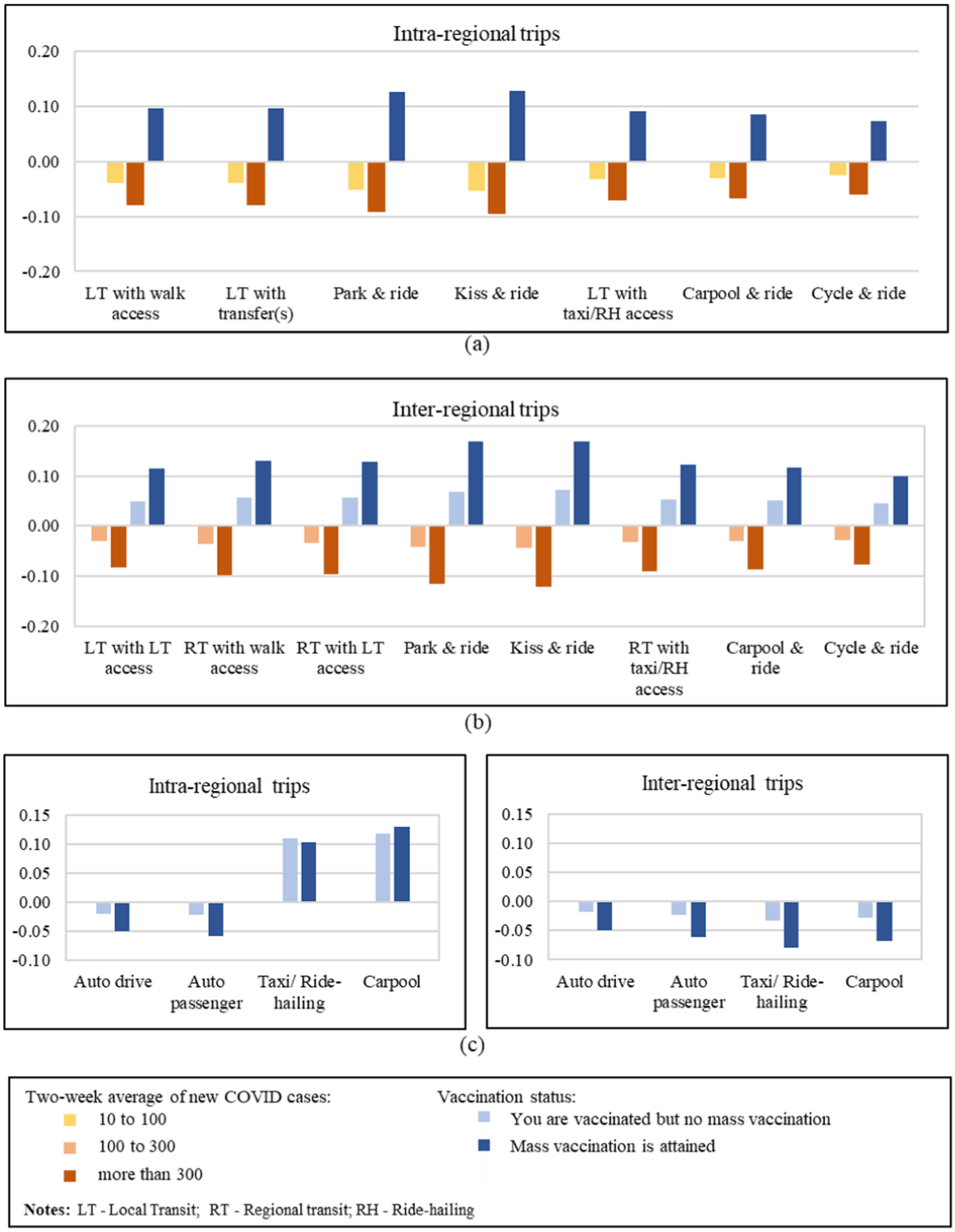

Fig. 11. Change in modal share due to pandemic-related factors.

All the models indicated significant disutility in transit alternatives with the increasing number of new COVID-19 cases for pandemic characteristics. However, the disutility can be offset by vaccination availability and mass rollout in the community. As for the listed transit safety policies, boarding and alighting at different doors and mandatory face covering were found to be most significant for inter-regional trips. Interestingly, enforcing capacity limits was not statistically significant in the C2 context, indicating that inter-regional travellers were less concerned about social-distancing onboard than transit travellers in the C1 context. This is reasonable because commuter trains and buses were usually operated within capacity, whereas subways and local buses were more likely to be overcrowded. However, inter-regional travellers still intended to take their ride with mandatory facing covering applied to all onboard passengers. Also, the moments of boarding and alighting might require passengers to flow through vehicle gates within a short amount of time. Therefore, arranging them to board and alight at different doors will significantly reduce the risk of unnecessary contact between passengers. On the other hand, transit operators might consider extending dwelling time at each stop and station so that social distancing can be effectively maintained while passengers board the vehicles.

Most of the model outcomes were analogous to the C1 context regarding the socioeconomic and mobility ownership attributes.

Individuals who are older, have more household vehicles, and live with a household member at high risk of infection were shown to avoid specific or all transit modes.

However, trip makers currently having transit passes were also into using transit alternatives. Besides, all the models implied that those with annual income below $40,000 are more into transit alternatives only associated with local transits. This might be due to the fixed fare scheme of the local transit but distance-based fare for regional transit alternatives. Local transit fare is fixed in each region, mostly ranging from $3.10 to $3.25 for a single trip, whereas regional transit has a distance-based fare system with a fixed base fare of $3.70 with short-distant trips within 10 km (GO Transit).

7. Policy implications

The study further calculated the elasticities of significant variables to assess the impact of transit safety policy decisions and pandemic-related variables on the probability of choosing transit alternatives. Arc-elasticities were calculated because all pandemic and policy variables are dummy variables. The probability-weighted sample enumeration (PWSE) procedure was also used. In discrete choice models, changes in probability calculated from arc-elasticity can also be interpreted as changes in alternatives' modal share. Figs. 10 and 11 illustrate the change in transit modal share (in percentage) due to transit safety policies and pandemic-related factors in contexts C1 and C2. All the elasticities were calculated from the corresponding context's mixed logit models, except for "the daily number of cases" attributes in the intra-regional context. It was because the respective ML model found these attributes insignificant. However, considering the study's objective of exploring the impact of such critical pandemic-related factors, corresponding elasticities were calculated from the second-best model (Nested logit model) for the respective context that rendered significant and intuitive signs for these attributes.

Regarding transit safety policies, it was found that local transit trips were more sensitive toward limiting passengers on the transit vehicles. Adopting this policy for local transit might increase the market share of local transit alternatives by at least 3.8 %. Alternatively, the more influential policy for inter-regional trips was boarding and alighting passengers at different doors. It has the prospect of increasing the regional transit share by at most 3.6 %. Also, mandatory face covering had the prospect of increasing the transit modal share by almost 2 % in both contexts. It implies that the sensitivity towards transit safety policies varied with transit services, as discussed in previous sections.

It is evident from Fig. 11(a-b) that passengers were sensitive to the daily number of new covid cases and vaccination rollouts. However, the sensitivity is much higher in the case of inter-regional trips and transit alternatives associated with private cars (e.g., park & ride and kiss & ride). For intra-regional trips, the probability of choosing each transit alternative decreased by 5.9 to 12.1 %, with park and kiss & ride being the lowest when the two-week average covid cases were above 300 ceteris paribus. However, the probability increases by 7.3 to 17.0 % in case of mass vaccination attainment in the residing regions.

This has significant policy implications. Overall, it was observed that the travellers were highly susceptible to vaccination status in the region. Therefore, cross-elasticities regarding vaccination were also quantified and demonstrated in Fig. 11(c). Once mass vaccination has been achieved, the market share for driving will be decreased by nearly 5 % in contexts C1 and C2. Conversely, the market share of taxi/ride-hailing services tended to be increased by almost 10.2 % for intra-regional trips (C1). Similar behavior was observed for carpooling. Thus, the rapid vaccination roll-out should be critical for restoring the lost transit demand and shared mobility, which has the prospect of reducing the auto dependencies.

Apart from model results, the survey also found that roughly 80 % of the respondents are willing to use transit when COVID-19 is no longer a threat. It is an optimistic stance for transit demand post the pandemic. However, transit agencies should not take the potential recovery of transit demand for granted. Instead, they need to adopt proactive policies to strengthen such trust for the travellers and maintain positive images for their services. Transit agencies could increase their infrastructural investments and train their employees to provide better travel services. For example, enforcing social distancing will reduce vehicular capacity. It will surely increase the waiting time, which would lure travellers away from the transit. Thus, agencies should consider investing in additional fleet size or implement transit priority policies such as bus-only lanes to maintain the service frequency (Codi, 2020). Further, investment in online applications may be another alternative. It is vital to provide real-time information to the commuters on the crowding and waiting time status of the transit vehicles and other reliable trip planning information (Beck and Hensher, 2020).

Moreover, transit agencies should continue to strive to implement hygiene safety policies. Amongst the transit policies presented to the respondents, the study found that respondents unanimously agreed that maintaining the highest cleaning standards would improve ridership. For example, more than 80 % of respondents agreed that providing hand sanitizer at the stations and in the transit vehicles will contribute to transit demands. It aligns with the report produced by TTC (Toronto Transit Commission, 2020) and is also supported by the modeling outcomes in the study. Therefore, policies assuring social distancing and maintaining hygiene safety in transit vehicles would certainly reinstate the demand. In addition, transit authorities should keep these policies for an extended period and plan for multiple pandemic waves.

8. Conclusion and further research

The COVID-19 outbreak and the subsequent restriction on mobility had an unparalleled impact on travel demand. It posed unexamined changes to the travellers' mode choice behavior. Among all the travel modes, public transit was the most affected, with ridership dropping almost 80 % during the first wave of the COVID-19 pandemic in the study area. What was or would be the travellers' modal choice behavior during the pandemic is a burning question. This study focused on travellers' transit usage and mode choices behaviors during the pandemic. The study found that, during the pandemic, transit usage frequencies decreased unanimously for all socioeconomic groups. As for the health & safety policies during the pandemic, nearly 81.3 % expressed positive attitudes towards the policies to ensure social distancing and mandatory facing covering onboard.

Six modal choice models (e.g., multinomial, nested, and mixed logit models) were estimated to investigate travellers' behavior on intra- and inter-regional trips. This study found that an increasing number of daily new cases negatively affected the transit ridership for both trip contexts. However, successfully rolling out of mass vaccination influenced the transit demand positively. Overall, mass vaccination was found to be the most impactful measure to restore the lost transit demand. It was depicted to increase the transit market share by as much as 17 %. Regarding the health & safety policies, boarding and alighting at a different door were found to be significantly affecting inter-regional trip makers. Conversely, ensuring social distancing by limiting the passengers in the transit vehicles was found to be highly influential in attracting intra-regional transit demands.

The study also proposed policy recommendations for retaining transit demands. First, transit agencies should seek policies that meet travellers' safety concerns. Second, an additional budget should be allocated for infrastructural and fleet development and enable their employees to provide attractive transit services during and after the pandemic. Lastly, the successful rollout of vaccination is vital for recovering lost transit demand.

The study was conducted during the first pandemic wave in the study area. The pandemic developed its second and third waves afterward. Thus, travellers' behavior might be subjected to changes after multiple waves of the COVID-19 pandemic. Furthermore, there might impact of vaccination administration on altering mode choice, which was missing in the first cycle of the survey. Further evidence-based studies are required to understand the altered travel behavior after the subsequent waves and vaccine campaign.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

See Table A1, Table A2, Table A3.

Table A1
The distribution of the transit usage based on socioeconomic attributes.

	Prior transit users	Transit user at present
Gender (%)		
Female	63.88 %	30.80 %
Male	70.81 %	41.89 %
Age (%)		
below 34	74.54 %	48.71 %
34–54	66.48 %	34.89 %
above 54	59.63 %	22.96 %
Possess Driving license (%)	63.64 %	32.14 %
Having access to private vehicle(%)	62.96 %	30.91 %
Having Transit pass (%)	87.96 %	60.19 %
Current employment status (%)		
Working at workplace	67.30 %	44.76 %
Work from home	71.08 %	27.71 %
Hybrid workplace (both at workplace and home)	87.72 %	59.65 %
Not employed	60.00 %	29.13 %
Household income(%)		
below $ 50,000	67.00 %	40.89 %
$50,000 -$100,000	69.14 %	37.96 %
above $100,000	66.20 %	30.28 %

Table A2
MNL and NL Model estimates for intra-regional trips context (C1).

Variables	Modes	MNL	NL
		Estimate (*t*-stat)	
Level of service variables			
Alternative specific constants	Auto drive	taken as a reference	
	Auto passenger	0.295 (0.98)	0.313 (1.04)
(mean)	Taxi/Ride-hailing	**−0.977 (−2.7)**	**−0.971 (−2.67)**
	Carpool	**−1.33 (−2.66)**	**−1.338 (−2.67)**
	Local transit with walk access	**−1.105 (−3)**	**−1.095 (−2.83)**
	Local transit with transfer(s)	**−1.263 (−3.12)**	**−1.248 (−2.83)**
	Park & ride	**−3.741 (−5.8)**	**−2.048 (−2.21)**
	Kiss & ride	**−3.677 (−5.35)**	**−2.03 (−2.41)**
	Local transit with taxi/ride-hailing access	−1.373 (−1.81)	−1.386 (−1.9)
	Carpool & ride	−1.067 (−1.58)	**−1.604 (−2.2)**
	Cycle & ride	−1.63 (−1.17)	−1.704 (−1.81)
	Cycle	−0.07 (−0.18)	−0.203 (−0.52)
	Walk	−0.583 (−1.71)	**−0.862 (−2.39)**
In-vehicle travel time	Transit alternatives	**−0.007 (−1.97)**	−0.005 (−1.27)
	Non-transit alternatives	**−0.018 (−4.93)**	**−0.016 (−4.34)**
Out-of-vehicle travel time	All modes other than Auto drive/ passenger and active modes	−0.009 (−1.75)	−0.008 (−1.58)
Travel cost	All modes	**−0.017 (−4.2)**	**−0.017 (−4.16)**
Coefficient of expected maximum utility	Nest: All transit alternative	—	**0.974 (3.42)**
	Nest: Transit with other vehicle access	—	**0.515 (1.97)**
Trip Characteristics			
Commuting trip(i.e., going to work/school) [1]	Auto drive & Auto passenger	taken as a reference	
	Active transport	0.169 (1.72)	**0.264 (2.52)**
Pandemic Characteristics			
Avg. daily new cases in the last two weeks			
Zero case		taken as a reference	
10 – 100 [1]	Taxi/Ride-hailing & Carpool	−0.169 (−1.06)	−0.177 (−1.11)
	Transit alternatives	−0.125 (−1.08)	−0.139 (−1.19)
more than 300 [1]	Transit alternatives	**−0.215 (−2.09)**	**−0.225 (−2.17)**
Vaccine or treatment availability			
No vaccination		taken as a reference	
You are vaccinated but no mass vaccination [1]	Taxi/Ride-hailing & Carpool	**0.314 (2.8)**	**0.351 (3.09)**
	Active transport	0.159 (1.29)	**0.296 (3.09)**
Mass vaccination (herd immunity achieved) [1]	Taxi/Ride-hailing & Carpool	**0.452 (2.64)**	**0.496 (2.87)**
	Transit alternatives	**0.3 (2.75)**	**0.326 (2.94)**
	Active transport	0.194 (1.01)	**0.387 (2.62)**
Transit safety policies			
Mandatory face covering [1]	Transit alternatives	0.112 (1.52)	0.077 (1.17)
Enforcing strict passenger limits on vehicles [1]		0.146 (2.22)	0.124 (1.9)
Installation of hand sanitizers [1]		0.079 (1.08)	0.082 (1.3)
Temperature scan prior to boarding [1]		−0.132 (−1.95)	−0.088 (−1.14)
Socio-demographic variables			
Auto drive		taken as a reference	
Age	Auto passenger	**−0.018 (−3.51)**	**−0.019 (−3.58)**
	Taxi/Ride-hailing	**−0.028 (−3.52)**	**−0.029 (−3.57)**
	Carpool	**−0.048 (−4.05)**	**−0.049 (−4.1)**
	Local transit with walk access	**−0.014 (−2.33)**	**−0.014 (−2.43)**
	Local transit with transfer(s)	**−0.015 (−2.11)**	**−0.015 (−2.2)**
	Park & ride	—	**−0.026 (−2.4)**
	Kiss & ride	—	

(*continued on next page*)

Table A2 (*continued*)

Variables	Modes	MNL	NL
		Estimate (*t*-stat)	
			−0.026 (−3.14)
	Local transit with taxi/ride-hailing access	**−0.059 (−3.13)**	**−0.05 (−3.26)**
	Carpool & ride	**−0.069 (−3.52)**	**−0.054 (−3.8)**
	Cycle & ride	−0.05 (−1.87)	**−0.048 (−2.74)**
	Cycle	**−0.034 (−4.47)**	**−0.034 (−4.5)**
	Walk	−0.008 (−1.36)	−0.009 (−1.42)
Gender: Female [1]	Auto passenger	**0.346 (2.55)**	**0.35 (2.58)**
	Carpool	**−0.536 (−2.02)**	**−0.524 (−1.97)**
	Cycle & ride	−0.917 (−1.46)	—
	Cycle	**−0.654 (−3.32)**	**−0.643 (−3.28)**
Currently have a transit pass [1]	Auto passenger	−0.155 (−1.08)	−0.15 (−1.04)
	Local transit with walk access	**0.558 (3.13)**	**0.579 (3.27)**
	Local transit with transfer(s)	**0.43 (2.12)**	**0.454 (2.21)**
	Park & ride	**2.01 (4.48)**	**1.493 (3.16)**
	Kiss & ride	**1.231 (2.92)**	**1.074 (3.14)**
	Local transit with taxi/ride-hailing access	—	**0.793 (2.14)**
	Carpool & ride	—	**1.029 (2.47)**
	Cycle & ride	0.946 (1.37)	**1.093 (2.46)**
Vehicle per household members	Auto passenger	**−1.313 (−5.45)**	**−1.308 (−5.43)**
	Taxi/Ride-hailing	**−1.593 (−4.08)**	**−1.61 (−4.09)**
	Local transit with walk access	**−1.712 (−5.65)**	**−1.723 (−5.68)**
	Local transit with transfer(s)	**−1.787 (−4.79)**	**−1.794 (−4.84)**
	Park & ride	**−2.23 (−2.35)**	**−1.683 (−2.43)**
	Kiss & ride	−1.189 (−1.35)	**−1.243 (−2.01)**
	Local transit with taxi/ride-hailing access	−1.109 (−1.49)	−1.088 (−1.95)
	Carpool & ride	**−1.847 (−2.88)**	**−1.45 (−3.07)**
	Cycle & ride	**−3.451 (−2.81)**	**−2.124 (−2.4)**
	Cycle	**−1.648 (−4.5)**	**−1.655 (−4.51)**
	Walk	**−1.008 (−3.37)**	**−1.026 (−3.41)**
Current workplace: Home [1]	Cycle	0.344 (1.67)	0.337 (1.63)
	Walk	0.302 (1.67)	0.31 (1.71)
Lost employment during the pandemic [1]	Auto passenger	0.468 (1.92)	0.465 (1.91)
Identify household members as high risk of getting infected [1]	Local transit with walk access	−0.327 (−1.88)	−0.309 (−1.71)
	Local transit with transfer(s)	−0.33 (−1.53)	−0.312 (−1.39)
	Carpool & ride	**−1.536 (−2.00)**	—
	Cycle	**−0.528 (−2.43)**	**−0.516 (−2.37)**

Notes: 1. The variables are dummy.
2. estimates having $p < 0.05$ are in boldface.

Table A3
MNL and NL Model estimates for inter-regional trips contexts (C2).

Variables	Modes	MNL	NL
		Estimate (*t*-stat)	
Level of service variables			
Alternative specific constants	*Auto drive*	*taken as a reference*	
	Auto passenger	0.157 (0.54)	−0.002 (−0.01)
(mean)	Taxi/Ride-hailing	0.298 (0.62)	−0.079 (−0.11)
	Carpool	**−1.025 (−2.17)**	**−1.396 (−2.07)**
	Local transit with local transit access	**−0.771 (−1.97)**	**−1.083 (−2.33)**
	Regional transit with walk access	−0.535 (−1.38)	−0.798 (−1.67)
	Regional transit with local transit access	**−1.104 (−2.79)**	**−1.352 (−2.85)**
	Park & ride	**−3.072 (−16.19)**	**−2.076 (−3.47)**
	Kiss & ride	**−1.589 (−2.81)**	**−1.424 (−2.72)**
	Regional transit with taxi/ride-hailing access	**−2.472 (−4.88)**	**−1.741 (−3.26)**
	Carpool & ride	**−1.328 (−2.48)**	**−1.257 (−2.52)**
	Cycle & ride	0.064 (0.1)	−0.562 (−0.95)
Travel time (Mean)	Transit alternatives	**−0.006 (−5.32)**	**−0.005 (−5.1)**
	Non-transit modes	**−0.005 (−4.06)**	−0.003 (−1.32)
Travel cost (Mean)	All modes	**−0.009 (−3.36)**	**−0.009 (−3.01)**
	Non-transit modes	33.000	20.000
Coefficient of expected maximum utility	Nest: Auto drive and passenger	—	0.563 (1.05)
	Nest: Transit with other vehicle access	—	**0.475 (3.19)**
Pandemic Characteristics			
Avg. daily new cases in the last two weeks			
Zero case		*taken as a reference*	
100–300 [1]	Transit alternatives	−0.164 (−1.93)	−0.156 (−1.83)
more than 300 [1]	Transit alternatives	**−0.393 (−4.67)**	**−0.378 (−4.49)**
Vaccine or treatment availability			
No vaccination		*taken as a reference*	
You are vaccinated but no mass vaccination [1]	Transit alternatives	**0.326 (4.17)**	**0.301 (3.79)**
Mass vaccination (herd immunity achieved) [1]	Transit alternatives	**0.493 (4.62)**	**0.458 (4.17)**
Transit safety policies			
Mandatory face covering [1]	Regional transit alternatives	0.078 (1.22)	0.076 (1.67)
Boarding and alighting at different doors [1]		**0.203 (3.2)**	0.114 (1.89)
Socio-demographic variables			
Auto drive		taken as a reference	
Age	Auto passenger	**−0.016 (−2.93)**	−0.009 (−0.99)
	Taxi/Ride-hailing	**−0.053 (−4.87)**	**−0.049 (−4.44)**
	Carpool	**−0.049 (−4.25)**	**−0.046 (−3.91)**
	Local transit with local transit access	**−0.018 (−2.79)**	**−0.014 (−2.1)**
	Regional transit with walk access	**−0.014 (−2.06)**	−0.011 (−1.47)
	Regional transit with local transit access	**−0.018 (−2.81)**	**−0.015 (−2.16)**
	Kiss & ride	−0.013 (−1.71)	−0.012 (−1.75)
	Regional transit with taxi/ride-hailing access	−0.019 (−1.64)	**−0.021 (−2.57)**
	Carpool & ride	**−0.063 (−4.5)**	**−0.041 (−3.49)**
	Cycle & ride	**−0.059 (−3.91)**	**−0.04 (−3.18)**
Gender: Female [1]	Auto passenger	**0.364 (2.53)**	0.217 (1.02)
	Taxi/Ride-hailing	−0.41 (−1.49)	−0.425 (−1.55)
Currently have a transit pass [1]	Local transit with local transit access	0.304 (1.62)	0.292 (1.58)
	Regional transit with local transit access	**0.566 (3.07)**	**0.549 (3.03)**
Vehicle per household members	Auto passenger	**−1.442 (−5.34)**	−0.828 (−1.06)
	Taxi/Ride-hailing	**−1.629 (−3.05)**	**−1.474 (−2.59)**
	Carpool	−0.691 (−1.5)	−0.541 (−1.05)
	Local transit with local transit access	**−1.596 (−4.41)**	**−1.483 (−3.51)**
	Regional transit with walk access	**−1.682 (−4.31)**	**−1.56 (−3.43)**
	Regional transit with local transit access	**−1.708 (−4.69)**	**−1.578 (−3.68)**
	Park & ride	—	−0.611 (−1.51)
	Kiss & ride	**−2.014 (−3.57)**	**−1.443 (−3.05)**
	Regional transit with taxi/ride-hailing access	**−1.619 (−2.94)**	**−1.094 (−2.61)**
	Carpool & ride	**−1.833 (−3.08)**	**−1.275 (−2.73)**
	Cycle & ride	**−3.213 (−4.38)**	**−1.868 (−2.92)**
Current workplace: Home [1]	Regional transit with taxi/ride-hailing access	−0.858 (−1.84)	−0.386 (−1.45)
Income: below $40,000 [1]	Auto passenger	**0.548 (2.4)**	0.296 (0.79)
	Local transit with local transit access	**0.656 (2.98)**	**0.633 (2.93)**
Identify household members as high risk of getting infected [1]	Carpool & ride	—	—
	Cycle & ride	−0.716 (−1.79)	−0.337 (−1.34)

Notes: 1. The variables are dummy.
2. estimates having $p < 0.05$ are in boldface.

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