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Impact of the COVID-19 pandemic on the comfort of riding a crowded bus in Metro Vancouver, Canada

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ABSTRACT

The COVID-19 pandemic had a profound impact on transit ridership around the world, including in Metro Vancouver, Canada. The regional transit agency there, TransLink, faced the challenge of not only tackling the sudden revenue loss but also ensuring the safety and comfort of its riders that could be affected by crowding. As the tide of restrictions subsided, and riders are gradually coming back to public transport, their feelings of safety and comfort must be ensured so that they do not deflect to other modes. To guide TransLink and agencies alike in this process, this study aimed to understand the factors that affected the decision to board a bus and level of comfort of riding it for different behavioral classes of transit riders before and during the COVID-19 pandemic. It employed a classification of transit riders based on their attitudes towards personal safety and flexibility both before and during the COVID-19 pandemic and investigated the effect of crowding on their decision to board and the comfort of boarding a bus at various crowding levels. The findings of this study are expected to guide the development of relevant policy interventions that can engage diverse groups of riders to continue using transit in a way that is convenient, comfortable, and safe for them.

1. Introduction

The COVID-19 pandemic decimated transit ridership worldwide (Transport Strategy Centre, 2020) due to government restrictions aimed at reducing the spread of the virus (Gramsch et al., 2022) and the rise in telecommuting that leveled the necessity to travel to work for many employees (Mouratidis and Papagiannakis, 2021; Nordbakke, 2022). At the same time, the divergence between the concept of mass transit and the ability to socially distance from other users (Musselwhite et al., 2020), and the overall image of public transportation as a place suitable for the quick transmission of coronaviruses negatively affected transit ridership as well (Gutiérrez et al., 2021; Sun and Zhai, 2020). These trends were also true in Metro Vancouver, the third largest region in Canada (Statistics Canada, 2022), that in the first months of the COVID-19 pandemic saw a decline in transit ridership to a fifth of what it was before March 2020 (TransLink, 2020b). With the ease of restrictions and increase in economic activities, transit patronage restored to 70% of its pre-pandemic level before the end of 2021 (TransLink, 2022a), however, even in the best-case scenario it is expected to fully rebound no earlier than in 2025 (TransLink, 2022b).

To bring the riders back to transit, it is important that public transport operators, including TransLink (a regional transit agency in Metro Vancouver), focus on customer satisfaction and account for the changes in preferences that took place during the COVID-19 pandemic and expectations of the transit services in the post-pandemic world. Past research indicated the strong impact of crowding and safety on the satisfaction and loyalty of public transport users (van Lierop and El-Geneidy, 2017b) and with health concerns that the pandemic brought up, it is of no surprise that the substitution of numerous transit trips with driving took place during that period (Bucsky, 2020; Kapatsila et al., 2022). As expected, this shift did not involve captive riders - transit users who cannot afford to use other modes due to financial, physical, or geographical constraints, however, the choices of choice riders – those who rode transit in the past but also have the possibility to drive – are more nuanced. The freedom and convenience of car ownership are valued much higher than the costs of ownership drivers endure (Moody et al., 2021). It should be expected that without targeted policy interventions that increase the appeal of other modes, the dominance of

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driving among those who can afford it is likely to continue.

Nevertheless, crowding mitigation is very likely to play an important role in the return of riders to public transport. Transit, a popular trip-planning smartphone application, surveyed 6,000 of its users during the pandemic in 2020 and learned that before the COVID-19 outbreak almost two-thirds of their sample boarded a crowded vehicle even if that caused them discomfort. This changed dramatically since March 2020, with almost 90% of respondents stating that they would not board a crowded bus when they were not in a rush, and a little more than 70% would do the same even if they were in a hurry (Transit, 2020). While it might take a while for the ridership to recover in Metro Vancouver systemwide, more popular routes that saw high congestion levels pre-pandemic (TransLink, 2019) are likely to reach their capacity sooner rather than later. In case no preventive actions are taken, TransLink may forgo an opportunity to sustain the patronage of its users and lose some of them to other modes due to crowding.

With the challenges that TransLink and agencies alike face, this study aimed to understand the factors that affected the decision to board a bus and level of comfort of riding it for different behavioral classes of transit riders before and during the COVID-19 pandemic. It employed a classification of transit riders based on their attitudes towards personal safety and flexibility both before and during the COVID-19 pandemic and investigated the effect of crowding on their decision to board and the comfort of boarding a bus at various crowding levels. The findings of this study are expected to guide the development of relevant policy interventions that can engage diverse groups of riders to continue using transit in a way that is convenient, comfortable, and safe for them. The COVID-19 pandemic has underscored the need for quick programmatic interventions that tackle transit demand and use, as time and resource constraints made expansion of system capacity too slow and inflexible to respond to the rapidly changing preferences and concerns regarding safety and comfort of transit riders. This knowledge remains relevant when the tide of the pandemic subsided, as the replacement of Vancouver's 99 B-Line – the most crowded bus corridor in North America pre-pandemic (Chan, 2022), with light rail is still years away from completion (Clement and Abelson, 2019). As such, this study will better equip TransLink and agencies alike in managing the demand for transit in a short run while growing ridership.

The remainder of the paper is structured as follows. We first discuss the relevant literature on transit crowding and the changes that the COVID-19 pandemic brought into the attitudes of transit riders. We then introduce the details of the study region, data, and methods used for the analysis. The main body of the paper is dedicated to the classification of survey respondents and evaluation of the choices they make in different crowding scenarios. We conclude with the policy implications of the study and guidance for future research.

2. Literature review

Satisfaction and loyalty to public transport users can be significantly impacted by transit crowding, as well as by travel time, level of service, and fares (de Oña and de Oña, 2015; dell'Olio et al., 2011; Eboli and Mazzulla, 2007; Haywood et al., 2017). An increase in public transport crowding makes the perceived travel time longer (Yap et al., 2020), and this relationship stays the same even after interventions, as riders value reduced crowding as high as shorter travel times (Li and Hensher, 2011). The three main negative aspects of crowding for riders are believed to be proximity to other people, inability to productively use time during the trip, and discontent with the inability to occupy a seat (Haywood et al., 2017). In this literature review, we summarize the main findings of transit crowding effects and change in riders' preferences during the COVID-19 pandemic while pointing out the necessity to evaluate preferences for population groups rather than average riders, increasing the reach of potential policy interventions.

2.1. Market segmentation in transportation

Until recently, segmentation of transport users has been primarily based on their access (or absence of) to specific modes (e.g. Wilson et al. (1984)), as well as their demographics (e.g. McLaughlin and Boyle (1997); Beimborn et al. (2003)). With the growth in understanding of the significant impact that preferences have on travel choices (Bohte et al., 2009), researchers introduced those factors in the classification of transport users as well. For example, van Lierop and El-Geneidy (2017a) used data on preferences and travel satisfaction of transit riders in Montreal, QC, and Vancouver, BC to better differentiate between those who used transit by choice and who had no other travel options, introducing the notion of a new class of users who decided to give up access to private vehicles by choice. While similar methodologically, Jacques et al. (2013) made an important contribution to the evolution of segmentation techniques in transportation by calling for non-deterministic classification approaches that account for the possibility of fluctuation between the classes. This paper takes that notion and applies probabilistic market segmentation of transit riders using their attitudes and demographics by estimating a probability of belonging to every class for every respondent, rather than assigning them to a single one deterministically. This makes classification more realistic and increases the potential for policy interventions to better engage different groups.

2.2. Public transit crowding effects

The operational measure of crowding lies within the relation between the physical limits of space and the number of people in it (Evans, 2001; Stokols, 1972). Nevertheless, research suggests that the term crowding is multifaceted, and its proper definition should go beyond the objective availability of space for a certain number of people but include the unmet subjective expectation of space for an individual (Cox et al., 2006; Stokols, 1972). That is why conceptually, the negative utility of crowding can be explained by the failure to control the level of privacy at the desired level (Evans and Wener, 2007). People use speech, emotions, and movement to regulate social interactions (Altman, 1975), and crowding takes place when that process is unable to reduce social engagement to the preferred level (Evans and Wener, 2007). Moreover, this experience of crowding has been found to cause emotional distress (Kaya and Erkíp, 1999).

In the context of public transportation, crowding can result in uneasiness (Cheng, 2010), exhaustion, and late arrival to work (Mohd Mahudin et al., 2012), as well as heightened concern for personal safety (Cox et al., 2006). Commuters who experienced the loss of privacy in a crowded transit vehicle can shift their travels to cars (Evans and Wener, 2007; Ibrahim, 2003; Joireman et al., 1997), while employers account for it when developing workers' schedules (Henderson, 1981). Given all of the above, many transit agencies change the definition of the "full capacity" of a vehicle at different times of the day (van Lierop and El-Geneidy, 2017c).

2.3. Public transit crowding and the COVID-19 pandemic

The challenges imposed by public transport crowding have become more acute during the COVID-19 pandemic, with the discomfort increasing in the absence of available seats (Aghabayk et al., 2021) and the presence of passengers without masks (Basnak et al., 2022). As one would expect, dissatisfaction with crowding increased in the midst of the pandemic (April 2021 and November 2021) compared to 2018 (Flügel and Hulleberg, 2022), however, it remained above the pre-pandemic level with the proliferation of vaccinations, effective treatments, and the removal of remaining restrictions (Cho and Park, 2021; Flügel and Hulleberg, 2022). It is only natural that the negative effect of the COVID-19 pandemic is visible not only in the heightened discomfort from transit congestion but also in the shift towards other modes, especially cars (Bucsky, 2020; Kapatsila et al., 2022; Vallejo-Borda et al., 2022). This trend has been also observed in the past, when people made changes to their transportation choices out of concern for personal health (Cahyanto et al., 2016; Floyd et al., 2000; Floyd et al., 2004; Lau et al., 2003; Lee et al., 2012; Leggat et al., 2010; Rubin et al., 2009). Unsurprisingly, public transportation became associated with a negative utility for commuters during the COVID-19 pandemic (Scorrano and Danielis, 2021).

Attitudes toward public transit crowding during the COVID-19 pandemic have been investigated with regard to different demographic characteristics. For example, Aghabayk et al. (2021) reported that men, youth, and frequent transit riders experienced lower levels of discomfort on transit during the COVID-19 pandemic. Similarly, Basnak et al. (2022) found women to be more concerned about the absence of masks on the riders who use public transport, while low-income and transit users below 30 years of age were less worried about crowding. These findings are useful when developing specific policy interventions aimed at retaining and returning commuters to transit, however, demographic characteristics have their limitations in explaining traveler's behavior. Other factors like social background, attitudes, and beliefs are also influential in transportation choices people make (Molander et al., 2012). Various market segmentation techniques allow one to account for those in evaluating travel behavior (Chou et al., 2014; Elmore-Yalch, 1998; van Lierop et al., 2018). Shelat et al. (2022) identified two classes of transit riders using a latent class choice model based on the decisions travelers make with regard to crowding and the degree of virus spread in the community, and labeled them as COVID Conscious Travelers and Infection Indifferent Travelers. The logic behind that classification was that crowding and infection rate had a lower negative impact on the choices of Infection Indifferent Travelers, who were also less likely to be women, and more likely to be younger and frequent riders (Shelat et al., 2022). Nevertheless, there are limitations to their approach since the classification in that study was hypothesized using the stated mode choices, and not estimated on the basis of respondents' preferences. At the same time, Vallejo-Borda et al. (2022) identified five latent variables (i.e. those that capture unobserved attitudes towards certain phenomena), namely COVID-19 impact (accounted for attitudes towards COVID-19), Entities response (captured attitudes towards authorities response), Health risk (represented opinion on personal and general health risks), Life-related activities comfort (a proxy for social interactions) and Subjective well-being (measured satisfaction with life), and tested their impact on modal preferences during the COVID-19 pandemic. They found that COVID-19 impact, Health risk, Life-related activities comfort, and Subjective well-being were positively associated with the shift from public transportation to private vehicles (Vallejo-Borda et al., 2022). Given that no classification was employed in that study, the use of the findings can be inhibited by the lack of generalizability to certain population groups that go beyond the demographics.

To address the limitations of the discussed literature, this study employs a classification of transit riders based on their attitudes and investigates their transport choices in response to crowding. By doing so, this research enriches the existing knowledge on the effects of the COVID-19 pandemic on transit users attitudes' and expectations towards safety and comfort onboard, and changes in transit ridership as a result of those. It also expands the growing body of literature on the effects of crowding on transport behavior in general. Finally, the findings provide guidance on how information on the choices of different behavioral classes can allow for public policy interventions to better facilitate transit use.

3. Data

The models developed in this study use data collected through the surveys conducted during the COVID-19 pandemic in December 2020 and May 2021. Both surveys used the same set of questions and were distributed to the panel of respondents by a marketing research company using hard age and gender quotas based on the estimates for Metro Vancouver. The sample was deliberately limited to adults who traveled for work or education using transit before the COVID-19 pandemic, to ensure that the attitudes and choices recorded in the survey represent those who had frequent experience with public transportation, resulting in 1,201 responses retained for the analysis. Not unexpectedly, out of those respondents, only 57.1% continued riding transit during the pandemic. Speaking of exogenous factors, it should be noted that authorities in Metro Vancouver announced stay-at-home orders synchronous to the rest of North American regions in March 2020, with a significant decrease in transit use and larger use of private vehicles that followed (Kapatsila et al., 2022). Nevertheless, no significant changes in government restrictions occurred between December 2020 and May 2021, though there was an overall decline in the number of new COVID-19 cases and hospitalizations from approximately 500 to 300 cases daily (British Columbia Provincial Health Services Authority & BC Centre for Disease Control, 2022). Moreover, no COVID-19 outbreaks were linked to transit use in Metro Vancouver.

3.1. Demographic and spatial representativeness of the study

The study region includes all the Vancouver Census Metropolitan area which is served by TransLink - the regional public transport agency. Metro Vancouver is home to almost 2.5 million people with a population density of 854.6 people per square kilometer, which makes it one of the most populous and concentrated parts of Canada (Statistics Canada, 2017). In the year preceding the COVID-19 pandemic, the region saw the highest transit ridership growth when compared to its North American counterparts, with many TransLink routes experiencing overcrowding daily (TransLink, 2019). The ten most overcrowded bus routes in 2019 were (in descending order) - 49, 99, 25, 41, 410, 319, 95, 100, 250, and 16, with the share of overcrowded annual hours being as high as 35% for route 49, and going down to 11% for route 16 (TransLink, 2020a). The study region with TransLink's light rail transit (LRT) lines and the 10 most overcrowded routes in 2019 are displayed in Fig. 1. There, it is easy to notice that the most congested bus routes in Metro Vancouver serve the City of Vancouver and its immediate suburbs, especially the campus of the University of British Columbia in the west, oftentimes overlapping with the LRT lines.

Inspection of Table 1 reveals that despite the imposed quotas set up in the sampling plan together with the survey panel company, there are discrepancies between the survey respondents' age groups and the population of Metro Vancouver as captured by the Statistics Canada 2016 Census. It is especially evident in the low representation of the 65+ age category, and significant overrepresentation in the 25–34, 35–44, and 45–54 age groups. At the same time, the shares of genders in the sample roughly match the Census data. It should be noted that the age disparity is most likely dictated by the focus on transit riders in this study, who are not a dominant group in the region. A little more than a fifth of commuters in Metro Vancouver traveled by public transport in 2016 (Statistics Canada, 2017), and it is valid to assume that they have a demographic profile slightly different from other residents of the region.

Our sample also lacks the representation of low-income people - those with individual earnings less than $50,000 annually, which given the high-cost living is a threshold used by local planning authorities (Metro Vancouver, 2016), made up 34.2% of residents in 2016, while their share in the study only comes down to 23.6%. Lastly, the overrepresentation of highly educated individuals in the sample should be mentioned. There are twice as many people with a bachelor's degree or higher among the survey respondents than there were in Metro Vancouver in 2016. The reason for this lies in the online nature of the survey, which traditionally limits the involvement of low-income and less-educated households (Jang and Vorderstrasse, 2019).

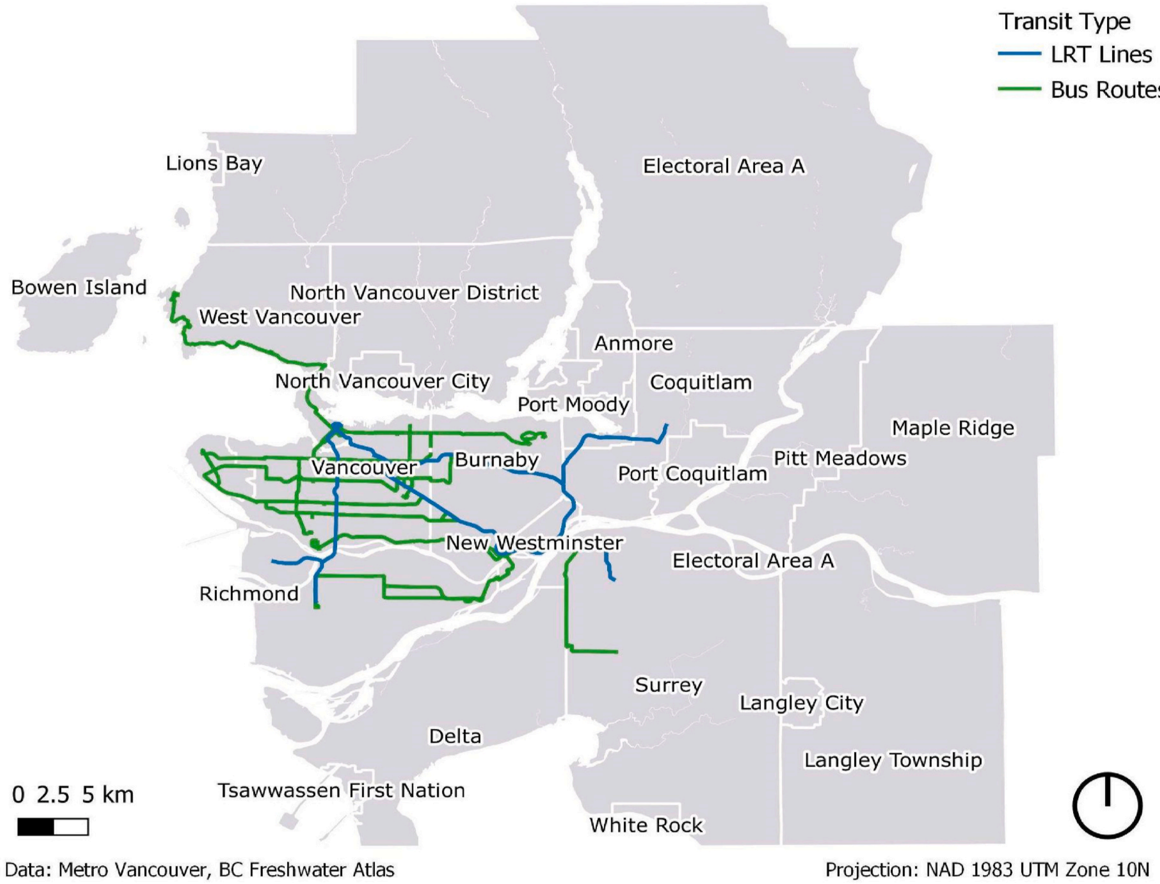

Fig. 1. Geography of the studied region, its LRT system and the 10 most overcrowded bus routes in 2019.

3.2. *Attitudinal statements*

Statements on attitudes towards safety, flexibility, crowding, transit use, and operator's response to the pandemic were recorded using 5-point Likert scales, both retrospectively (for the period preceding the pandemic) and capturing the sentiment during the pandemic. While the reliance on respondents' memory for the retrospective answers is a limitation of our study, we aimed to ensure their accuracy by limiting the sample to those who regularly commuted to work or education via transit, and likely could recall their preferences based on that established routine. Given the time constraints and pandemic-related limitations, the research team could not validate the attitudinal statements via additional focus groups and interviews, however, given their performance in the Principal Component Analysis (PCA) that met the expectations, that was not considered to be a concern. On the other hand, the internal consistency of the groups of attitudinal indicators was tested using Cronbach's alpha, producing values above 0.7 for each group, suggesting good reliability of the constructs (Cronbach, 1951). Summary statistics for the indicators retained for classification are provided in Table 2.

Our dependent variable for the analysis – respondents' degree of comfort with boarding a bus at different levels of crowding (low, medium, high) before and during the COVID-19 pandemic, was captured through a series of scenarios using illustrations presented in Fig. 2 and a 5-point Likert scale. Each respondent was presented with all crowding scenarios and evaluated their level of comfort for every case. Following the established practice, these levels of crowding were then translated into continuous variables as a ratio of passengers to the seating capacity of a bus (Altman, 1975), resulting in 13% for the low level of crowding, 69% for the medium, and 121% for the high level of crowding. These levels of occupancy go in line with the agency's passenger load standards (TransLink, 2018).

While the respondents could express their level of comfort using a 5-point Likert scale, they could also state that they would not board a bus (coded as 0). A series of dummy variables were also generated for the choice models. Using basic data transformations, the answers on the crowding comfort were recoded into a long format of 6 rows for each unique individual (3 levels of crowding times 2 time periods - before and during the COVID-19 pandemic), resulting in 7206 records in total. Summary statistics for the dependent variable used in the choice analysis are presented in Table 3. As it shows, responses follow intuition, with the level of comfort gradually going down as the crowding level increases for the period before the pandemic, and a more dramatic drop in satisfaction during the COVID-19 pandemic.

Demographic and non-demographic variables were iteratively tested in the estimated models and retained only if displayed statistical significance. Furthermore, we excluded the responses of those participants who spent less than 70% of the median response time on the survey (with the assumption that their input was more thought through) and obtained similar results in the estimation process. As such, the full sample of 1,201 respondents was used in the modeling process.

4. Methodology

This paper investigated the factors that affected the transport choices of different behavioral classes of transit riders before and during the COVID-19 pandemic. We first identified the behavioral classes of transit riders. We then modeled the attitudes of those classes towards boarding a crowded bus and the level of comfort when getting on a crowded bus if they choose to board it. As a result, the final joint model considered two outcomes separately - the probability of boarding a bus first, and then the stated level of comfort for the ones who indeed boarded the bus.

Table 1
Summary statistics of demographics.

		Respondents in the study sample	Vancouver CMA
N		1201	2,463,430
Gender	Female	50.9%	48.8%
	Male	49.1%	51.2%
Age	18–19	5%	N/A[a]
	20–24	9.8%	6.8%
	25–34	23.1%	14.7%
	35–44	19.5%	13.6%
	45–54	20.1%	15.3%
	55–64	14.7%	13.4%
	65+	7.8%	15.7%
Income	Less than $29,999	7.6%	19.0%
	$30,000 - $49,999	16%	15.2%
	$50,000 - $79,999	25.1%	20.3%
	$80,000 - $99,999	16.7%	10.8%
	$100,000 - $199,999	28.9%	26.5%
	More than $200,000	5.7%	8.1%
Highest education level	Elementary/grade school graduate	0.5%	13.9
	High school graduate	16.1%	28.6%
	College/tech./voc. school	21.8%	26.9%
	Undergraduate degree	40.6%	20.1%
	Prof. school (e.g. medicine)	5.1%	0.9%
	Post-graduate (e.g. Ms.)	15.9%	9.6%
Employment type	Fully employed (30+ h/w)	59.4%	31.9%
	Partly employed (1–30 h/w)	14.7%	35.9%
	Post-secondary student	8.5%	N/A[b]
	Contract employee	2.7%	
	Homemaker/Stay-at-home	1.3%	
	Other	2.5%	
	Permanently disabled	0.3%	
	(Temporarily) unemployed	6.2%	
	Retired	4.4%	
Household size	1	18.3%	28.7%
	2–4	71.5%	61.6%
	5 and more	10.2%	9.7%
Number of children	No children	66.1%	N/A[c]
	1	19.6%	
	2 and more	14.3%	

[a] 2016 Census has information for the 15–19 age group that accounts for 5.8% of Metro Vancouver population.
[b] 2016 Census has information only on full-time and part-time employment for those who worked a full year.
[c] 2016 Census has information on couples and children in Metro Vancouver (45.3% without children, 22.5% with 1 child, 32.2% with 2 and more children), and lone parents with children (64% with 1 child, and 36% with 2 and more children).

The behavioral classification was conducted based on unobserved latent variables (LV) using the methodology proposed by Bahamonde-Birke and Ortúzar (2020). This approach is grounded in the Hybrid Choice Model (HCM) framework (Ben-Akiva et al., 2002), and estimates latent classes (LC) using unobserved attitudinal traits. Within this framework, observed characteristics of individuals, like their demographics, affect the likelihood of exhibiting their underlying traits, leading to the likelihood of association with a certain behavioral class (Bahamonde-Birke and Ortúzar, 2020). While the main advantage of this approach is that it does not introduce new error terms, its main limitation is the absence of a closed-form solution and the necessity to perform estimation via simulation, which is something common to all approaches based on HCM framework (Ben-Akiva et al., 2002; Bierlaire, 2003). To the best of the authors knowledge, there have been no other studies (aside from the initial formulation in Bahamonde-Birke and Ortúzar (2020)) that combined HCM and LC frameworks without introducing additional error terms. Walker and Ben-Akiva (2002) indicated this as a possibility, but did not implement it empirically, while Hess et al. (2013) and Motoaki and Daziano (2015) used the latent variable latent class (LVLC) approach.

Table 2
Summary statistics of latent class attitudinal statements.

Indicator	Average	SD
LV1: Concerned		
Prior to the pandemic I felt concerned for my personal safety aboard crowded transit vehicles	3.06	1.39
Prior to the pandemic I was bothered by the crowding which I experienced on transit	3.76	1.2
Prior to the pandemic I needed a seat to feel comfortable onboard transit	3.19	1.35
Prior to the pandemic, if traveling at morning or afternoon peak time, I chose to take an alternative to transit (i.e. Mobi bike, walk, Uber, Lyft, Evo etc.)	2.45	1.42
Prior to the pandemic I chose to travel at off-peak (less busy) hours to avoid crowding on transit	3.17	1.35
I am concerned that the health measures put in place by TransLink are not sufficient or will not be followed on public transit	3.56	1.15
LV2: Flexible		
Flexible in time to travel to work via public transit	2.39	1.4
Flexible in time to travel from work via public transit	2.92	1.47

Following the assumption that individuals can be characterized using unobserved LVs, we model a given LV η_q for a respondent q using a structural equation of the following form:

$$\eta_q = X_q \bullet \alpha_X + \upsilon_q \tag{1}$$

where X_q captures observed characteristics of a given respondent, α_X represents a vector of parameters to be estimated, while υ_q is an error term that has a distribution considered according to the theoretical framework for the model.

Observed variability in the collected attitudinal indicators is assumed to be captured via unobserved LVs (Bollen, 1989). Furthermore, it is assumed that some of those indicators are a direct expression of the underlying LVs. Using linear specification, an indicator I for a directly expressed LV can be introduced as:

$$I_q = X_q \bullet \gamma_X + \eta_q \bullet \gamma_\eta + \varsigma_q \tag{2}$$

where ς_q is an error term that has a distribution with a mean of zero, while γ_X and γ_η are the estimated parameters. Indicators that are gathered using answers on a Likert scale allow for the use of the Ordinal Logit (OL) specification that has a Logistic distribution with a mean of zero and produces thresholds for each level that have to be crossed to obtain the value on the observed answer. This leads to a probability of observing a given indicator n taking the following form:

$$P(I_{qn}) = \frac{e^{\mu_{n,I_{qn}} - \varsigma_{I_n}\eta_q}}{1 + e^{\mu_{n,I_{qn}} - \varsigma_{I_n}\eta_q}} - \frac{e^{\mu_{n,I_{qn}-1} - \varsigma_{I_n}\eta_q}}{1 + e^{\mu_{n,I_{qn}-1} - \varsigma_{I_n}\eta_q}} \tag{3}$$

where $\mu_{n,I_{qn}}$ is the parameter to be estimated, and ς_{I_k} captures the effect of the LV η_q on the given indicator.

We consider indicators that are left to be an expression of unobserved LCs, which, in turn, are also explained by the underlying LVs. This means that while all indicators are influenced by the underlying attitudinal traits, some of those experiences this impact continuously, while for the others it has a discrete nature of falling into one of the LCs. These LCs group individuals with similar scores in underlying LVs, resulting in the probability of belonging to every LCs for each individual:

$$P_{qk} = P(\psi_B < \eta_q < \psi_T | X_q, \alpha, \Sigma_\eta) \tag{4}$$

$$P_{qk} = P(X_q \bullet \alpha_X + \upsilon_q < \psi_T) - P(X_q \bullet \alpha_X + \upsilon_q < \psi_B)$$

Fig. 2. Levels of crowding (low, medium, high) visualization used in the survey.

Table 3
Summary statistics of comfort to board a bus.

Time/Crowding	Low Crowding		Medium Crowding		High Crowding	
	Average	SD	Average	SD	Average	SD
Before COVID-19	4.53	1.02	3.62	1.40	2.87	1.59
During COVID-19	3.49	1.60	1.42	148	0.91	1.39

where ψ_B is the bottom class threshold and ψ_T is the top one that the LV has to cross to produce the individual probability. Although this study used one LV for each class, the approach also allows for the classification to be performed using the combination of two LVs.

The last element of the classification component is an indicator D that is believed to be a direct expression of an LC and is assumed to take the form of a latent class-specific utility function:

$$U_q = X_q \bullet \beta_{Xc} + \varepsilon_q \tag{5}$$

where β_{Xc} is a vector of estimated latent class-specific parameters, and ε_q is an error term with an assumed i.i.d. EV1 distribution with a mean of zero.

The probability of boarding a bus B^p, is modeled by means of a Binary Logit (BL) model, whose parameters are latent-class specific. Whether a person boarded a bus or not is captured by the exponent p that is equal to zero if a person did not get onboard and one otherwise. Provided that an individual boarded the bus, their stated level of comfort C is modeled using the OL specification, with latent-class specific parameters. As a result, the joint likelihood function to be maximized is comprised of a summation over all different latent classes of the joint probability of boarding the bus (BL), stating a given level of comfort (OL), stating the indicators considered as an expression of the LC (OL), and the probability of belonging to the aforementioned LC (OL). Outside the summation we consider the probability of observing the measurement indicators considered as continuous expressions of the LVs and the distribution of the latent variables over whose domain the whole function is integrated over:

$$L_q = \int_\eta \left[\sum_k \begin{matrix} P\left(B_q^p \middle| X_q; \alpha, \beta_b, \Sigma_U, \Sigma_\eta\right) \bullet P\left(C_q \middle| X_q; \alpha, \beta_l, \Sigma_U, \Sigma_\eta\right) \bullet \\ P\left(D_q \middle| \alpha, \beta_k, \Sigma_U, \Sigma_\eta\right) \bullet P\left(k \middle| X_q, \alpha, \Sigma_\eta\right) \end{matrix} \right] \\ P\left(I_q \middle| X_q, \eta_q; \alpha, \gamma, \Sigma_I, \Sigma_\eta\right) \bullet f\left(\eta_q \middle| X_q, \alpha, \Sigma_\eta\right) \bullet d\eta \tag{6}$$

In the absence of a closed-form solution for (6), LV η_q is identified via simulation which leads to discontinuity in equation (4) and may result in the algorithm failing to converge and identify the thresholds (Bahamonde-Birke and Ortúzar, 2020). This is remediated through the introduction of an auxiliary LV η_q^a that is specified exactly the same as LV η_q, and also follows an i.i.d. Logistic distribution with a mean of zero. This allows for equation (4) to have a closed-form expression (i.e. an Ordered Logit probability kernel), and avoid discontinuity when integrating (6) numerically.

Data privacy regulations prohibited the use of cloud computing services, which combined with the absence of access to a supercomputer for the research team introduced computational constraints for model estimation. As a result, a sequential estimation approach was used, hence, Equation (6) was first maximized by keeping the first two elements inside the summation constant, and then it was maximized again by keeping the previously estimated parameters fixed and varying the parameters of the first two elements only. While it may have led to losses in statistical efficiency, the results remained unbiased as the latent classes were computed by integrating over their entire domain. Given that crowding may be perceived more negatively in longer trips, interaction terms between travel time for commuting and crowding level were considered but were not found to be statistically significant. Similarly, adding random disturbances to the perception of crowding did not lead to meaningful results This is likely the outcome of the scenario-based data collection approach that did not capture the influence of trip time on the utility of crowding. Collecting this information through the revealed behavior means (e.g. GPS tracking) would likely provide more insights, though we would not expect a change in overall trends. We also tested the effect of the scale parameter between the waves, which was estimated to be 0.9 for the bus boarding model and 1.1 for the level of comfort model, suggesting no need for that small difference to be accounted for. Estimation was performed using the Apollo package (Hess and Palma, 2019) in the R statistical software (R Core Team, 2013) using maximum simulated likelihood with 1000 Sobol draws (Sobol', 1967) approximating the integration distribution. Multiple starting values were tested in the estimation process to prevent the use of the results that came out of convergence at a local optimum.

5. Findings

This study identified behavioral classes of transit riders in Metro Vancouver and evaluated their transport behavior when faced with crowded buses. The modeling process was performed in two stages. We first identified the underlying associations between the attitudinal statements using PCA. These findings were then used to specify the classification model based on the HCM framework. In the second stage, individual class allocation probabilities were used in the estimation of a joint choice model that evaluated the likelihood of boarding a bus for all respondents in the sample and the level of comfort when boarding a bus for those who did that. The complete framework of the analysis is schematically represented in Fig. 3 and the findings of each stage of the analysis are reported in the respective sections below. The sequential estimation approach was selected to provide savings in computation time and allow for more flexibility in selecting the best model fit.

5.1. Classification model

Performing PCA identified four potential LVs that captured 41.2% of the variance (Chi-square statistic 257.8 on 41 degrees of freedom, p-

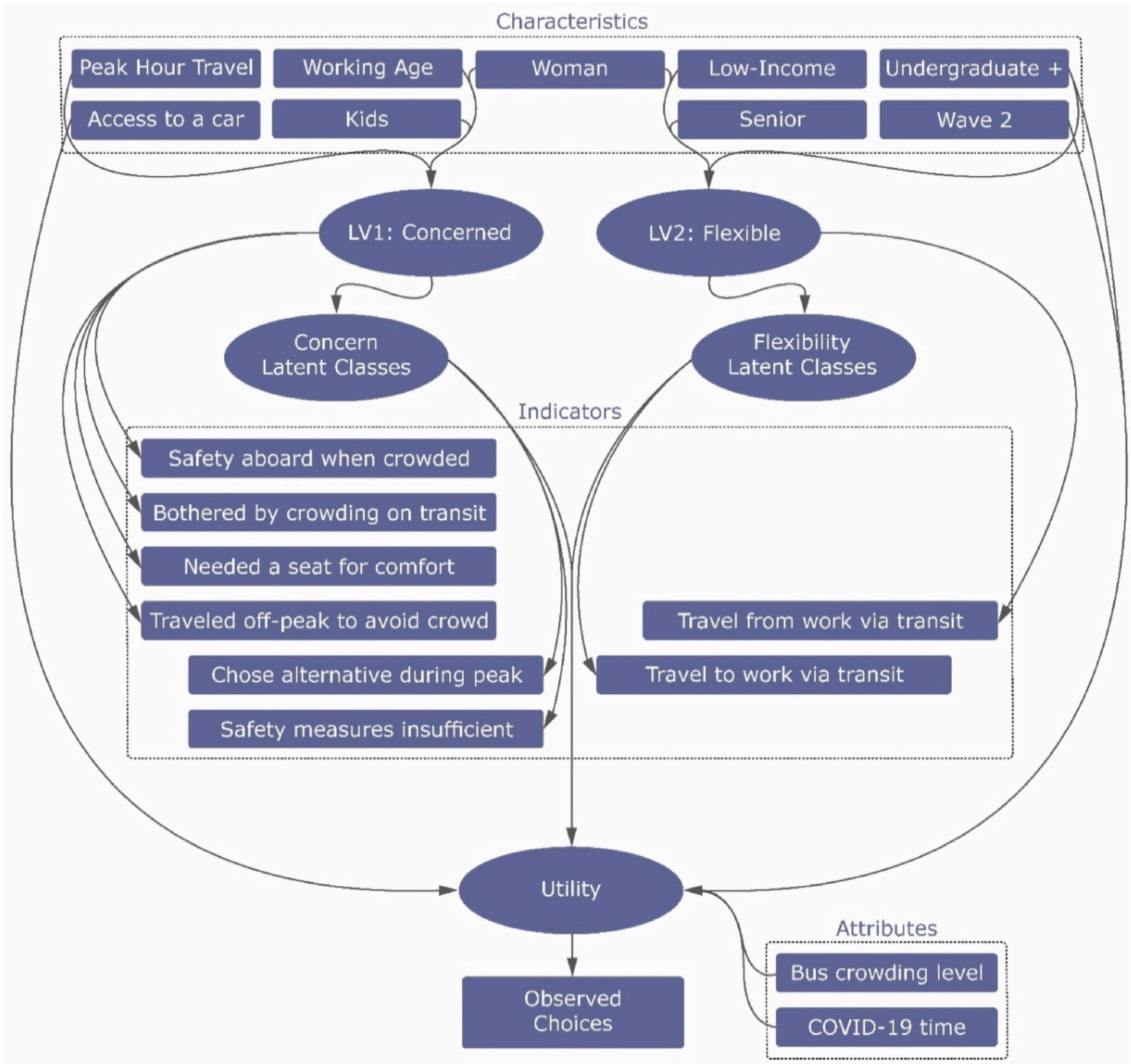

Fig. 3. Diagrammatic representation of the model.

value = 0), and in line with existing practice (Hair et al., 1995) only indicators that had loadings larger than 0.3 were retained for further analysis. The full results of the PCA analysis are presented in Appendix A. Furthermore, two of the identified LVs, named tech-savvy and transit-friendly, were found to be unsuitable for categorization as their continuous representation showed superior log-likelihood, while classes were discernible only between the majority of respondents and extreme cases in the categorical treatment of those LVs. As a result, the final classification was performed using the remaining two LVs - LV1 concerned (sum of squared loadings 1.9), which encompasses respondents' sentiment regarding crowding, and LV2 flexible (sum of squared loadings 1.4) that captured the riders' flexibility when commuting to and from work or education. Using the iterative estimation process, the indicators Chose alternative during peak, and Safety measures insufficient were selected as an expression of LCs for LV1 concerned, where Safety aboard when crowded, Bothered by crowding on transit, Needed a seat for comfort, and Traveling off-peak to avoid crowding indicators were used in a direct manner. Similarly, the indicator Travel to work via transit was employed as an expression of the LCs for LV2 flexible, and the Travel from work indicator was considered as a direct manifestation of LV2 flexible. Based on the log-likelihood for every LV, three LCs were selected as optimal for LV1 concerned (low concern, medium concern, and high concern), and two for LV2 flexible (low flexibility, high flexibility). Measurement equations for every indicator were specified using Ordered Logit, and only demographic variables that were statistically significant were retained for the final estimation of structural equations. The results of this stage of the modeling process are presented in Table 4.

In the process of classification, several demographic variables were found to impact LV1 concerned. As estimates suggest, women and members of households with kids seem to show higher concern for crowding and safety on transit, which goes along the lines of existing research for the former (Ouali et al., 2020a; Shelat et al., 2022) and the latter groups (McCarthy et al., 2017). This is of no surprise, as women tend to be more cautious of transit in general, potentially due to the assaults and harassment that happened there (Börjesson and Rubensson, 2019; Ouali et al., 2020b). Similarly, riders of a working age, which is a label applied to the 25–44 age group cohort in this study, are also more concerned about crowding and safety on public transportation. It is possible that the inability to work while commuting on crowded transit, as well as a potential decrease in reliability (e.g. due to longer boarding times), raised concern for that group (Haywood et al., 2017). Only one sociodemographic variable indicated the negative impact on being concerned about the safety and crowding on transit - morning peak travelers. It suggests that those traveling between 6 a.m. and 9 a.m. in Metro Vancouver most likely experience crowding more often than the

Table 4
Structural and measurement equations estimates of classification model.

Variable	Equation	Estimate	SD	t-stat.
Woman	S.E. LV1: Concerned	0.314	0.127	2.477
Work age		0.277	0.118	2.344
Has kids		0.479	0.132	3.621
Morning peak traveler		−0.255	0.123	−2.078
Threshold 1.1	LV1 Classification	−1.624	0.494	–
Threshold 1.2		0.551	0.385	–
Woman	S.E. LV2: Flexible	−0.509	0.139	−3.662
Low-income		0.296	0.148	2.004
Senior		−0.705	0.236	−2.987
Undergraduate degree +		0.424	0.129	3.281
Threshold 2.1	LV2 Classification	−0.068	0.198	–
LVs correlation term	S.E. LV1 & S.E. LV2	1.255	0.088	14.215
Threshold 1	M.E. Safety aboard when crowded	−2.537	0.218	–
Threshold 2		−0.625	0.169	–
Threshold 3		1.084	0.183	–
Threshold 4		2.710	0.238	–
Threshold 1	M.E. Bothered by crowding on transit	−3.663	0.193	–
Threshold 2		−2.079	0.136	–
Threshold 3		−0.437	0.113	–
Threshold 4		1.008	0.119	–
Threshold 1	M.E. Needed a seat for comfort	−2.024	0.121	–
Threshold 2		−0.833	0.102	–
Threshold 3		0.489	0.100	–
Threshold 4		1.778	0.116	–
ASC Class Low & Medium	M.E. Chose alternative during peak	−0.621	0.310	−2.002
ASC Class High		3.839	0.744	5.157
Threshold 1		0	–	–
Threshold 2		1.783	0.410	–
Threshold 3		3.571	0.595	–
Threshold 4		4.801	0.650	–
Threshold 1	M.E. Traveled off-peak to avoid crowd	−1.871	0.109	–
Threshold 2		−0.811	0.091	–
Threshold 3		0.384	0.088	–
Threshold 4		1.740	0.104	–
ASC Class Low	M.E. Safety measures insufficient	1.156	0.422	2.741
ASC Class Medium & High		4.301	0.506	8.503
Threshold 1		0	–	–
Threshold 2		1.715	0.284	–
Threshold 3		3.686	0.487	–
Threshold 4		5.116	0.504	–
ASC Class Low	M.E. Travel to work via transit	−1.361	0.314	−4.341
ASC Class High		8.417	13.498	0.624
Threshold 1		0	–	–
Threshold 2		6.997	13.507	–
Threshold 3		8.578	13.505	–
Threshold 4		9.612	13.504	–
Threshold 1	M.E. Travel from work via transit	−1.927	0.453	–
Threshold 2		−0.664	0.215	–
Threshold 3		0.967	0.291	–
Threshold 4		2.534	0.613	–

Notes: Given the nature of the Ordered Logit model and thresholds, t-tests against zero are not relevant; First thresholds of categorical indicators were fixed to avoid correlation with constants.

others and have a higher tolerance for it, something that psychologists define as an exposure effect. Past research has indicated that the definition of crowding should not be static and should change for different times of the day (van Lierop and El-Geneidy, 2017b), and this study provides another argument for that.

When it comes to the second set of LCs based on LV2 flexible, we see that women and seniors are less likely to be flexible in their traveling. We hypothesize that for women this can be explained by their higher share of caregiving responsibilities without flexible starting and finishing times (i.e. school hours, care-related appointments, etc.) (Golob and McNally, 1997; Lang, 1992; Primerano et al., 2008; Root et al., 2000) and tendency toward part-time employment (Patterson, 2018) that impedes their flexibility when it comes to commuting via transit. As for seniors, this lack of flexibility is likely the result of low digital skills to plan more flexibly for travels or the fixed scheduling of appointments they go to (e.g. medical check-ups). On the contrary, low-income and highly educated riders (those with an undergraduate degree, or higher) seem to possess high flexibility in traveling. While it is to be expected for individuals with university degrees (Alexander et al., 2010), it comes as a surprise for low-income riders. We believe that the latter is the result of the sample composition, where highly educated individuals (with a college or professional school degree (like medicine) and higher) represent two-thirds of the respondents, compared to only a third that there is in Metro Vancouver. These individuals with advanced degrees account for about half of the low-income respondents in our sample, which is way over their share in the region, and most likely influence the observed effect on the flexibility LV. There are also more students among low-income respondents in our sample than in the region, which together with other characteristics formed a category of individuals with variable schedules or young professionals at the beginning of their career ladder who have relatively low incomes, but high flexibility based on their skills.

This stage of the research culminated with the calculation of posterior cross probabilities for each of the six identified classes (low concern, low flexibility class; low concern, high flexibility class; medium concern, low flexibility class; medium concern, high flexibility class; high concern, low flexibility class; high concern, high flexibility class) for every respondent via generating 10,000 random error terms and integrating over the entire domain. The average class allocation probabilities are presented in Table 5.

These classes are an important finding on their own, as they provide avenues to engage different groups of riders with marketing campaigns based on their attitudes towards crowding that intend to influence travel behavior. For example, classes that are more sensitive about crowding can be targeted with dedicated messaging on how alternative routes are less crowded, while those who are more flexible can be nudged or incentivized to travel at off-peak times. The next section of the study supplements these findings with the knowledge of the actions riders from different classes take in response to crowding.

5.2. Choice models

Two models were estimated jointly by looking at the utilities for the six latent classes identified above (low concern, low flexibility class; low concern, high flexibility class; medium concern, low flexibility class; medium concern, high flexibility class; high concern, low flexibility class; high concern, high flexibility class). The first one evaluated the likelihood of boarding a bus, where a response expressing any level of comfort (from very uncomfortable to very comfortable) was considered to be a decision to board the bus, while the respondents who stated that they would not board a bus were excluded from the second model that evaluated the comfort of boarding the bus. The decision to evaluate the

Table 5
Average latent class allocation probabilities.

Latent Class		Average Allocation Probability
Concern	Flexibility	
Low	Low	12.97%
	High	6.26%
Medium	Low	19.77%
	High	16.99%
High	Low	15.91%
	High	28.11%

data using two models was based on the violation of the proportional odds assumption by the single model that would evaluate the choice of not bordering a crowded bus and the level of comfort when bordering it. We assume that there is a difference between the decision to not board a bus and feeling even the lowest level of comfort of boarding the bus, so the two choice models were estimated simultaneously. Given the binary nature of the Bus boarding model, and the ordinal responses of the Level comfort model, BL and OL specifications were selected respectively.

Prior to diving into the estimation results of the choice models presented in Table 6 and it is worthwhile to discuss the final specification of the models. We investigated class-specific estimators for the constants, crowding level, the effect of the COVID-19 pandemic, the interaction between the crowding level and the pandemic, as well as the second wave of the survey, hypothesizing that utilities might be significantly different between various latent classes for these variables. We observed the best Bus boarding model performance when specified constants, and crowding levels during the pandemic to be different for combined classes of low and medium concern (including both low and high flexibility), and high concern (that also include low and high flexibility classes). The crowding level, the effect of the COVID-19 pandemic, and the wave were kept generic across all classes. This suggests that attitudes towards flexibility likely did not play any significant role in the decision to board a crowded bus, given that in the scenario the rider was already committed to making the trip. On the other hand, the finding that there is a difference in perception of crowding between various latent classes only during the pandemic goes in hand with the Transit app survey that highlighted the increase in concern due to crowding during the COVID-19 spread (Transit, 2020). In other words, only during the pandemic, those who were the most concerned for personal safety and health started making choices differently from the others.

The Level of comfort model displays an opposite trend in terms of the latent class specification. There is no difference between the utility of different latent classes during the pandemic, but it exists prior to it. This is most likely the result of a smaller subsample of users who considered boarding a crowded bus during the pandemic (thus providing a response on the level of comfort), and since those who were most concerned stayed away from it, the variability for the estimate of crowding during the COVID-19 pandemic was negligible. In addition, we observe a difference in the effect of the second wave between low and high flexibility classes (both low and high concern). Combined with the opposite signs for the utility of these classes, it can be explained as the result of flexible riders using transit when they can be more comfortable, unlike those who do not have that flexibility, thus feeling less at ease.

Looking at Table 6, the Bus boarding model provides estimates that follow the intuition. Riders who are more concerned with crowding are less likely to board a bus in general, and this remains true with the increase in the level of crowding during the COVID-19 pandemic. The general effect of the increase in bus occupancy and the pandemic is uniform across all classes and decreases the likelihood of boarding a bus. On the other hand, by looking at the second wave of the survey estimate, we see that compared to December 2020, riders were more likely to board a bus in May 2021. This comes as no surprise since at the end of 2020, the Province of British Columbia was having more than 500 new COVID-19 cases daily, while at the beginning of the summer of 2021 there were fewer than 300 daily instances with a downward trend (British Columbia Provincial Health Services Authority & BC Centre for Disease Control, 2022). It is also likely that the uptake in immunization played its role - by mid-May 2021 about 50% of eligible British Columbia residents received their first doses of the vaccine (BC Office of the Premier, 2021).

We also see that educated individuals and those that have kids are generally more likely to board a bus. The former is to be expected in the context of Metro Vancouver, where office jobs are located downtown, and individuals with a bachelor's degree or higher are likely to hold those. Driving there is complicated due to high congestion in the City of Vancouver (TomTom, 2021) and scarcity of parking (Canseco, 2018),

Table 6
Estimates of a combined choice model.

	Variable	Estimate	SD	t-stat.
Bus boarding model	Low-Med Concern Class constant	8.353	0.617	13.535
	High Concern Class constant	4.582	0.348	13.160
	Crowding level	−2.174	0.271	−8.024
	COVID-19	−2.039	0.314	−6.493
	Second wave of the survey	0.246	0.134	1.833
	Low-Med Concern Class Crowding level * COVID-19	−1.913	0.480	−3.982
	High Concern Class Crowding level * COVID-19	−3.031	0.403	−7.518
	Undergraduate degree or higher	0.439	0.139	3.166
	Has children	0.485	0.150	3.229
	Has access to a car	−0.993	0.209	−4.753
Level of comfort model	Constant	0	–	–
	Low-Med Concern Classes Crowding level	−1.366	0.099	−13.795
	High Concern Classes Crowding level	−4.153	0.121	−34.381
	COVID-19	−1.684	0.096	−17.552
	Low Flexibility Classes Second wave of the survey	−1.040	0.089	−11.629
	High Flexibility Classes Second wave of the survey	1.196	0.098	12.190
	Crowding level * COVID-19	−0.705	0.136	−5.197
	Has access to a car	−0.170	0.084	−2.029
	Threshold 1	−4.999	0.122	–
	Threshold 2	−3.858	0.114	–
	Threshold 3	−2.669	0.107	–
	Threshold 4	−1.538	0.102	–

Bus boarding model number of observations: 7206
Level of comfort model number of observations: 5849
Number of parameters: 21
Log-likelihood of the whole model: −9765.04

Notes: Given the nature of the Ordered Logit model and thresholds, t-tests against zero are not relevant; The constant for the level of boarding comfort was fixed at 0 to avoid correlation with the first threshold.

facilitating the use of public transportation. On the other hand, we also know from the previous research that families with kids are more likely to drive than use public transport (Kløckner, 2004; Lanzendorf, 2010; Prillwitz et al., 2006; Westman et al., 2017), so the observed propensity to board a bus by an individual who has kids is an unexpected discovery of this study. It is possible that this is a regional phenomenon, as documented in a qualitative study that captured Vancouver parents' conscious effort to drive less and use sustainable modes more (McLaren, 2018). At the same time, this goes in hand with the city's brand of being a sustainable transport leader in Canada and the US (Siemiatycki et al., 2016).

Lastly, the ability to access a car has a negative impact on the individual's likelihood to board a bus - something that follows the findings of the previous studies as well (Blumenberg and Pierce, 2012; Boisjoly et al., 2018; Clark, 2017; Manville et al., 2022), as well as emerging literature on travel preferences during the COVID-19 pandemic (Abdullah et al., 2020).

The estimates for the Level of comfort model display the same trends as the Bus boarding model. We see that members of all latent classes are less likely to feel comfortable as the crowding level onboard increases, however, the disutility of riders in the high concern classes (with both low and high flexibility) is significantly larger. Similarly, all latent classes were less likely to feel comfortable during the COVID-19 pandemic, especially on the crowded bus. As expected, we also observed the negative effect of access to a car on the overall feeling of comfort onboard for a rider.

Overall, the estimated choice models were successful at providing results that follow common sense in terms of riders' behavior with the increase of crowding during the pandemic. They also point out the equity concerns that arise from the negative effect of access to a car and inflexibility to travel on the feeling of comfort onboard. They suggest that being a captive rider, i.e. not having other transport mode or travel time alternatives due to income, schedule, or other limitations, forces some transit riders to take a bus despite the concern they feel.

6. Discussion

This paper evaluated the effect of bus crowding on the likelihood to board a bus and feeling comfortable onboard before and during the COVID-19 pandemic among the behavioral classes of transit riders in Metro Vancouver. The study adds evidence to the growing body of literature on the increased sensitivity to transit crowding among transit users due to the COVID-19 pandemic (Drabicki et al., 2023; Flügel and Hulleberg, 2022; Shelat et al., 2022) and accurately defines the behavioral classes to target with policy interventions. Average class allocation probabilities for the identified classes offer transit agencies the basis for the development of potential demand management measures, though their effects on the specific groups will have to be evaluated. For example, the high flexibility, high concern class has the highest potential membership of 28.11% which means that for about a third of respondents even the provision of crowding information via smartphones (something trip planning applications like Transit already provide in selected cities), on-station announcements (both visual and audio), or promotion of other transit routes alternative to the most crowded links of the system may influence their choice to travel at a less crowded time or route. Existing research offers support for this hypothesis. An experiment at the Stockholm subway station communicated information about crowding levels of the incoming train cars to evenly redistribute passengers aiming to board it, and its evaluation found a 4% decrease in the number of riders who entered the first two cars of the train (Zhang et al., 2017). On the other hand, classes with similarly high flexibility but medium (average probability of 16.99%) and low (average probability of 6.26%) concerns may be engaged with an incentive program that would offer an increase in their utility for avoiding traveling at peak crowding levels. These incentives can take the form of simple fare discounts, however, an introduction of gamification elements may further facilitate their effect, as it was reported for the reward points that riders could earn in exchange for their travel at off-peak times and later exchange for prizes in the Incentives for Singapore Commuters (INSINC) program administered by Singapore Land Transport Authority (Fwa, 2016). At least in the context of rail transit, such incentive programs were found to be a cost-effective intervention that provides savings larger than the revenue they foregone (Currie, 2009; Yang and Lim, 2017). The suggested measures could be tailored to the groups we identified and the agencies could explicitly assess how they would perform for those groups, which would substantially reduce the implementation costs when considering many alternatives.

Further insights can be gained from investigating the changes in perceptions of crowding. The level of crowding is the only continuous variable in our model, so we can calculate a marginal rate of substitution captured as an increase in crowding that different categories of respondents would on average tolerate and still board a bus. For the pre-COVID-19 scenario, we see that a person who has kids would endure additional 22 percentage points of crowding and still board the bus compared to those without children, while that goes down to 12 percentage points for low and medium concern classes, and to just 9 percentage points for high concern class during the pandemic. On the other hand, under normal conditions, a person with access to a car would be unwilling to accept a crowding level increase of 46 percentage points (unlike those without a vehicle) to board a bus, while the difference shrinks to 24 percentage points for low and medium concern classes, and to just 19 percentage points for the high concern class in the context of COVID-19. This effect of crowding can be illustrated further with elasticities. We observe that pre-COVID-19 the crowding elasticity of the probability of boarding the bus is inelastic for larger probabilities and elastic for small probabilities. During the COVID-19 pandemic, the demand elasticity of crowding increased, doubling for low and medium concern classes and getting 150% higher for highly concerned individuals. For instance, for an initial boarding probability of 0.1 and a medium level of crowding (69%) the demand is elastic ($E_{P,Cr} = -1.35$), while for a boarding probability of 0.4 and the same level of crowding the demand is inelastic ($E_{P,Cr} = -0.9$). On the other hand, using the same assumptions but during the COVID-19 pandemic the crowding elasticity becomes elastic for both the low and medium concern classes ($E_{P,Cr} = -1.69$), as well as for the high concern class ($E_{P,Cr} = -2.15$).[1]

The observed differences or absence of those between the estimates for different classes also provide guidance for nuanced policy interventions. Our models show that attitudes towards flexibility (as captured by the respective latent classes) do not affect the likelihood of boarding a bus, neither before nor during the COVID-19 pandemic, but there is a difference between classes of low and high flexibility in the feeling of comfort during the second wave of the survey (May 2021). The finding that riders with high flexibility were more likely to feel comfortable onboard means that some riders were likely to change their behavior and reduce demand for transit services during peak times. As Table 5 suggests, this could be a substantial portion of riders, as more than half of the respondents are likely to belong to a flexible behavioral class (with no regard to the level of concern). It is possible that the considerable size of that class emerged as a result of an increase in remote work opportunities and more relaxed office attendance policies by employers (Duxbury and Halinski, 2021), and given the societal benefit, it should be encouraged among the employers by transit agencies as it is likely to keep more space available for those who do not have that flexibility. Direct communication and engagement of employers are necessary to both educate and persuade companies and institutions to preserve or allow for less rigid work schedules. Employers operating in the fields and with organizational structures that allow selective office attendance (i.e. only during some days of the week) or fluid work hours should be encouraged to do so, while those that depend on the simultaneous presence of their workers should consider staggering the hours of employment to allow for the people commuting by public transport to travel outside of the peak hour time. Staggering work schedules for 400 companies with 220,000 employees proved to be effective in reducing transit congestion in New York in the 1970s, as it drove demand down by 26% at the three busiest transit stations between 9:00 and 9:15 a.m. (O'Malley, 1974). Part of the success of the program should be attributed to the engagement of companies' workers in the selection of new work schedules, which resulted in increased satisfaction from the commute for almost 50% of the surveyed, while only 10% were less satisfied (O'Malley, 1974). Obviously, allowing employees to be flexible in their commute does not guarantee their willingness or ability to choose the socially optimal time to do so, however that can be further affected with appropriate pricing schemes, like pre- or post-peak hour discounts or incentives, tested and proved to be effective in Singapore, Hong Kong, Sydney, and San Francisco (Currie, 2009; Greene-Roesel et al., 2018; Halvorsen et al., 2016; Pluntke and Prabhakar, 2013). Overall, it should be expected that effective crowding management on transit is rooted in collaboration between employers and transit providers.

The generic increase in the likelihood of boarding a bus in May 2021 highlights the impact of exogenous factors on the likelihood of using transit during the pandemic. This coincided with the drop in daily COVID-19 cases and vaccination of around half of the eligible population, suggesting the importance of sustained governmental response and proper communication to encourage more people to use public transportation. Primarily, this concerns extreme events like the COVID-19 pandemic, as studies reported that riders who were better informed

[1] Elasticities are computed on the basis of $E_{P,X} = \beta * X * (1-P)$ (Ortúzar and Willumsen, 2011).

about the agency's safety measures on transit were more likely to feel safer onboard (Kapatsila and Grise, 2021). However, this can be translated into regular times as well. Designing informational campaigns on the successes in reducing congestion, disarray, or crime on transit is likely to increase the appeal of public transportation and bring more riders to it.

Lastly, this study underscores the importance of ensuring the feeling of comfort and safety for the riders who have access to other modes of transportation like cars. It is an absolute equity concern during the extreme event, as those dependent on public transportation have to ride it even if they feel distressed, so it is recommended that transit agencies maintain rainy day budgets to provide a response to the next pandemic or another extreme event in the way that ensures the health and safety of its riders. On the other hand, it also highlights how easily an agency can lose riders due to crowding, and the need to implement policy interventions that manage crowding on public transportation. It is recommended that more agencies implement the sharing of crowding levels with the users via screens at stops and smartphones, incentives that nudge riders with the flexibility of travel to take advantage of it and travel at off-peak times and collaborate with employers to introduce the staggering of work schedules and broader adoption of remote work arrangements.

7. Conclusions

This study classified transit riders into probabilistic behavioral classes based on their attitudes towards safety and flexibility and evaluated the effect of crowding levels on the likelihood of boarding and comfort of boarding a bus before and during the COVID-19 pandemic. We were able to empirically confirm that riders more concerned about personal safety are less likely to board a bus, that increase in congestion reduces the likelihood of boarding and feeling comfortable on a crowded bus, while flexible transit riders were more likely to feel comfortable on transit in May 2021 when compared to December 2020.

Overall, the estimated choice models were successful at providing results that follow common sense in terms of riders' behavior with the increase of crowding during the pandemic. They also point out the equity concerns that arise from the negative effect of access to a car and inflexibility to travel on the feeling of comfort onboard. It is evident that being a captive rider, i.e. not having other transport modes or travel time alternatives due to income, schedule, or other limitations, forces some transit riders to take a bus despite the concern they feel.

The paper expands the toolkit of transit operators for dealing with crowding in several domains. First of all, it provides empirical findings that can be used to test strategies that involve the change of vehicle size or service frequency and understand their effect on riders. Secondly, it points out the dependence of riders' flexibility on their professional schedule and the necessity for agencies to proactively engage with large employers who can shift the commute patterns of their employees to less crowded off-peak times. Lastly, we underscore the importance of agencies' continuous efforts to be in close communication with their patrons both in extreme events (like advertising health protection policies during the pandemic) and on a daily basis (in-vehicle crowding information at station screens and via smartphones) to maintain their loyalty.

Several limitations of this study should also be acknowledged. First of all, the survey that gathered the information for the analysis was collected during the tight COVID-19 restrictions and was heavily focused on the impact the pandemic had on riders. It is possible, that with the change in the available treatments and vaccination levels, as well as the resumption of economic activities, the preferences and attitudes of transit riders might have changed. It is also possible that the findings of this study captured the local phenomena and apply mainly to the Metro Vancouver context. It is recommended that future researcher focuses on evaluating the preferences of transit riders as the tide of the pandemic-related restrictions subsided, collaborating with transit navigation providers to study revealed choices of transit riders, as well as investigating contexts other than the Pacific Northwest.

Author contribution statement

The authors confirm their contribution to the paper as follows: study conception and design: Emily Grisé and Dea van Lierop; data collection: Francisco J. Bahamonde-Birke, Emily Grisé, Bogdan Kapatsila, Dea van Lierop; analysis and interpretation of results: Francisco J. Bahamonde-Birke, Emily Grisé, Bogdan Kapatsila, Dea van Lierop; draft manuscript preparation: Francisco J. Bahamonde-Birke, Emily Grisé, Bogdan Kapatsila, Dea van Lierop. All authors reviewed the results and approved the final version of the manuscript.

Data availability

The data that has been used is confidential.

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APPENDIX A. Attitudinal Statements Factor Analysis Results

Survey Question	Factor loadings			
	Concerned	Flexible	Tech-Savvy	Transit-Friendly
Prior to the pandemic I felt concerned for my personal safety aboard crowded transit vehicles	**0.756**			
Prior to the pandemic I was bothered by the crowding which I experienced on transit	**0.629**	−0.102		−0.101
Prior to the pandemic I needed a seat to feel comfortable onboard transit	**0.542**			
Prior to the pandemic, if traveling at morning or afternoon peak time, I chose to take an alternative to transit (i.e. Mobi bike, walk, Uber, Lyft, Evo etc.)	**0.507**	0.155		0.109
Prior to the pandemic I chose to travel at off-peak (less busy) hours to avoid crowding on transit	**0.482**	0.2		0.132
I am concerned that the health measures put in place by TransLink are not sufficient or will not be followed on public transit	**0.351**		0.107	
Flexible in time to travel to work via public transit		**0.839**		0.114
Flexible in time to travel from work via public transit		**0.763**		
I feel comfortable using mobile payment systems			**0.788**	0.207
I feel comfortable downloading and using new smart-phone travel applications			**0.767**	0.19
TransLink can get me anywhere I need to go		0.123		**0.579**

(*continued on next page*)

(*continued*)

Survey Question	Factor loadings			
	Concerned	Flexible	Tech-Savvy	Transit-Friendly
I am aware of the measures put in place by TransLink to keep customers safe while riding public transit			0.133	**0.507**
I make an effort to travel using environmentally sustainable modes of transport			0.177	**0.49**
I feel comfortable sharing my personally identifiable information with companies and government agencies		0.102	0.162	**0.408**

Variance: 41.2%.

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