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What can bring transit ridership back: An econometric study on the potential of usage incentives and operational policies in the Greater Toronto Area

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A R T I C L E I N F O

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A B S T R A C T

The COVID-19 virus has unimaginably disrupted the transit system and its overall functions. Users' vigilant safety concerns posed by the pandemic and the consequent transit avoidance behaviour for a prolonged period could have lasting impacts on their transit preferences, leaving transit agencies to search for effective post-pandemic transit resilience policies. This study examines potential post-pandemic interventions and pandemic-induced psychological attributes impacting the future transit choice behaviour of non-transit users of the pandemic. It utilised data from a transit demand and choice adaptation survey in the Greater Toronto Area, Canada. A two-stage model was formulated to jointly capture the pre-pandemic transit usage choices of those who did not make transit trips during the pandemic and the respective post-pandemic transit choices for these user groups. The models depicted that the post-pandemic transit choices were inversely affected by one's pandemic concerns. In contrast, the choices were positively influenced by respondents' views on post-pandemic transit usage and keeping the adopted safety policies in place. Regarding the conventional level of service attributes, paid park and ride facilities enhanced the probability of post-pandemic transit choice almost by 15% for occasional users. In comparison, the changes due to reliable service ranged from 10 to 11% for pre-pandemic users. Analogous propensity was seen for fare schemes offering free transfers between cross borders and 25% or more off-peak discounts on base fares. Moreover, more direct transit routes and increased parking costs by vehicular modes post the pandemic encourage travellers to retake transit.

1. Introduction

The concept of *resilience* has been explored and defined in many ways. Henry et al. describe it as "the ability of an entity to bounce back" (Henry and Emmanuel, 2012). Jiao et al., meanwhile, define it as "the ability of a system to resist, recover, and adapt to natural disasters [or other kinds of disruptions]" (Jiao et al., 2021). Regardless of how we define it, it is apparent, now more than ever, that resiliency is imperative to any effective transportation system. Wan et al. highlight that today's transportation networks are integral in moving people and goods (Wan et al., 2018). Given the global nature of our supply chains, transportation systems provide access to the goods and resources that people and businesses need to survive. However, these systems are also incredibly complex and vulnerable to various potential natural and artificial disruptions (Bruyelle et al., 2014; Jiao et al., 2021; Wan et al., 2018).

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The recent COVID-19 pandemic is perhaps the greatest example of such a disruption. Since its onset in early 2020 (World Health Organization (WHO), 2020), governments worldwide have implemented social distancing and safety measures such as lockdowns, travel restrictions, and mask mandates to reduce virus transmission and limit case numbers (International Monetary Fund (IMF), 2021; Kłos-Adamkiewicz and Gutowski, 2022). Consequently, almost one-third of the world's travel was restricted by the end of spring 2020 (Buchholz, 2020) This, coupled with industry experts recommending people avoid travel and work from home (Zhang et al., 2021), resulted in massive changes to people's travel behaviour, which may be long-standing. Nevertheless, the most drastic effects have been felt by shared transportation modes, specifically public transportation (Aaditya and Rahul, 2021; Przybylowski et al., 2021; Shakibaei et al., 2021). Since the COVID virus is airborne and easily transmitted when in proximity to others, public transportation modes were seen as significantly riskier than personal vehicles and walking (Shamshiripour et al., 2020). The result was a drop in ridership unimaginable just a year before, as transit agencies worldwide lost anywhere from 50 to 90% of their ridership almost overnight (Abdullah et al., 2021; American Public Transportation Association, EBP US Inc., 2021; Kłos-Adamkiewicz and Gutowski, 2022; Loa et al., 2021).

However, with the rise in global vaccinations and the gradual uplifting of governmental lockdown restrictions (World Health Organization, 2022), many transit agencies are now looking for ways to reinstate the lost transit demand as quickly as possible. Before COVID, one's intention to take transit was governed mainly by socioeconomic attributes (i.e., gender, age, home locations), mobility tool ownerships (i.e., private vehicle accessibility, transit pass), employment status and perceptions of transit (Badoe and Yendeti, 2007; Deka and Fei, 2019; MetroLinx, 2018; van Lierop et al., 2018; Webb, 2010). Pre-COVID studies also concluded that individuals' transit usage was significantly influenced by various transits' operational and infrastructural attributes, such as reliability, safety, security, accessibility, park and ride facility, and auto demand management policies (i.e., parking fees) (Akar et al., 2012; Alonso et al., 2020; Dirgahayani and Sutanto, 2020; Imaz et al., 2015; Proulx et al., 2014; van Lierop et al., 2018). However, for post-pandemic transit planning, the agencies should be equipped with a comprehensive knowledge of the altered travel preferences of different groups of pre-pandemic transit users (i.e., occasional, moderate, and frequent transit users) as well as the non-transit users, who did not take transit trips during the pandemic. In doing so, effective transit policies could be implemented, which will not only reinstate the pre-COVID transit demand but also attract new passengers.

Given this context, this paper explores and identifies practical actions that transit agencies can take to recover lost ridership and make people feel more comfortable retaking public transportation after the pandemic. Hence, this study focuses on factors including, but not limited to, incentives centred around post-pandemic transit usage and operational improvements designed to attract those who avoided transit during the pandemic period. With a choice experiment data centred around this group, this study jointly modelled their pre-pandemic transit usage and post-pandemic transit choice decisions. As a result, it enabled capturing the influential attributes that would impact the post-pandemic transit choice for different groups of pre-pandemic transit users. In doing so, this paper endeavours to provide decision-makers and transit operators with plausible actions for improving the resiliency of their transit system and avoiding the long-term negative impacts posed by the pandemic.

The remainder of this paper is organised as follows. Section 2 summarises prior studies on improving the resiliency of transportation systems and the impacts of COVID on travel behaviour. Next, Section 3 describes the survey dataset, while Section 4 explains the empirical modelling framework used in this analysis. Later, Section 6 discusses the results and policy implications for transit operators. Finally, the concluding remarks and critical findings are summarised in Section 7.

2. Literature review

The transportation system is a critical system that keeps our cities and economies thriving. Hence, it needed to be resilient to any unprecedented disruption incurring massive restrictions to mobility as well as interruptions to supply lines. One of the key characteristics of resilience is recoverability (Wan et al., 2018). As such, resilience studies focusing on the recoverability aspect of transportation systems have gained much interest in recent years. For instance, research in Spain highlighted the disruption management issues in the rapid transit system. It proposed approaches that optimised timetables and rolling stock schedules considering the impacted passenger demand while dealing with such disruption (Cadarso et al., 2013). Similarly, Bruyelle et al. focused on exploring ways to make transit vehicles resilient against terrorist attacks by analysing incidents on rail-based vehicles and the system's responses to them (Bruyelle et al., 2014). Upon conclusion of this analysis, the authors highlighted how clear, calm, and efficient communication can alleviate both fear and panic while encouraging social cooperation and efficient operation in tackling such events. This emphasises people's important role within a system, especially within a transportation network. Riders' perceptions and interactions with the system were thus noted to be integral in maintaining the system's essential operation in the event of any disruption and regaining the system's inherent state as the disturbance diminishes (Vodopivec and Miller-Hooks, 2019).

Nothing illustrates this point better than the drastic changes in travel behaviour posed by the recent COVID-19. For example, in the Greater Toronto Area, almost 70% of travellers thought there was more risk in leaving their homes than staying home, which meant fewer people were willing to travel (Mashrur et al., 2022). Similar changes in travel behaviour were seen worldwide (Bucsky, 2020; Burfeind, 2020). In addition to such pandemic-induced fear, the widespread adoption of telecommuting, e-shopping, and online socialising throughout the pandemic period significantly reduced the overall trip rate (Beck and Hensher, 2020; Paul et al., 2021). This alteration in travel behaviour was further coupled with a drastic shift in people's travel preferences and perceptions. While personal vehicles and active transport gained massive popularity (Wang et al., 2021), shared modes, especially public transit, saw unprecedented drops in ridership worldwide, primarily due to being perceived as a more likely source of infection (Dong et al., 2020; Mashrur et al., 2022). For example, in the US, the American Public Transportation Association reported an almost 80% drop in ridership nationwide (American Public Transportation Association, EBP US Inc., 2021). Another study from New York investigated the impacts of telework and transit capacity restrictions on post-pandemic mobility using an agent-based simulation tool. The study found a 27% drop in transit demand compared with pre-pandemic demand with no capacity restrictions. Moreover, car trips increased by 42%, suggesting more congestion post the COVID (Wang et al., 2021). Moreover, pandemic-related factors, such as high hygiene vigilance, policies ensuring social distancing, and mask mandates, quickly became more of a priority than other conventional trip-related factors (Aaditya and Rahul, 2021; Abdullah et al., 2021).

However, the decline in transit demand varied amongst different population groups. For instance, a study in Chicago found that the areas with the most significant ridership drops were areas with a higher portion of high-income, educated, and white individuals. This indicates that individuals in these areas were more able to reduce their trips and shift to alternative transportation modes much more quickly than those living in other areas (Hu and Chen, 2021). Meanwhile, Loa et al. found that those without access to a private vehicle continued to undertake non-mandatory trips in transit even if it was perceived to be a riskier transportation mode (Loa et al., 2021). This highlights that, even during a pandemic, a portion of the population still relied on public transportation. It also emphasises the prospect of recovering the lost transit demand after the pandemic through safe, reliable, and resilient transit services.

Unfortunately, before COVID, many transit agencies and cities did not have a plan in the case of a pandemic (Bereitschaft and Scheller, 2020). As a result, some studies during the early pandemic stage (during the first year of the pandemic) primarily underlined various post-pandemic challenges, such as long-term car dependency, unstable transit operation and financial uncertainty arising from public transit avoidance (Christidis et al., 2022; Currie et al., 2021). For instance, Bagdatali and Ipek used logistic regression to investigate university students' post-pandemic modal preferences. The work revealed that students were more into e-scooter/hoverboards and active travel modes than using public transport post the pandemic. Another study examined the effect of virtual schooling and telecommuting on the post-pandemic travel demand (i.e., changes in the trip rate and departure time) in the Greater Toronto Area. However, another group of researchers focused on outlining a series of actions these agencies could take to help them navigate the current pandemic. For example, Matherly et al. outlined a playbook for transit operators to maintain appropriate service levels, ensure their vehicles are safe and maintain morale among employees and riders (Matherly et al., 2021). Similarly, Shaheen and Wong emphasised the importance of maintaining a positive customer experience and public support while moving towards a more multimodal transit service (Shaheen and Wong, 2021).

While the COVID-19 pandemic is certainly not over, we are certainly through the culminating parts of it. With some parts of the world achieving high vaccination rates (World Health Organization, 2022), many transit operators have shifted to getting people back in transit. However, paving the road to recovery will not be easy as it will be a completely new and challenging task for transit agencies. While there is avalanche studies examining COVID impact on transit usage (He et al., 2022; Kaplan et al., 2022; Liu et al., 2020; Parker et al., 2021; Qi et al., 2021), only a handful of studies have adopted a data-driven approach to investigate factors affecting an individual's decision to use transit after the pandemic. For example, Mashrur et al. found that transit safety policies (TSP) provided a source of comfort for riders. Using the structural equation model (SEM), the research emphasised that those intending to use transit during the pandemic upon the TSP's implementation and vaccination administrations were more optimistic about returning to transit post the pandemic (Mashrur et al., 2022). Another study, using a similar modelling approach, remarked that considering travel well-being instead of travel satisfaction would be more insightful for post-pandemic transit service planning (Wang and Gao, 2022). In addition, Downey et al.'s random parameter bivariate probit model identified potential factors such as pre-lockdown travel choices, COVID-19 risk perception, household size and region significantly, which could affect an individual's preference towards future public transit usage in Scotland (Downey et al., 2022). Policies addressing mode-specific safety concerns along with reliable and consistent transit service were also influential in reviving some of this lost transit demand (Mashrur et al., 2022). Several cities have tried to regain some of this lost demand through various incentives. For example, Kyoto, Hangzhou, Ningbo, and Xiamen implemented fare incentive policies such as discounted or giving free transport to riders in response to COVID-19 to attract people to transit. The policies effectively increased the ridership (Dai et al., 2021; Sun et al., 2022). However, these studies did not capture heterogeneous perceptions of these policies across users who avoided transit during the COVID. As such, this paper addresses the research gap by exploring the potential attributes such as transit usage incentive policies and operational improvements to attract those who avoided transit during the pandemic back to transit mode. Thus, the paper will contribute to the research by providing actionable policy insights into effective post-pandemic planning for building a health-crisis resilient transit system.

3. Methodology

3.1. The survey and data collection

The data used in this study is collected from the 2021 Stated Preference Experiment on Travel mode and especially the Transit choice behaviour (SPETT'21) survey. The SPETT project monitors the impacts of the COVID-19 pandemic on transit demand in the Greater Toronto Area (GTA), Canada (Mashrur et al., 2021). The survey was administered on a web-based platform in the summer of 2021. Samples were randomly drawn from commercial survey panels maintained by a market research company. The final data set of the SPETT'21 survey contained 923 responses. Among those, 513 reported using public transit in early 2020 before the declaration of a state of emergency in the region and had never used transit since the pandemic. Given the paper's objective, these 513 samples were used to investigate their possibility of returning to transit using a stated preference (SP) experiment. Besides the SP experiment, the SPETT'21 survey also collected information on personal and household socioeconomic characteristics, variables describing respondents' travel-related behaviour during a pandemic, such as frequency of transit usage and telecommuting, their general behaviour during the pandemic, and their attitudes towards post-pandemic transit usage. Further details on the survey sample can be found in (Mashrur et al., 2021).

Fig. 1 illustrates the change in TTC (Toronto Transit Commission) ridership and weekly service hours with the daily number of new cases in Ontario, Canada, during the pandemic with some key dates (Ontario.ca. Health - Organizations - Ontario Data Catalogue; Toronto Transit Commission). Before the pandemic, TTC served 85 % of the local transit ridership in the GTA, having 1.7 million weekday ridership (Toronto Transit Commission). Even after the pandemic, when the transit ridership dropped significantly, as shown in Fig. 1, the proportion of the GTA ridership served by the TTC was nearly unchanged. At the time of data collection, the third wave of the pandemic was in the declining phase with decreasing number of daily new COVID cases (i.e., 14-day average cases were 167). It was the period before the Omicron variant hit Toronto. However, 80.8% of adults above age 18 were partially vaccinated (having one dose), with 67.9% being fully vaccinated (having two doses) (Ontario.ca. COVID-19 Vaccination Tracker, Ontario Canada). The figure also highlights that lost transit ridership is recovering at a slow pace, even after the transit service is almost the same as in the pre-pandemic period. Such context also fits this study that aims to investigate the policies to attract transit users who were not returning to transit as the pandemic situation improved.

3.2. Stated preference experiment design

SP choice experiments are extensively used in research to capture individual behaviour to facilitate effective transportation planning measures in contexts that may or may not be present in the real world during the survey data collection period (Cherchi and Hensher, 2015). It overcomes the drawback of the revealed preference (RP) method, such as insufficient variation in RP data, difficulties in capturing trade-offs between strongly correlated variables (i.e., travel time and cost), hypothetical scenario evaluations, constrained to explanatory variables having objectivity or quantifiable units (i.e., time) (Kroes and Sheldon, 1988). In addition, SP surveys were noted to be more economical in terms of time and cost (Louviere et al., 2000) than conducting RP surveys (i.e., before, during and after COVID-19) to capture one's travel preferences. As the study's key objective is to explore the potentials of usage incentives and operational policies to attract more riders to transit during the post-pandemic context, the SP choice experiment best fits the study.

3.2.1. Scenario contexts and alternatives

The study presented a series of hypothetical scenarios to the respondents who did not take transit during the pandemic. In each scenario, the respondents were provided with a hypothetical trip for two different time contexts: *The current situation* (i.e., during the pandemic when data was collected) and the *Post-COVID situation* (i.e., COVID is no longer a threat). It was assumed that they did not choose transit for the trip made during the pandemic, as they were non-transit users of the pandemic. However, some informed transit usage intensive programs and/or operational changes were introduced for a trip to be made during the post-pandemic era, and respondents were asked if they would choose transit for the same trip in future considering the changes. Each respondent was provided with six such hypothetical scenarios through implicit blocking. The scenarios were randomly pooled from 24 scenarios. The scenarios were designed in NGENE using a D-efficient design (Bliemer and Rose, 2011; ChoiceMetrics, 2018; Rose et al., 2008). While designing, multiple factors were considered, including but not limited to alternative labelling, selection of attributes and their levels, and balancing attribute level and the number of choice tasks (ChoiceMetrics, 2018). There were two specific alternatives in each scenario, whether the respondents would take transit or not for their future trip.

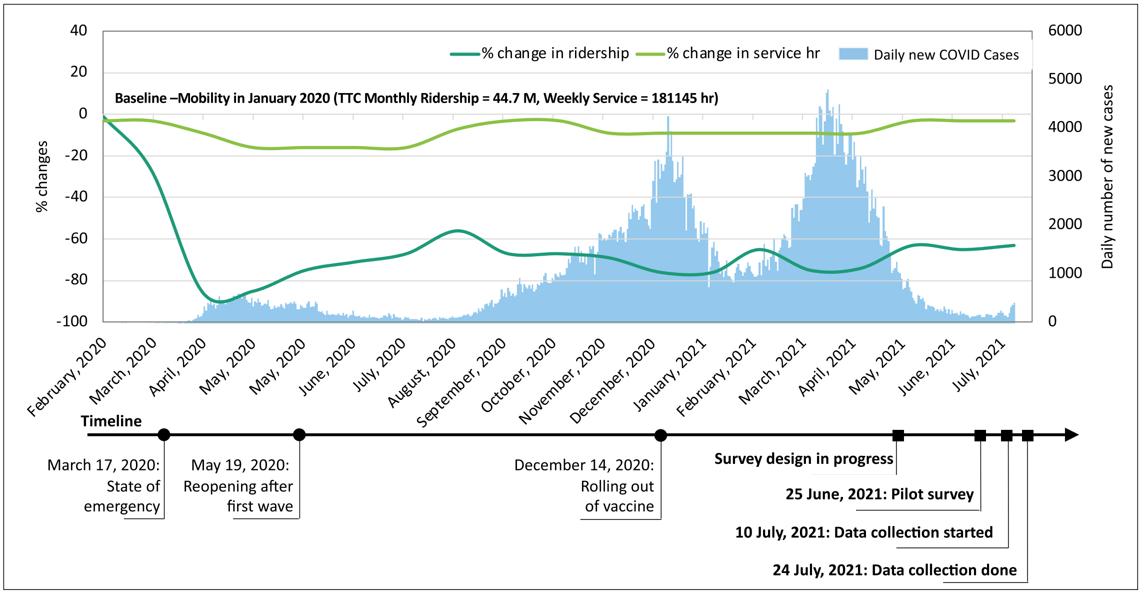


Fig. 1. Changes in TTC ridership and service hours with the daily number of new cases in Ontario.

3.2.2. Attributes consideration

The selection of the number of attributes and their levels were based on their relevancy to the study context and the best practices for SP experiments to capture realistic travel behaviours in the GTA (Arentze and Molin, 2013; Danaf et al., 2019; Frei et al., 2017; Hess and Daly, 2014; Idris et al., 2014; Imaz et al., 2015). Each scenario was characterised by five attributes: trip purpose (commuting/non-commuting), transit trip characteristics, auto trip characteristics, post-pandemic TSPs, and post-pandemic transit usage incentive fare schemes (i.e., off-peak discount). Transit trips in both contexts (during and after the pandemic) were characterised by conventional trip attributes such as transit vehicle types (Buses, Subway), in- and out-of-vehicle time, the number of transfers, crowding level, transit reliability, and park and ride facilities. Auto travel times and parking costs were also presented in each scenario. Auto travel times attribute was provided for respondents to have travel information regarding non-transit motorised alternatives. It was done to ensure that respondents could make informed transit mode choice decisions.

However, each temporal attribute had four levels (-25% to + 50%). The travel times were pivoted around the average transit and auto travel time required to traverse the mode-specific average distance. The average distances for the respective trip purpose (commuting /non-commuting) were extracted from the 2016 Transportation Tomorrow Survey (TTS) (Ashby, 2016) to have a realistic representation of the GTA residents' travel pattern. The 2016 TTS is the regional household travel survey covering the study area of the SPETT'21. In addition, the average speed was informed from the traffic indices of Toronto and earlier studies (Mashrur et al., 2022; TomTom; University of Toronto). Moreover, additional conditions were applied to the temporal attributes for realistic representations of the scenarios. Such as, more transfers will induce more waiting and transfer time. The difference in transit travel time components across the situations indicated various service alterations. Such as faster transit service during the post-pandemic situation might be due to dedicated bus lanes, express service, or more direct routes. Similarly, lesser waiting time may refer to more frequent transit service. The primary objective was to capture whether these changes in the level of service attract the users to retake transit. However, the average auto travel time for the post-pandemic context was modified considering the anticipated increase in congestion due to altered modal preferences posed by the pandemic. The modification was based on a simulation study suggesting an approximated 29% increase in auto travel time during the reopening stages (Wang et al., 2021). The levels for non-temporal LOS attributes (i.e., crowding level) were informed from earlier literature (Imaz et al., 2015).

Amongst many TSPs, only the mask mandate and enhanced cleaning were considered in the SP experiment. Other safety policies, such as transit capacity restrictions, should not be required when COVID is no longer a threat. Moreover, such a policy will constrain the transit system to provide inadequate service when the demand rises. Furthermore, several post-pandemic transit fare schemes (i.e., off-peak discount, free cross-municipalities transfer, weekly transit fare capping) were tested to observe their capability to recover the lost transit demand. These policies were chosen considering the local transit agency's reports on future transit fare policy (Transit, 2021). One could argue that these policies would always attract riders to take transit. While it is valid to some extent, some critical questions remain; will these policies work in the same manner for passengers (especially those who shifted from transit during the pandemic) as they used to do before the pandemic? If so, what level of such schemes (i.e., how much discount, what should be the maximum weekly fare) would attract them? Moreover, the COVID-19 pandemic made the riders more vigilant about hygiene safety than before, which is also essential to investigate. Having understood the urge for such policies to be effectively implemented for recovering the transit demand, the study considered not only the traditional fare incentive schemes having multiple levels (see Table 1) but also the safety policies (i.e., enhanced cleaning) to address the hygiene concern induced by the COVID-19.

However, some attributes either were not considered or kept at a singular level in the *Current Situation* across the scenarios. The respondents were notified about this fact upfront. Moreover, definitions of each attribute were also provided before the experiment began. All these were done to reduce the cognitive burden on the respondents and, thus, to effectively capture the participants' realistic behavioural responses. In addition, a pilot experiment was conducted before the field administration amongst the researchers, professionals, and non-professionals to improve the SP design. The levels of non-temporal attributes considered in the SP scenarios are shown in Table 1. A sample SP scenario is shown in Fig. 2.

Table 1
Levels of non-temporal attributes considered in the SP experiment.

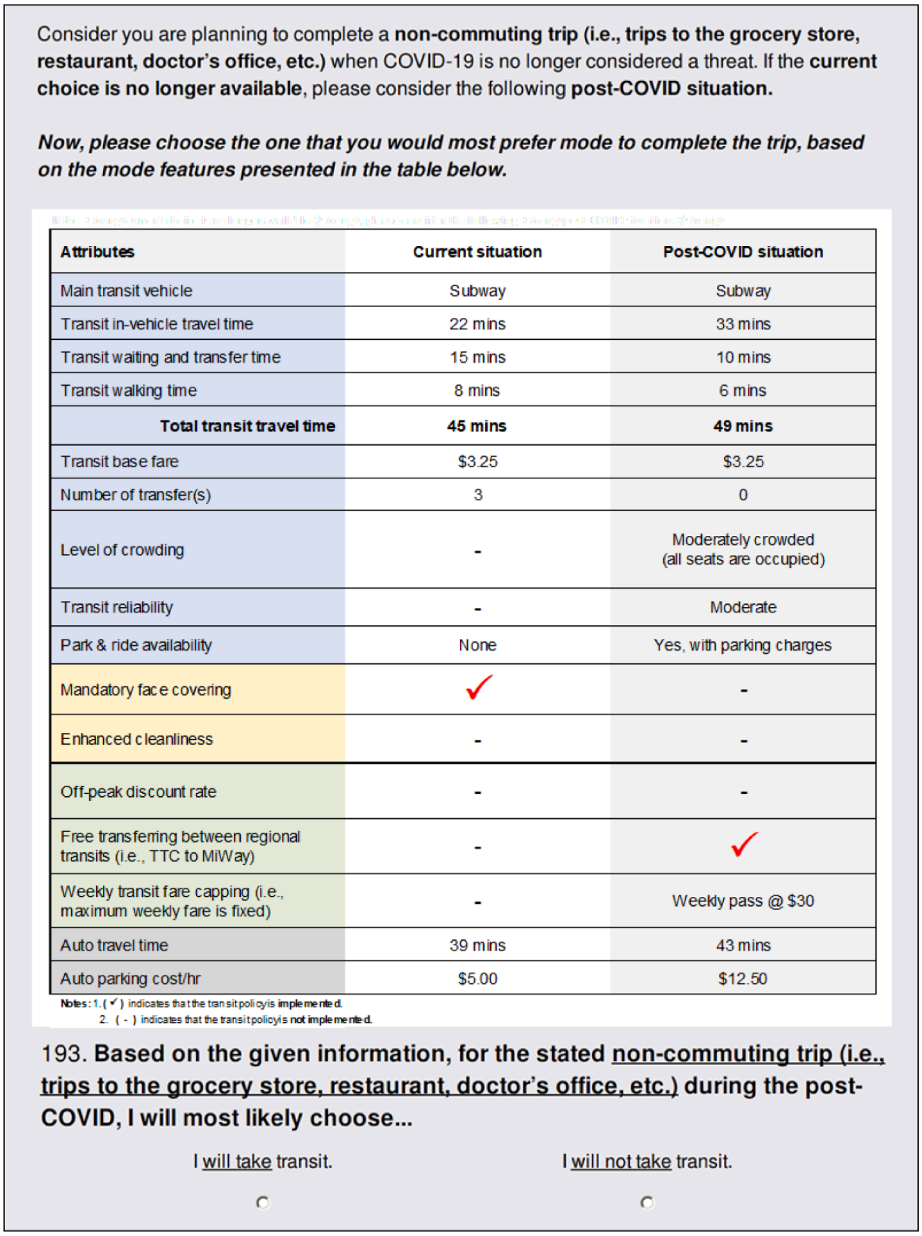
Attributes	Current Situation	Post-pandemic Situation
Main transit vehicle	Subway / (Bus or Streetcar)	Subway / (Bus or Streetcar)
Level of crowding	—	No crowding / Moderately crowded / Highly crowded
Transit reliability	—	Low / Medium / High
Park & ride availability	None / Yes, with parking charges / Yes, with free parking	None / Yes, with parking charges / Yes, with free parking
Mandatory face covering	Implemented (✔)	Not implemented (—) / Implemented (✔)
Enhanced cleanliness	—	Not implemented (—) / Implemented (✔)
Off-peak discount rate	—	Not implemented (—) / 10% / 25% / 50% on base fare
Free transferring between regional transits	—	Not implemented (—) / Implemented (✔)
Weekly transit fare capping (i.e., the maximum weekly fare is fixed)	—	Not implemented (—) / Weekly pass @$30 / @$40

Note: "—" refers to "Not considered" in the respected situation.

3.3. Descriptive statistics of the sample

The descriptive statistics of the samples used in this study are presented in Table 2. Sample statistics are compared against the 2016 Transportation Tomorrow Survey (TTS). The TTS is the regional household travel survey covering the study area of the SPETT'21 survey (Ashby, 2016). Moreover, the 2016 TTS was expanded to match the 2016 Canadian Census. Overall, non-transit users (during the pandemic) were older (73.1% aged above 40), females (61.2%), had greater access to private vehicles (92.4%), and were wealthier than the general population (58.4% having an income above CAD 60,000 compared to 43.8% in the TTS). This is expected since the samples represent the group that demonstrated greater risk aversion towards the pandemic and had the flexibility to use modes other than public transit. In addition, previous studies confirmed that females and the elderly were more fearful of the pandemic than other groups (Cerda and García, 2021; Hotle et al., 2020).

Moreover, wealthy families and private vehicle owners were entitled to greater flexibility in travel modes than other groups in the population (He et al., 2022). However, Table 2 also revealed that 48% were pre-pandemic transit users, nearly 40% making transit trips at least once a week. Given the study's objective, the sample seems well-fitted to conduct the intended investigation overall.



Consider you are planning to complete a **non-commuting trip (i.e., trips to the grocery store, restaurant, doctor's office, etc.)** when COVID-19 is no longer considered a threat. If the **current choice is no longer available**, please consider the following **post-COVID situation.**

Now, please choose the one that you would most prefer mode to complete the trip, based on the mode features presented in the table below.

Attributes	Current situation	Post-COVID situation
Main transit vehicle	Subway	Subway
Transit in-vehicle travel time	22 mins	33 mins
Transit waiting and transfer time	15 mins	10 mins
Transit walking time	8 mins	6 mins
Total transit travel time	**45 mins**	**49 mins**
Transit base fare	$3.25	$3.25
Number of transfer(s)	3	0
Level of crowding	-	Moderately crowded (all seats are occupied)
Transit reliability	-	Moderate
Park & ride availability	None	Yes, with parking charges
Mandatory face covering	✓	-
Enhanced cleanliness	-	-
Off-peak discount rate	-	-
Free transferring between regional transits (i.e., TTC to MiWay)	-	✓
Weekly transit fare capping (i.e., maximum weekly fare is fixed)	-	Weekly pass @ $30
Auto travel time	39 mins	43 mins
Auto parking cost/hr	$5.00	$12.50

Notes: 1. (✓) indicates that the transit policy is implemented.
2. (-) indicates that the transit policy is not implemented.

193. **Based on the given information, for the stated non-commuting trip (i.e., trips to the grocery store, restaurant, doctor's office, etc.) during the post-COVID, I will most likely choose...**

I will take transit.   I will not take transit.

Fig. 2. A sample of post-pandemic transit choice task.

Table 2
Descriptive statistics of key attributes in the sample.

Attributes	Data used (N = 513)	2016 TTS
Age (%)		
18–29	9.2	19.9
30–39	17.7	17.9
40–49	20.7	18.5
50–59	22.0	19.3
Above 60	30.4	24.4
Household attributes (mean)		
Size	2.7	2.7
Gender (%)		
Female	61.2	52.1
Mobility tools (%)		
Possess Driving license	92.6	81.9
Having access to a private vehicle	92.4	83.8
Studentship (%)		
Part-time student	2.9	2.6
Full-time student	4.7	7.4
Current employment status (%)		
Full Time	50.7	53.8
Part-Time	12.3	11.3
Not employed	34.9	34.9
Household income (%)		
below $14,999	2.9	5.4
$14,000 - $39,999	11.7	15.7
$40,000 - $59,999	15.4	15.3
$60,000 - $99,000	29.4	23.8
above $100,000	29.4	20.1
The region where resided (%)		
Toronto	30.4	47.9
Peel	25.3	9.8
York	22.6	15.3
Halton	11.5	18.5
Durham	10.1	8.3
Pre-pandemic transit usage frequency (%)		
Never	52.0	—
Once a month	22.2	—
Once every two weeks	4.1	—
Once a week	3.1	—
Twice or more in a week	6.0	—
At least once a day	12.5	—

Notes: "—" refers to "Not Available.".

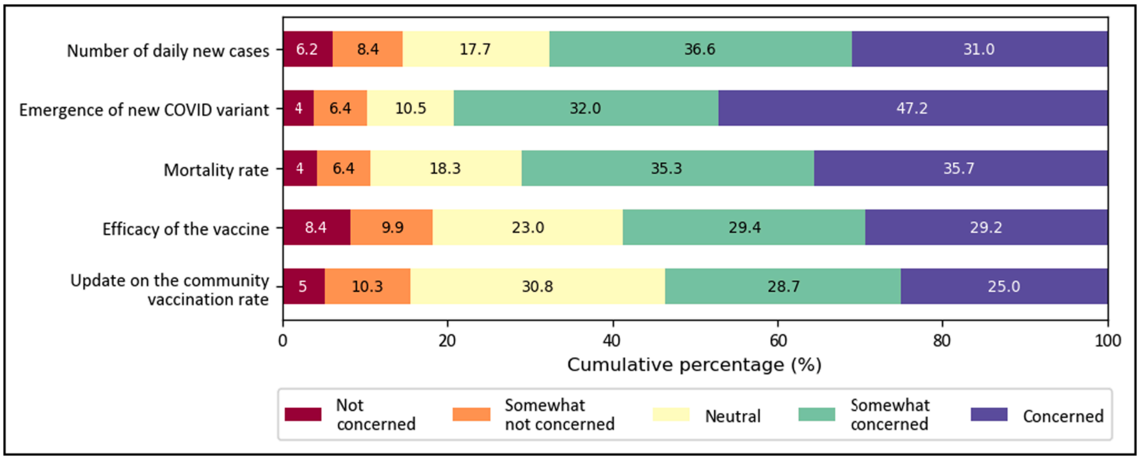


Fig. 3. Respondents' level of concern about the COVID-19 pandemic.

Regarding the attitudinal questions, the respondents were primarily concerned about emerging variants of COVID-19. 79.2% of the respondents were concerned about new variants (see Fig. 3), and 57.9% stated that transit would not be their primary travel mode in the nearest future. Moreover, 60.6% were not interested in purchasing monthly transit passes after the pandemic (see Fig. 4). On the other hand, more than 60% of the respondents were glad to keep TSP, such as mandatory face covering and social distancing on-board transit vehicles (see Fig. 5), even though most of them were unwilling to ride transit.

4. Estimated models

The study followed a sequential modelling approach to incorporate individuals' latent attitudes and other factors to examine their post-pandemic transit choice behaviour. Even though this approach does not jointly account for all the available information in the simultaneous approach, earlier literature noted that both models render similar estimates (Raveau et al., 2010).

4.1. Psychometric modelling

Psychometric modelling reviews the identification and validation of latent constructs and then estimates their expected value for each individual using a Multiple Indicator and Multiple Causes (MIMIC) model. Three attitudes (i.e., latent constructs) of the non-transit users were of interest in this study: *Concerns regarding pandemic characteristics*, *post-pandemic transit usage, and continuation of transit safety policies during the post-pandemic context*. The questions (i.e., indicators) capturing these latent attitudes were coded on a 5-point Likert scale (*"1": not concerned /Strongly disagree, "5": concerned /Strongly agree*). The distributions of the responses are demonstrated in Figs. 3 to 5. The respective indicators and corresponding scales were informed by prior literature (Posey et al., 2015; Webb, 2010; Zheng et al., 2021). Once the latent constructs were validated (see Table 3), the MIMIC model was specified to incorporate them in the subsequent analysis. In addition, the model specified the relationship between the latent constructs and the socioeconomic attributes (i.e., "cause" variables) (Bollen, 1989) The path diagram is illustrated in Fig. 6, and model estimates are presented in Table 3. Overall, the fit indices of the model were within acceptable limits (Hair, 2009). The results align with a prior study using the SPETT'2021 dataset comprising both transit and non-transit users. Interested readers are referred to that paper for more information (Mashrur et al., 2022).

4.2. Empirical model formulation

A two-stage modelling framework was specified to capture the post-COVID transit usage behaviour of those who did not take any transit trips during the pandemic. The first stage examined the factors influencing their pre-pandemic transit usage behaviour. Next, a set of binary discrete choice models was formulated to explore these user groups' post-pandemic transit choice behaviour. It is to be noted that the data used in the first stage were from the respondents' RP (i.e., revealed preference) pre-pandemic transit usage questions, while the data for the second stage were from SP experiments discussed earlier. A schematic diagram of the modelling framework is illustrated in Fig. 7.

For the first stage, let us consider that, y_i represents individuals' pre-pandemic transit usage choices, ranging from *Never* $(j = 0)$ to *At least once a day* $(j = 5)$. It is modelled in two layers. Firstly, a binary logit model in a layer a captures one's decision not to take transit before the pandemic (i.e., $y_i = 0$). Let the utility for this transit choice decision be defined by:

$$U_{ij}^{1} = V_{ij}^{1} + \varepsilon_{ij}^{1} = \boldsymbol{\beta} x_i + \varepsilon_{ij}^{1} \quad [1]$$

Where V_{ij}^{1} indicates the systematic utility and can be specified as a function of explanatory variables, x_i(i.e., individuals' demographic attributes and household characteristics). Here, $\boldsymbol{\beta}$ is the vector of parameters to be estimated. However, ε_{ij}^{1} refers to the

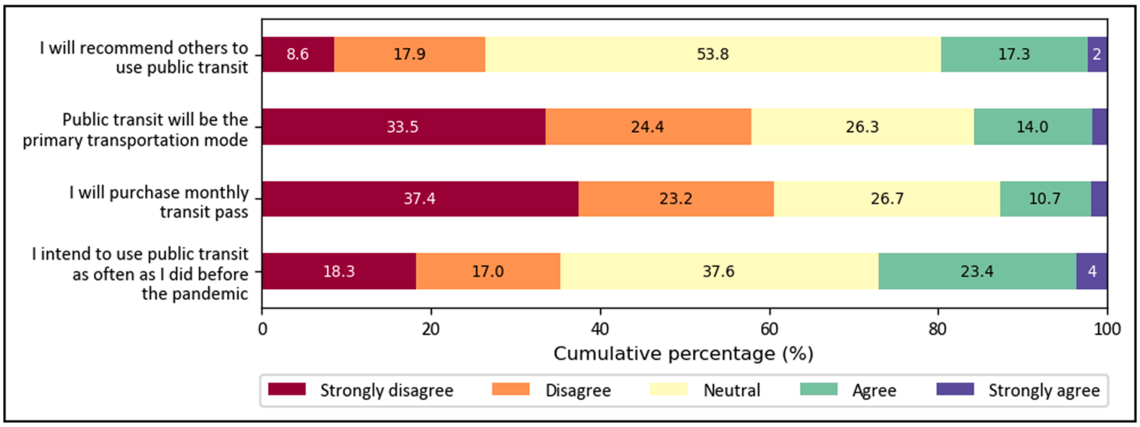


Fig. 4. Respondents' attitude towards post-pandemic transit usage.

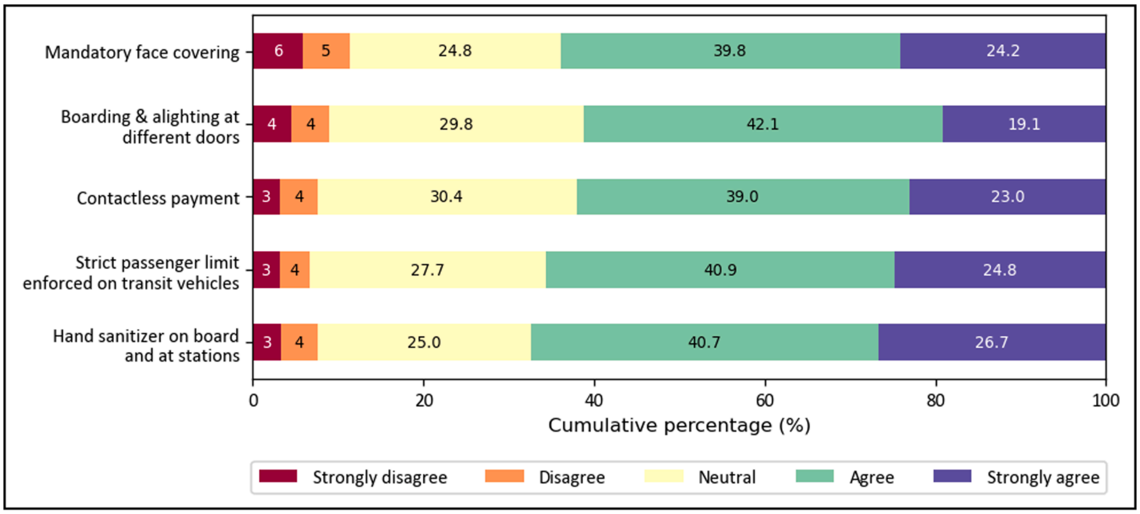


Fig. 5. Respondents' attitudes towards TSP implementations post the pandemic.

utility function's random (i.e., unobserved) components. It is assumed to be Independent and Identically Distributed Extreme Value Type I distributed. Therefore, the probability of never using transit before the pandemic can be written as:

$$P_{ij}^{1a}(y_i = 0) = \frac{e^{V_{ij}^1}}{1 + e^{V_{ij}^1}} = \pi_{ij}^1 \qquad [2]$$

$$P_{ij}^{1a}(y_i \neq 0) = 1 - \pi_{ij}^1 \qquad [3]$$

In the subsequent layer, b, of Stage 1, the study aimed at determining the attributes that influenced pre-pandemic transit users' extent of taking transit trips. The usage was recorded in discrete ordered choices, y_i, ranging from *Once a month (*i.e.*, $j = 0$)* to *At least once a day (*i.e.*, $j = 5$)*. An Ordered Generalised Extreme Value (OGEV) model was utilised as the question coded in the ordered discrete choice format. The model belonged to the Generalised Extreme Value (GEV) class of Random Utility maximisation models and was first coined by Small (Small, 1987). Therefore, the utility of choosing transit usage before the pandemic can be written similarly to Equation 1. However, the OGEV model allows portraying the systematic heterogeneity by estimating distinct coefficients, β_j, for the explanatory variables considered in the systematic components of the corresponding ordered discrete choices. Moreover, it accounts for the correlation between the random utility components of choices based on their closeness in the ordering, overcoming the Independence from Irrelevant Alternatives (IIA) features of the conventional multinomial (MNL) models. For instance, the higher the distance between the choice outcomes, j and k ($j, k = 1, 2, \cdots, J; j \neq k$), the lesser the correlation between the respective random components of the choices,ε_{ij}^1 an ε_{ik}^1. Furthermore, the model considers zero correlation if the $|j\text{-}k|$ is greater than a pre-selected integer, Q, that arbitrarily defines the window of the correlated choices. However, a larger Q significantly increased the model complexity, accruing the estimation cost. Therefore, the study considered $Q = 1$, implying that only the unobserved components of the immediate choice outcomes were correlated. Thus, the OGEV probabilities for $y_i = 1, .., J$ and $Q = 1$ are specified as follows (Small, 1987):

$$P_{ij}^{1b} = e^{\left(\rho^{-1}V_{ij}^1\right)} \frac{\left[\left(e^{\rho^{-1}V_{i,j-1}^1} + e^{\rho^{-1}V_{ij}^1}\right)^{\rho-1} + \left(e^{\rho^{-1}V_{i,j}^1} + e^{\rho^{-1}V_{i,j+1}^1}\right)^{\rho-1}\right]}{\sum_{r=1}^{J+1}\left(e^{\rho^{-1}V_{i,r-1}^1} + e^{\rho^{-1}V_{ir}^1}\right)^{\rho}} \qquad [4]$$

Where, $V_{ij}^1 = \beta_j x_i$ ($j = 1, ..5$) and with the principle that $e^{\left(\rho^{-1}V_{i0}^1\right)} = e^{\left(\rho^{-1}V_{i,J+1}^1\right)} = 0$ and $0 < \rho < 1$. The model converges to the MNL model as $\rho \to 1$ (Small, 1987). The study further parameterised ρ as follows to meet the OGEV criterion:

$$\rho = \frac{1}{1 + e^{(\alpha z_i)}} \qquad [5]$$

Where α is the vector of parameters to be estimated, and z_i is an individual's non-zero and continuous demographic and household attributes (i.e., age, household size).

Thus, the unconditional probability for the individual, i, choosing pre-pandemic transit usage, j, is given by:

$$P_i^1(y_i = j) = \ P_{ij}^{1a}(y_i = 0) \ = \pi_{ij}^1 \ \ ifj = 0 \qquad [6]$$

$$P_{ij}^{1a}(y_i \neq 0)^* P_{ij}^{1b}(y_i = j|j \neq 0) \ = (1 - \pi_{ij}^1)^* P_{ij}^{1b} ifj \neq 0$$

The second stage considered public transit during the post-pandemic context presented in the SP scenarios as a binomial discrete

Table 3
Psychometric modelling results.

Factor structure of the Latent Constructs					
Latent Constructs and Relevant Observed Indicators		**Mean**	**Standard Deviation**	**Factor Loading[1]**	**Cronbach's alpha[2]**
***pandFear:* Concerns regarding pandemic characteristics (see Fig. 3)**					
conc_ncase: Number of daily new cases in the province		3.78	1.16	0.826	0.878
conc_var: Emergence of the new variant of the COVID-19		4.12	1.08	0.898	
conc_mrate: Mortality rate of the disease		3.92	1.09	0.887	
conc_vacc_eff: Efficacy of the vaccine/medical interventions currently available		3.61	1.24	0.622	
***transitUseFut:* Post-pandemic transit usage (see Fig. 4)**					
pt_f_recom: I will recommend others to use public transit		2.87	0.88	0.583	0.808
pt_f_pri_mode: PT will be primary transport mode for my daily trips.		2.26	1.12	0.895	
pt_f_tpass: I will purchase monthly transit pass.		2.17	1.10	0.858	
pt_f_often: I intend to use public transit just as often as I did before the pandemic.		2.77	1.11	0.503	
***tspFut:* Continuation of transit safety policies post the pandemic (see Fig. 5)**					
tsp_fc: Mandatory face covering		3.71	1.07	0.844	0.933
tsp_door: Boarding & alighting at different doors to lessen the interaction between riders		3.67	0.98	0.882	
tsp_pay: Contactless payment		3.74	0.96	0.823	
tsp_crowd: Strict passenger limit enforced on transit vehicles to ensure social distancing		3.81	0.95	0.916	
tsp_hand: Hand sanitiser is made available in the transit vehicles		3.83	0.98	0.831	
Validity test results of the latent constructs					
Latent Constructs	**Composite reliability[3]**	**AVE[3]**	**Discriminant validity[4]**		
Pandemic fear	0.886	0.647	**0.804**	−0.109	0.355
Attitude towards post-pandemic transit usage	0.812	0.553	−0.109	**0.743**	0.113
Attitude towards continuing transit safety policies during post-pandemic	0.934	0.738	0.355	0.113	**0.859**
MIMIC model results					
Latent constructs	**Socio-demographic attributes**			**Estimates**	**t-stat**
Concerns regarding pandemic characteristics (*pandFear*)	Gender: Male			**−0.187**	**−2.152**
	Age: above 54			**0.328**	**3.88**
	Fully vaccinated			**0.444**	**4.795**
Post-pandemic transit usage (*transitUseFut*)	Gender: Male			0.088	1.891
	Age: above 54			**−0.134**	**−2.913**
	Have access to private vehicle			−0.125	−1.484
	Have transit pass			**0.422**	**6.646**
Continuation of transit safety policies during the post-pandemic era (*tspFut*)	Gender: Male			−0.128	−1.532
	Have transit pass			**0.277**	**2.786**
	Fully vaccinated			**0.237**	**2.75**
Fit Indices					
Comparative Fit Index	**0.949**				
Tucker-Lewis Index	**0.938**				
Root Mean Square Error for Approximation	**0.061**				
Standardised Root Mean Square Residual	**0.044**				

Notes:
1. An observed indicator of a latent construct should have a factor loading 0.40 and above (Hair, 2009).$p < 0.001$ are presented in boldface.
2. The acceptable threshold for Cronbach's alpha and Composite reliability is 0.70 (Tavakol and Dennick, 2011).
3. For the convergent validity, all the latent construct's composite reliability and AVE (average variance extracted) should be above 0.70 and 0.50, respectively (Hair, 2009).
4. The correlation amongst the constructs should be lower than the square root of each construct's AVE, which is at the diagonals and boldfaced.

choice problem. However, unlike the population segmentation in the first stage ($J = 6$), the pre-pandemic transit users were grouped into four classes l (see Fig. 7): non-transit ($l = 1$), occasional ($l = 2$), moderate ($l = 3$), and frequent ($l = 4$) transit users. Furthermore, let us consider that, t_s represents individual post-pandemic transit choices in the SP scenario s, (i.e., one if one chooses to take transit, 0 otherwise). Thus, the utility function, systematic component, and the probability of considering transit in each scenario, s, for individual, i, belonging to a class, l, can be written as:

$$U^2_{ils} = V^2_{ils} + \varepsilon^2_{ils} \quad [7]$$

$$V^2_{ils} = \gamma_l c_s \quad [8]$$

$$P^2_{ils}(t_s = 1) = \frac{e^{V^2_{ils}}}{1 + e^{V^2_{ils}}} = \pi^2_{ils} \quad [9]$$

$$P^2_{ils}(t_s = 0) = 1 - \pi^2_{ils} \quad [10]$$

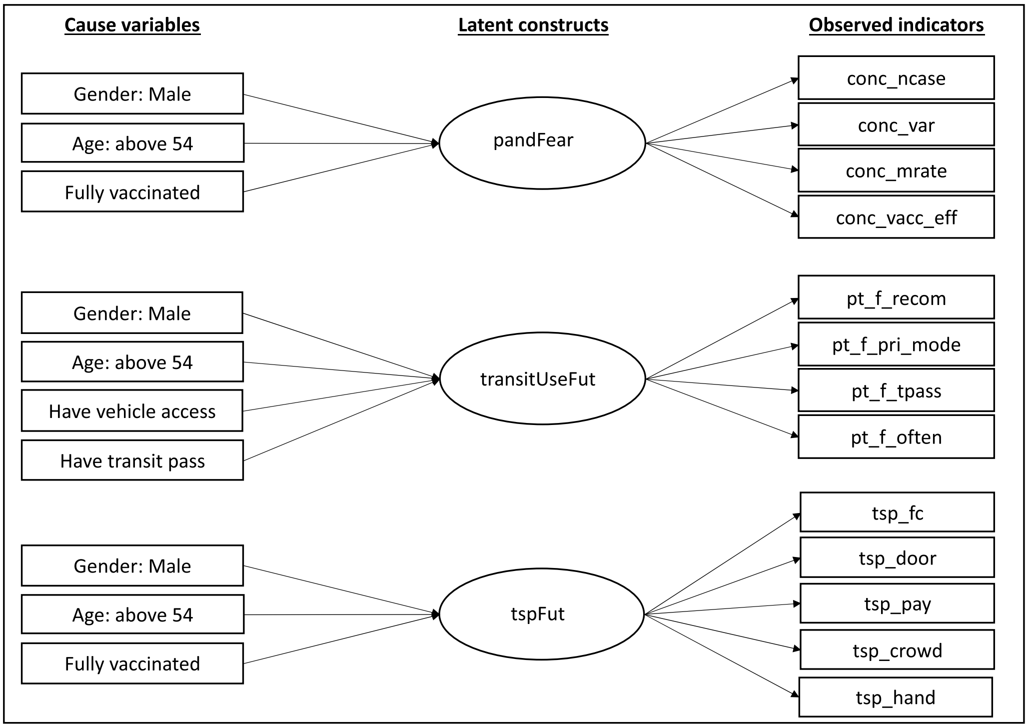


Fig. 6. Path diagram of the MIMIC model. **Notes:** The full form of the abbreviated observed indicators are provided in Table 3.

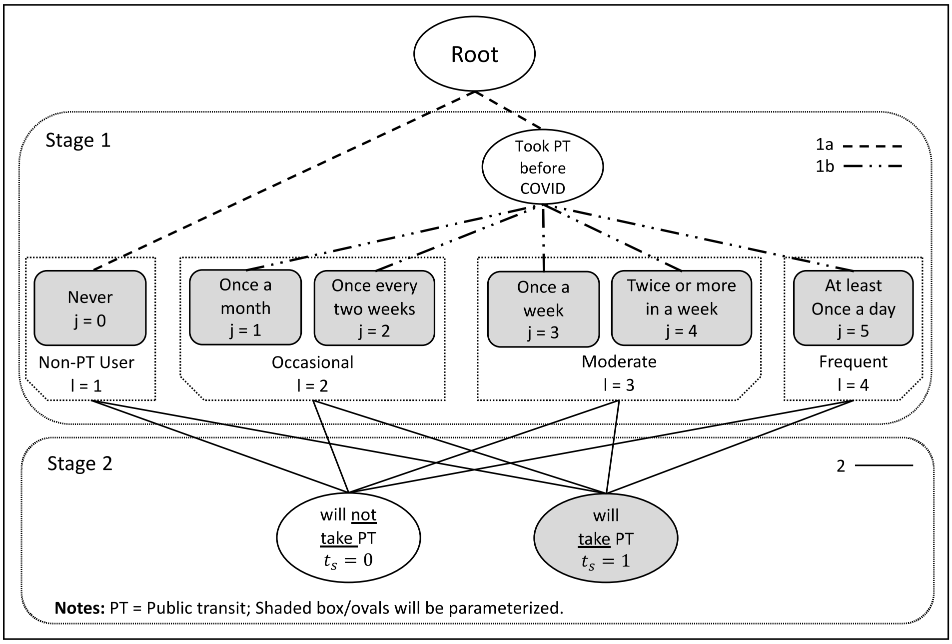


Fig. 7. Empirical modelling framework.

Where V_{ils}^2 is specified as a function of SP choice attributes, c_s. Here, γ_l are corresponding parameters for each class. ε_{ils}^2 refers to the unobserved components of the respective class's utility function and is assumed to be IID Extreme Value Type I distributed.

Each respondent had six post-pandemic SP scenarios. Therefore, accounting for the population segmentation, the joint likelihood of the pre-pandemic transit usage choices and post-pandemic transit consideration for each observation becomes:

$$L_i = [\prod_{l=1}^{4} (P_i(l))^{\delta_{il}}] * [\prod_{s=1}^{6} [(\pi_{ils}^2)^{\delta_{is}} * (1 - \pi_{ils}^2)^{1-\delta_{is}}]$$

$$P_i(l) = P_i^1(y_i = 0)\, iff = 0 and l = 1 \quad [13]$$

$$P_i^1(y_i = 1) iff = 1 and l = 2$$

$$P_i^1(y_i = 2) iff = 2 and l = 2$$

$$P_i^1(y_i = 3) iff = 3 and l = 3$$

$$P_i^1(y_i = 4) iff = 4 and l = 3$$

$$P_i^1(y_i = 5) iff = 5 and l = 4$$

Where δ_{il} and δ_{is} are dummy variables. The δ_{il} takes the value 1 if none has belonged to the class, *l*, while δ_{is} is 1, if one chooses to take transit in the SP choice, *s*. The model was estimated through a program using the *MaxLik 5.0* application of a matrix programming language *GAUSS* (Aptech Systems Inc., 2012).

5. Results and discussion

The study's key objective was to identify the factors that will play vital roles in reinstating transit demand during the post-pandemic era. As such, non-transit users of the pandemic era were investigated. A two-stage model was estimated that jointly modelled the pre-pandemic transit usage frequency of those who avoided transit during the pandemic and their post-pandemic transit choices. Several configurations were tested before reaching the final specification of the model. The final model was selected considering its covariates' behavioural intuitiveness and statistical significance. The model's fit indices and results are shown in Tables 4, 5 and 6. Overall, goodness-of-fit values (see Table 4) implied that the model is well-fitted to the data capturing the said investigations. While most of the covariates were chosen with a 95% confidence level, some insignificant (but not<20% confidence level) were kept considering their behavioural insightfulness. However, the inclusion of OGEV in the modelling framework was also validated, as the covariate (household size) associated with the $\boldsymbol{\rho}$ was significant (see Table 5).

5.1. Stage 1: Pre-pandemic transit usage frequency

Various attributes regarding socioeconomic characteristics, mobility tools ownership, and employment status were significantly associated with one's pre-pandemic transit usage (See Table 5). Those who were male and young adults were more into taking transit trips frequently, which is in line with prior findings (Deka and Fei, 2019). Furthermore, one's tendency to avoid transit decreased with their academic level. A similar tendency was observed for those residing in regions with well-connected transit systems (i.e., the City of Toronto) (CTV News, 2019).

Intuitively, vehicle accessibility acted as a significant factor in respondents' extent of transit usage. High vehicle access and the number of vehicles per household member made one more likely to use modes other than transit before the pandemic, aligning with prior observations (Badoe and Yendeti, 2007; Deka and Fei, 2019). Conversely, those with bike access were not likely to be in the transit avoidance group, implying their mindset of using sustainable transportation. On the contrary, the tendency to entirely avoid transit before the pandemic was not prevalent among workers, especially those in professional and managerial occupations, which validated prior findings (Badoe and Yendeti, 2007). However, emergency workers during the pandemic were seen to have the opposite tendency. This might be due to their work requiring them to own private vehicles. Further looking into the dataset revealed that more than 90% of them had access to a private vehicle, either as a driver or passenger. Interestingly, those with income above CAD 50,000 were observed to take transit at least once daily. Even though the depiction might be counterintuitive, it can be argued that this group's mobility activity might be concentrated in central business districts (CBD), given their income level. It is to be noted that the CBD in the GTA regions has well-connected transit networks that cater to a wide range of inter-and-intra-regional transit trips (Farber and Jeff, 2019; MetroLinx, 2018). Furthermore, high parking fees in the CBDs were seen to encourage one to take transit trips (Auchincloss et al., 2015).

Table 4
Goodness-of-fits of the Model.

Fit Indices	Values
Loglikelihood of equiprobable	−2871.09
Loglikelihood of the entire model	−2113.54
Rho-Square value (against the equiprobable model)	0.26
Akaike information criterion	4355.09
Bayesian information criterion	4626.47

Table 5
Model estimates for Stage 1.

Frequency of using PT before the pandemic (Binary logit and OGEV model)					
	Binary Logit	**OGEV (taking once a month as a reference)**			
Pre-COVID transit usage frequency [j] **Attributes**	**Never** **[0]**	**Once every two weeks** **[2]**	**Once a week** **[3]**	**Twice or more in a week** **[4]**	**At least once a day** **[5]**
ASC	0.6398 (1.572)	**−2.2364 (-5.776)**	**−1.4399 (-3.735)**	**−0.7853 (-2.272)**	**−3.3697 (-5.193)**
ρ(for OGEV)					
Household Size	—	−2.7007 (-1.622)			
Socioeconomic attributes					
Gender: male	—	—	0.43 (1.538)	0.43 (1.538)	0.43 (1.538)
Age: below 34	—	—	—	—	**2.7079 (4.911)**
Age: 34–54	—	—	—	—	**1.6631 (3.558)**
have at least a diploma	**−0.5669 (-2.869)**	—	—	—	—
marital status: separated	**0.7962 (2.009)**	—	—	—	—
Region: Toronto & Peel	**−0.6501 (-3.04)**	0.844 (1.84)	—	—	—
Mobility tools ownership					
have access to vehicle	**0.8505 (2.203)**	—	—	—	—
have access to a bike	−0.3698 (-1.837)	—	—	—	—
Vehicles per household member	—	—	**−1.2171 (-2.346)**	**−1.2171 (-2.346)**	—
Employment status					
Pre-COVID Full-time worker	−0.3637 (-1.661)	—	—	—	0.5611 (1.356)
Occupation: professional	−0.4566 (-1.509)	—	—	—	—
Occupation: management	−0.5052 (-1.512)	—	—	—	—
Emergency worker	**0.5077 (2.178)**	—	—	—	—
Income: 50–100	−0.4247 (-1.643)	—	—	—	0.7142 (1.426)
Income: above 100	−0.4796 (-1.637)	—	—	—	

Notes: Estimates having $p < 0.001$ are in boldface.
"—" refers to "Not applicable".

Table 6
Model estimates for Stage 2.

Post-pandemic PT choice (Binary logit)				
Pre-COVID transit usage frequency [l] **Attributes**	**Non-PT User** **[0]**	**Occasional** **[1]**	**Moderate** **[2]**	**Frequent** **[3]**
ASC	**−1.7532 (-6.341)**	−0.3487 (-1.145)	**−0.9876 (-2.488)**	**−1.3176 (-3.41)**
Latent Attitudes				
Concerns about pandemic characteristics	**−0.2373 (-3.009)**	−0.1512 (-1.519)	**−0.4543 (-2.397)**	—
Post-pandemic transit usage	**0.6712 (4.486)**	**1.9377 (9.956)**	**1.1951 (3.915)**	**1.6433 (5.688)**
Continuation of transit safety policies during the post-pandemic era	**0.2036 (2.415)**	0.1369 (1.164)	**0.6843 (3.265)**	**0.4802 (2.818)**
Public Transit Level of Service				
PT mode: Subway	0.359 (1.888)	—	—	—
In-vehicle travel time	−0.007 (-1.804)	−0.007 (-1.804)	−0.007 (-1.804)	−0.007 (-1.804)
Out-vehicle travel time	—	−0.0192 (-1.682)	−0.0192 (-1.682)	−0.0192 (-1.682)
Level of crowding: High	−0.251 (-1.677)	—	**−0.7781 (-2.364)**	**−0.6471 (-2.491)**
Level of Reliability: Moderate	—	—	0.3562 (1.737)	0.3562 (1.737)
Level of Reliability: High	—	**0.3833 (2.016)**	—	—
Paid park & ride facility	0.3331 (1.87)	**0.5301 (2.519)**	—	—
Free park & ride facility	—	—	0.4247 (1.238)	—
Post-COVID PT safety policies				
Mask mandate	—	−0.3302 (-1.82)	—	—
Enhanced cleaning	0.2049 (1.438)	0.2877 (1.622)	—	—
Post-COVID PT usage incentive policies				
Free transfer between cross-borders	—	—	0.2794 (1.382)	0.2794 (1.382)
25% or more off-peak discount on base fare	0.1963 (1.616)	0.1963 (1.616)	**0.4054 (2.081)**	**0.4054 (2.081)**
Post-COVID operational improvement				
Transfer improvement	—	—	0.3683 (1.908)	0.3683 (1.908)
Higher parking cost	—	—	0.2976 (1.331)	0.2976 (1.331)

Notes: Estimates having $p < 0.001$ are in boldface.
"—" refers to "Not applicable".

5.2. Stage 2: Post-pandemic transit usage

In the second stage, the model examined determinants for non-transit users during the pandemic returning to public transit in the post-pandemic era (See Table 6). The modelling results revealed five groups influential factors affecting travellers' decisions to return to transit. The factors include latent attitudes towards the pandemic and transit system, level of service describing the transit system's performance, health & safety policies on-board transit vehicles, post-pandemic transit fare incentives and operational improvements. Moreover, the model considered preference heterogeneity through class-specific formulation. Four classes were identified based on the frequency of individuals' transit usage before the pandemic. Firstly, the non-PT user class never used transit before the pandemic. Second, the occasional user class used transit once a month or every two weeks before the pandemic. Third, the moderate users class used transit on a weekly basis before the pandemic. Lastly, the frequent user class used transit at least once a day before the pandemic.

The modelling results of the non-PT user class identified determinants to attract individuals who never used transit to use the service in the post-pandemic era. Successfully converting this group of travellers to transit users will create additional transit ridership. As expected, the model revealed individuals with higher pandemic concerns had lower propensity to make transit trips in the future. Compared to other classes, individuals in the non-PT user class have the lowest utility gain regarding post-pandemic transit usage attitudes. This reflects that non-PT users were psychologically less willing to use transit than travellers who already used transit before the pandemic. Furthermore, continuing health and safety policies for a period of time during the post-pandemic era will increase the likelihood of converting non-PT users into transit users. More specifically, non-PT users were indifferent towards mask mandate on-board transit vehicles. However, enhanced cleaning on transit vehicles would increase their likelihood of using transit. Lastly, providing a fare discount during the off-peak period could encourage non-PT users to adopt public transit.

The determinant that attracts occasional transit riders before the pandemic returning to transit is a function of latent attitudes, transit performance, safety policies on-board and fare discount incentives. Like the modelling results for the non-PT user class, occasional transit users with higher pandemic concerns showed decreased tendency to return to transit in the future. Conversely, positive attitudes towards transit usage and the continuation of health and safety policies during the post-pandemic era will increase the likelihood of the return of occasional transit users. For transit performance, in-vehicle and out-of-vehicle travel time would impose disutility. In contrast, occasional users value high service reliability and availability of paid park & ride facilities. Interestingly, modelling results showed that occasional users dislike mask mandates. The reasoning could be two-fold. First, this might be reasoned by the discomfort of wearing a mask in an enclosed space when the threat of COVID is nullified. Second, they could dislike the compulsory nature of mandate, which was not uncommon in the Canadian context (Dubinski and Margison, 2022). On the other hand, enhanced cleaning in transit vehicles could increase the likelihood of occasional transit to return to transit. Like the non-PT group, fare discounts during the off-peak period would also encourage occasional users to return to transit.

The behaviours of moderate and frequent transit users were similar. The determinants are functions of latent attitudes, transit

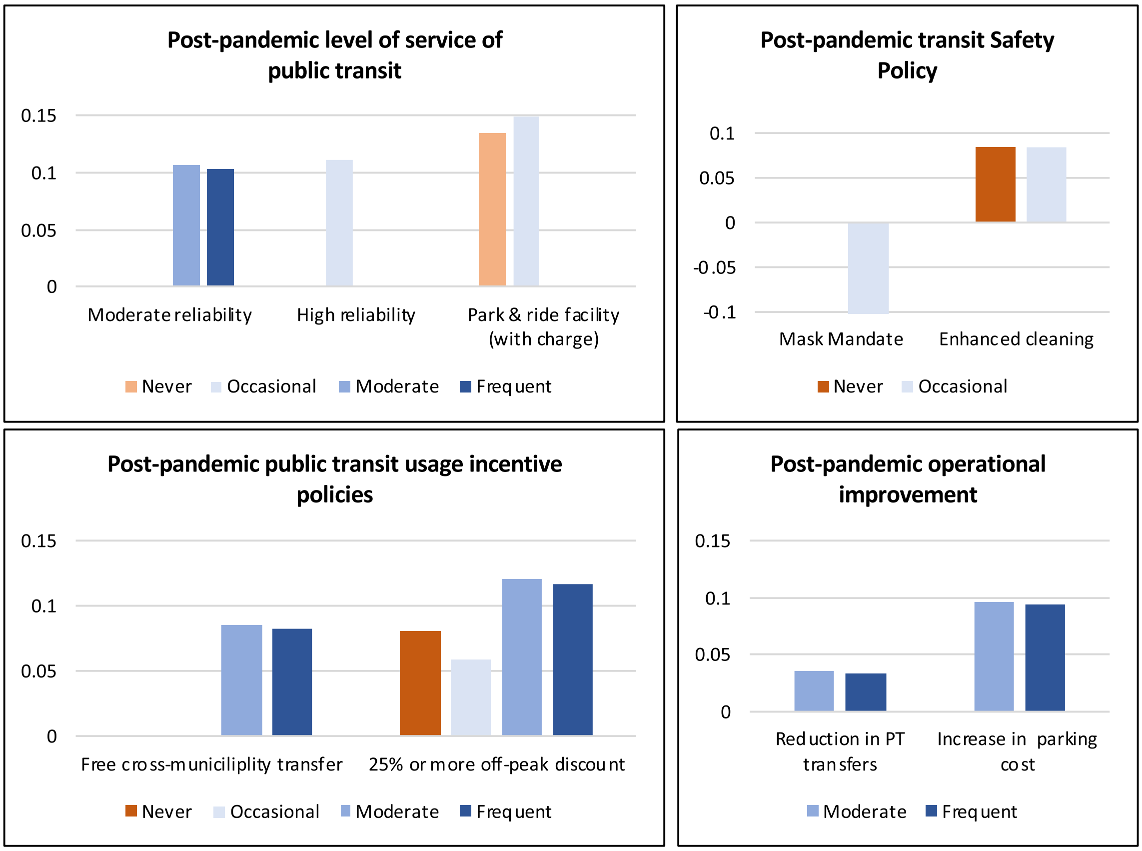


Fig. 8. Marginal effects of policy variables in post-pandemic transit choice.

performance, fare incentives and operational improvements. Modelling results regarding latent attitudes are similar with the non-PT and occasional users. Likewise, the negative coefficients for in-vehicle and out-of-vehicle are also expected. High crowding levels negatively affected the decisions of moderate and frequent users to return to transit. It is surprising that moderate and frequent transit users demonstrated statistically significant acceptance towards a moderate level of service reliability. Unlike the other group that valued paid parking facilities, moderate transit users valued the availability of free parking facilities. This is expected since free parking significantly reduces the cost for users with higher transit frequency. In contrast, the financial benefit might be less significant for occasional users who only expect to use transit a few times per month. Therefore, moderate users valued free park & ride parking, whereas non-PT and occasional users valued the availability of park & ride parking, and they don't mind paying parking fees. Moderate and frequent pre-pandemic transit users valued both fare incentives and operational improvements in their decision to return to transit. Amongst the post-pandemic incentive policies, the off-peak discount of 25% or more significantly encouraged pre-pandemic moderate and frequent transit users to return. They were also inclined to use transit if no additional transit fare was charged in case of transferring between different municipalities. It was further observed that frequent pre-pandemic users were persuaded if the transit routes were more direct, meaning fewer transfers. Furthermore, higher on-street parking costs could also effectively convince them to return to transit.

6. Policy implications

All the discussions above provided an in-depth empirical analysis of influential factors for non-transit-users during the pandemic to return to public transit. Based on insights derived from modelling results, the section will suggest specific policies. Policy recommendations will be categorized into the following parts: long-term planning, health and safety, fare, and operational planning policies.

Long-term transit planning efforts should aim to provide grade-separated rail transit infrastructures. Modelling results in this study clearly indicate that providing grade-separated rail transit services, such as subway, would attract additional transit ridership. Grade-separated rail transit infrastructures will increase the likelihood for travellers who never took transit before to consider using transit. This is in line with the psychological rail factor described in the literature (Scherer and Dziekan, 2012). Many travellers considered rail-based transit systems superior compared to bus systems. Long-term transit planning efforts should sufficiently recognize the psychological rail factor, planning for a system that attracts travellers who habitually distanced themselves from transit. Secondly, the transit system should be planned and designed to optimize route directness, namely, minimizing the number of transfers. Thirdly, transit stations, especially mobility hubs, should be designed with sufficient parking facilities, allowing park-and-ride. Modelling results in this study showed that non-PT, occasional and moderate users all preferred parking facilities. Marginal effects were calculated using the probability-weighted sample enumeration (PWSE) method (see Fig. 8) to measure the impact of the policy variables. Providing paid park-and-ride facilities with charges increased the probability of choosing transit for a post-pandemic trip almost by 13.5% and 15% for non-transit and occasional users, respectively.

For health and safety policy, mask mandate on-board transit vehicles should be removed. Instead, face-covering should be strongly encouraged while travelling in transit systems. The flexibility could convince individuals having disutility toward mandates while protecting travellers who still feel face-covering is necessary. Implementing mask mandate could reduce occasional users' likelihood of returning to transit by around 10%. Meanwhile, it would not increase the transit-returning likelihood for any other classes. Also, transit providers should continue enhanced cleaning action implemented during the pandemic (Draaisma and Yuen, 2020). Estimated marginal effects show that enhanced cleaning could increase the probability for non-PT and occasional users returning to transit by around 7.5% (see Fig. 8). In the post-pandemic era, transit providers in the study area should consider the implementation of peak and off-peak fare schemes. Fig. 8 shows fare discounts during off-peak hours could unanimously increase the likelihood for travellers from all classes to return to transit. Moreover, transit agencies should consider providing an integrated cross-municipality transit fare system. Transferring between transit systems should become free. The free transfer policy will bring moderate and frequent transit users back to the service. Transit agencies should also focus on improving their level of service. For example, service planning should be carefully conducted to avoid crowding in transit vehicles. Moreover, transit signal priority, reserved bus lanes, and automated train control should be examined and implemented to improve service reliability (Diab et al., 2015).

Lastly, transit agencies should be effectively communicated the policies mentioned above with the public through awareness campaigns. Evidence from the literature showed that combining policy actions with communication campaigns significantly boosted policy effectiveness by affecting travellers' attitudes and behaviour (Faus et al., 2021). More specifically, communication campaigns should create public awareness of operational indicators (such as crowdedness on board), reliability measurements (such as on-time performance and travel time and waiting time indicators) and continuation of enhanced cleaning in transit vehicles (Kathuria et al., 2020). For instance, TransLinks (transport providers in British Columbia, Canada) launched Reconnect Campaign to encourage transit use (TransLink, 2021). As part of the campaign, they launched interactive trip planning tools helping transit riders to plan their trips with real-time level of service information. Other transit providers could follow similar approaches. In summary, communication campaigns should promote a responsible and reliable image of transit services and encourage travellers to return to it.

7. Conclusion

COVID-19 has unimaginably disrupted the transit system and its overall functions. As a result, transit, perceived as riskier than its competing modes, saw a drastic drop in ridership. Moreover, such transit avoidance behaviour for a prolonged period might alter their transit choice preferences. Therefore, many uncertainties arose amongst the concerned authorities regarding its post-pandemic resilience planning.

Thus, this study aimed to investigate post-pandemic interventions that potentially affect the future transit choice behaviour of non-transit users of the pandemic. The interventions included but were not limited to operational changes in the transit system, adopting transit usage incentive programs, and adopting transit safety policies. In addition, influential pandemic-induced psychological attributes were also examined. With that, the study proposed a two-staged model that jointly captured pre-pandemic transit usage choices of those who did not make transit trips during the pandemic and respective post-pandemic transit choices for this user group.

The models revealed that while the post-pandemic transit choices were inversely affected by one's pandemic concerns, their choices were positively influenced by respondents' views on post-pandemic transit usage and keeping the TSP in place. Also, reliable transit services and park and ride facilities significantly encouraged pre-pandemic users to retake transit. Paid park and ride facilities with charges enhanced the probability of post-pandemic transit choice almost by 15% for occasional users. In comparison, the changes due to reliability ranged from 10 to 11% for pre-pandemic users. Interestingly, mask mandates did not encourage users to return, while enhanced cleaning did.

Regarding post-pandemic incentive policies, fare schemes offering free transfers between municipalities and off-peak discounts attracted users back to transit. Moreover, more direct transit services and increased parking costs after the pandemic were also seen to attract non-transit users back to the mode. Such interventions depicted the change in the probability of taking transit for future trips from 3.1% to 9.6%.

This study focused on understanding how to attract transit users back to the mode after the pandemic using the SP choice experiment. It provided some critical insights towards effective policy interventions that could fasten the transit recovery after the pandemic. However, the study has some limitations. First, the SP experiment can be susceptible to some cognitive bias, even after adopting various practices to mitigate it. Such as doing a pilot survey, randomly selecting participants, and recording time to provide choices for each scenario for post-filtering. As for addressing the hypothetical bias, the project aims to conduct another cycle of the survey during the post-pandemic era and conduct investigations using RP-SP panel data for better insight. However, transit ridership loss could be from other structural changes in activity-travel patterns—for example, work-from-home and hybrid workplace arrangements (Wang et al., 2022). Policy and measures suggested in this paper overlooked the transit ridership that could be lost by such systematic change in the future. Finally, latent variables used in this study focused on the pandemic. A recent survey by Metropolitan Transportation Authority (MTA) found that personal safety has become the most critical concern for subway riders instead of pandemic-related factors (Mayer, 2022). Future studies should work in this direction, investigating safety concerns, homelessness in transit, and riders with erratic behaviours. Nevertheless, the paper, with its certain limitations, can work as a basis for the decision-makers and transit authorities to have a data-driven understanding of how to plan for pandemic-resilient transit systems that will effectively regain the lost demand.

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.

Data availability

The authors do not have permission to share data.

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