The Use of Behavioural Insights for Crowding Management on Public Transit

by

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Abstract

Overcrowding causes transit riders' dissatisfaction and may lead to ridership loss while taking a toll on agencies' resources and forcing them to deal with service disruptions. While the COVID-19 pandemic led to a significant reduction in demand for transit trips, social distancing requirements challenged the capacity of available transit infrastructure to deliver services in a manner viewed as safe by the riders and authorities. Moreover, in the ongoing post-pandemic recovery, transit overcrowding has been outpacing ridership, pointing out the need for operators to address temporal spikes in transit demand. As such, this dissertation aims to answer the primary research question: How can knowledge about the preferences of different behavioural profiles be leveraged to develop policy interventions that affect the travel patterns of transit riders? The answer is developed by achieving four research objectives:

- To accurately identify distinct behavioural groups of transit users;
- To investigate the stated choices of distinct behavioural profiles of transit riders;
- To investigate the effect of preferences for incentives on the stated choices of transit riders;
- To investigate the effect of accessible information on the revealed choices of transit riders.

These research objectives are addressed in four corresponding analytical chapters of the paper-based dissertation. The analysis is preceded by a systematic literature review presented in a separate chapter that investigates the state of knowledge and practice on the application of demand management strategies on public transit and sets the stage for the empirical investigations of the identified opportunities and gaps. The chapters build on each other,

collectively advancing knowledge about how transit riders' travel behaviour can be influenced using policy tools.

Empirical findings in this dissertation are generated using the context of Metro Vancouver, British Columbia, Canada. Chapter 3 identifies specific behavioural groups of public transit users and their attitudinal preferences that can be used for policy interventions based on behavioural insights. The next chapter takes that classification and employs it to understand the effect of crowding on the class-specific decision to board a bus and the level of comfort of riding a bus at various crowding levels. The knowledge generated in these chapters can be used to develop interventions that appeal to preferences of transit riders and thus have higher chances of influencing a long-term change in travel behaviour.

Chapters 5 and 6 present insights into the effect of incentives and strategies based on the provision of crowding information. The former identifies how preferences for various incentives affect the actions riders may take in response to crowding, like the decision to change travel time being more influenced by fare-based incentives and the choice to switch to another transit route being more impacted by other incentives (like discounts for other modes, or opportunity to participate in a raffle). The latter investigates revealed preference data and confirms that providing crowding information in a smartphone trip-planning application influences the route choices of transit riders. The outcomes of this stage advance understanding of facilitating factors (like incentives and real-time information) and constraining aspects (e.g. flexibility and trip time) that influence transit riders to change their travel patterns in response to crowding.

The findings of all studies are consolidated in the concluding chapter, where the overarching contributions are summarized and avenues for future research are indicated. Specifically, this dissertation expands existing knowledge in the following ways:

- Reviews and evaluates existing policy approaches to public transit demand management based on ex-post studies;
- Identifies behavioural profiles of transit riders using a probabilistic market segmentation technique that allows for policy interventions to engage a significant share of users and to increase the likelihood of long-term changes in their travel behaviour;
- Evaluates the potential that monetary and behavioural insights-based incentives have on changing transit riders' travel time or route to avoid crowding;
- Provides empirical evidence on the effects of public transit demand management programs that use improved access to crowding information;
- Develops a framework of how behavioural insights can systematically inform transport policy planning.

Transit agencies that face crowding challenges can benefit by applying the findings of this thesis and potentially save costs by retaining and attracting riders, reducing system disruptions, and postponing infrastructure expansions. Policies based on the recommendations from this study could lead to higher rider satisfaction, loyalty, and a larger customer base through the attraction of users of other modes.

Preface

This dissertation is an original work by Bogdan Kapatsila. The research projects that collected data for the analyses performed in this dissertation received ethics approval from the University of Alberta Research Ethics Board 2, "Retaining loyalty in public transit post-COVID-19: Generating insights into how TransLink can meet customer needs", ethics ID *Pro00104577,* and "Understanding the influence of crowding information on the choices of transit riders", ethics ID *Pro00129784*. The dissertation is structured in an article format and consists of five manuscripts that have been submitted to peer-reviewed journals. All manuscripts were completed with co-authors; details of the authors' contributions are given below.

Chapter 2 "A systematic review of ex-post evidence on the impacts of public transit demand management programs." by Bogdan Kapatsila and Emily Grisé. Emily Grisé contributed intellectually and provided comments and edits to the manuscript. Bogdan Kapatsila was the primary author of the manuscript. He performed the analysis, interpretation of the results and writing.

Chapter 3 "Probabilistic segmentation of transit riders." by Bogdan Kapatsila, Francisco Bahamonde Birke, Dea van Lierop, and Emily Grisé. Francisco Bahamonde Birke, Dea van Lierop, and Emily Grisé contributed intellectually and provided comments and edits to the manuscript. Bogdan Kapatsila was the primary author of the manuscript. He performed all of the analysis, interpretation of the results and writing.

Chapter 4 "The impact of crowding on riders' class-specific behaviour." by Bogdan Kapatsila, Francisco Bahamonde Birke, Dea van Lierop, and Emily Grisé. Francisco Bahamonde Birke, Dea van Lierop, and Emily Grisé contributed intellectually and provided comments and edits to the manuscript. Bogdan Kapatsila was the primary author of the manuscript. He performed all of the analysis, interpretation of the results and writing.

Chapter 5 "The effect of incentives on the actions transit riders make in response to crowding." by Bogdan Kapatsila, Francisco Bahamonde Birke, Dea van Lierop, and Emily Grisé. Francisco Bahamonde Birke, Dea van Lierop, and Emily Grisé contributed intellectually and provided comments and edits to the manuscript. Bogdan Kapatsila was the primary author of the manuscript. He performed all of the analysis, interpretation of the results and writing.

Chapter 6 “The effect of digital crowding level information on the revealed route choice of transit riders.” by Bogdan Kapatsila, Francisco Bahamonde Birke, Dea van Lierop, and Emily Grisé. Francisco Bahamonde Birke, Dea van Lierop, and Emily Grisé contributed intellectually and provided comments and edits to the manuscript. Bogdan Kapatsila was the primary author of the manuscript. He performed all of the analysis, interpretation of the results and writing.

Acknowledgments

The work presented in this dissertation is a culmination of three and a half years of continuous learning, exploration, experimentation, occasional frustration, and professional growth. While I take full responsibility for the results (and possible mistakes), it is the support I received from my supervisors, mentors, colleagues, and family that allowed me to finish this journey in one piece and with such great pride for my accomplishments.

First of all, I want to acknowledge the pivotal role that Emily Grisé has played in my development as a researcher by investing countless amount of hours, efforts, and resources to answer my questions, support my learning, and guide me on the path to completing the Ph.D. I am especially grateful for the mentoring style which made me feel more like a junior colleague of yours, rather than a student, and provided a lot of academic freedom to pursue the topics I was interested in. I am also thankful for your trust in connecting me to your broader scientific network and the opportunities to teach and supervise other students that I truly enjoyed. This extended network is what made my Ph.D. studies a truly exceptional experience that exposed me to new topics, methods, and opportunities. It includes Francisco Bahamonde Birke, whom I am especially grateful for the cultivation of methodological rigour, development of analytical intuition, and overall interest in advanced research techniques that became the basis for this dissertation but also enhanced me tremendously as a researcher. You were always there, day or night, to walk me through my mistakes and push me forward, and this experience has been truly transformational. I am equally indebted to Dea van Lierop who introduced me to the systematic and conceptual approach to research and writing, and who despite the geographic and time differences has always been there to provide timely feedback. Having three of you as my supervisors felt like winning a jackpot, and I want to emphasize again how grateful I am for the support, mentorship, and guidance you provided me with.

I also want to express my gratitude to Ahmed El-Geneidy for his mentorship and exposure to research topics outside of my dissertation they provided. Working with Ahmed felt like training with an Olympic coach – no matter how much time I invested in a question (or I felt I already knew), he always had a suggestion on how the answer could be improved. I do not think that Ahmed had ever said no to any of my requests (of which there were many), and knowing the sheer size of his responsibilities, I feel truly honoured for getting that treatment and becoming (though through adoption) a part of the El-Geneidy academic family. I am also grateful for the academic guidance from Damian Collins, especially for helping me to learn how to communicate my research to those who have neither methodological nor subject matter expertise in the topic of my dissertation, as well as for sharing how to navigate the bureaucracy of academia. Lastly, many thanks to my candidacy and defence committees members Karim El-Basyouny, Feng Qiu, Stephen Wong, Tae J. Kwon, and Yusak Susilo whose feedback and questions improved this dissertation a lot.

I wish to thank my peers in the Transportation Research at McGill group, especially Meredith Alousi-Jones, Hisham Negm and Rodrigo Victoriano, for making me feel welcome in your tight Ph.D. circle and for the peer support that was a meaningful asset even thousands of kilometres away. My cat Lava, and friendly (though not mine) dogs Bart and Buster should also receive a deserved credit for the moral support they gave me during the completion of this dissertation.

Lastly, I want to acknowledge the support and encouragement that my parents provided and thank my wife Dara for being a reliable ally during those challenging years. You always brought me a smile even at the moments of greatest frustration and provided me with an extended credit of patience for the long hours and weekends devoted to research. You eagerly shouldered many of the challenges that doing a Ph.D. presents and provided me with much-needed extra energy to complete it. Thank you!

Table of Contents

List of Tables

List of Figures

Table of Abbreviations

BART – Bay Area Rapid Transit

BI – Behavioural Insights

BL – Binary Logit

DCLV – Direct Categorization Latent Variable

HCM – Hybrid Choice Model

ICLV – Integrated Choice Latent Variable

IID - Independent and Identically Distributed

INSINC - Incentives for Singapore Commuters

LC – Latent Class

LRT – Light Rail Transit

LTA – Land Transport Authority

LV – Latent Variable

LVLC – Latent Class Latent Variable

ML – Mixed Logit

MTR - Mass Transit Railway

OL – Ordered Logit

PCA – Principal Component Analysis

PTDM – Public Transit Demand Management

RUM – Random Utility Model

TDM – Transportation Demand Management

Disclaimer

The research and analysis included in Chapters two, three, four, five, and six of this dissertation were performed with the financial support of transit agency TransLink (Vancouver, Canada), and, in the case of Chapter six, data from transit trip planning company Transit. Nevertheless, the opinions expressed in this dissertation do not represent the views of TransLink or Transit.

Examining Committee Membership

The following academics served on the Examining Committee for this thesis:

External Examiner	Prof. Dr. Yusak Susilo Chair and BMK Endowed Professor, Institute of Transport Studies University of Natural Resources and Life Sciences, Austria
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Principal Supervisor	Dr. Emily Grisé Assistant Professor, School of Urban and Regional Planning Department of Earth and Atmospheric Sciences University of Alberta, Canada
Co-supervisor	Dr. Dea van Lierop Assistant Professor, Human Geography and Spatial Planning Utrecht University, the Netherlands
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Member	Dr. Damian Collins Professor, Human Geography Program Department of Earth and Atmospheric Sciences University of Alberta, Canada

Chapter 1: Introduction

1.1 Motivation

I grew up in a family of engineers, where the notion that everything can be fixed, if not improved, penetrated almost every household domain. Appliances were taken apart and assembled even if it was cheaper to buy new ones, while outsiders were called in to work on home renovations only if the use of specific tools was required. This philosophy of reliance on existing resources became so deeply ingrained in my consciousness that it is not hard to see its impact on my research as well. The main evolution that took place is my openness to rely not only on engineering when trying to improve something, but also on the knowledge from the other fields. And with this mindset, I embarked on the topic of dealing with crowding on public transit without significant dedication of new resources.

This thesis was inspired by two factors: first, the challenges that the COVID-19 pandemic has brought to transit agencies in delivering services in a manner that is perceived as comfortable to riders; and second, by the desire to apply advances in knowledge of how people make decisions to guide transit agencies in how to retain existing and attract new ridership by effectively managing demand for transit services. It investigated how the accurate identification of behavioural classes of transit riders based on their preferences can be leveraged in the context of crowding management and examined the potential of policies informed by those findings to manage crowding on public transit. The research focused on the context of Metro Vancouver, the third-largest urban region in Canada with a robust transit network system that already experiences a level of crowding comparable to pre-pandemic levels (8.2% compared to 9%), even without the full recovery of ridership (TransLink 2023a). By analyzing the choices of Metro Vancouver riders faced with crowding on public transit – and those riders' attitudes towards travel comfort, safety, and flexibility – relevant behavioural profiles were developed. These profiles can inform the introduction of new public transit demand management (PTDM) policies that appeal to riders' preferences by TransLink, the regional public transit agency in Metro Vancouver. At the same time, a comprehensive analysis of potential incentive schemes and their effect on riders' choices was undertaken. These policies are not expected to become a silver bullet to the crowding challenges that TransLink faces, nor they are perceived as an alternative to infrastructure expansion. Nevertheless, as Anthony Downs (2004) put it in his seminal book, *Still Stuck in Traffic,* transportation congestion can only be tackled with multiple strategies, since no single approach can succeed on its own. This thesis makes three main contributions. First, it provides Translink with guidance on several policy approaches to crowding on public transit. Second, it generates knowledge that will be of interest to transit agencies worldwide that aim to manage crowding on their network effectively. Third, it expands academic understandings of the use of behavioural insights to influence the travel behaviour of transit riders using empirical evidence.

1.2 Problem statement

Transit crowding has been found to have a major impact on customer satisfaction and loyalty for public transit users, together with fares, travel time, service frequency and coverage (Haywood, Koning, and Monchambert 2017; de Oña and de Oña 2015; dell'Olio, Ibeas, and Cecin 2011; Eboli and Mazzulla 2007). The COVID-19 pandemic has only exacerbated the negative effects of crowding. Due to concerns for personal health in the confined space of a transit vehicle, and sensitivity to crowding, riders' dissatisfaction was the highest amidst the public health crisis, and it remained above the pre-pandemic levels even with the end of governmental restrictions and the availability of immunizations and treatments (Cho and Park 2021; Flügel and Hulleberg 2022). As such, effective strategies must be utilized for public transit crowding management so that its users do not opt for other modes.

The traditional approach of adding system capacity offers a long-term solution to the challenges of transit crowding, however, it is usually a prolonged and expensive endeavour that requires years of planning and execution. For example, it will take some 6-10 years to extend Vancouver's existing light rail transit line to the University of British Columbia and relieve one of the most crowded transit corridors in North America (Chan 2022). On the other hand, managing demand on public transit using policy tools might be an equally feasible intervention, able to provide much faster and more affordable congestion relief. In the context of budget shortfalls and disinvestments that were only exacerbated by the COVID-19 pandemic (Canadian Urban Transit Association 2021), transit agencies require more guidance on policy approaches to crowding management. Nevertheless, empirical evidence of demand management benefits in public transit, unlike in the automobile congestion context, is scarce (de Palma, Lindsey, and Monchambert 2017). This thesis aims to enrich knowledge in this area.

Recently policymakers have become more interested in the use of behavioural science to advance the public good. A growing field that emerged at the intersection of social psychology and behavioural economics, it acknowledges the limitations of rational assumptions used to predict human behaviour. Instead, it seeks insights into the motivation for human actions to inform the design of policies that steer people to make socially and/or personally beneficial choices without limiting the ability to choose or penalizing/incentivizing alternatives. To put it simply, a shelf with fruits at eye level in a cafeteria is an example of behavioural science nudging toward healthy eating, while a higher price for unhealthy meals is not (Thaler and Sunstein 2021). Areas where behavioural science was successful in advancing the public good include personal finance, healthcare, and development policy (Metcalfe and Dolan 2012). Nevertheless, there has been only negligible progress in harnessing the benefits of behavioural insights in transportation. We all make numerous transportation-related decisions daily (e.g. which transport mode to use, what direction to take, when to start the trip) and there are policies in place that aim to affect those decisions (like congestion charges that discourage trips to certain parts of the city via personal vehicle, or employer-subsidized transit passes that aim to increase the use of public transit). However, those programs usually have a blanket approach that targets all users, without attempting to appeal to their specific attitudes, preferences, or constraints, and potentially foregoing opportunities for a more sustained change. This thesis aims to bridge the existing gap in knowledge on transportation demand management by investigating how preferences of different behavioural profiles can be leveraged to develop policy interventions that affect the travel patterns of transit riders. Specifically, it sought an answer to the question of *how can knowledge about the preferences of different behavioural profiles be leveraged to develop policy interventions that affect the travel patterns of transit riders?* It identified programmatic interventions that engage different behavioural profiles of transit riders who have the potential to move their travel to less crowded hours or routes and evaluated their potential effects. Given the evidence that constraints, attitudes and preferences affect human decision-making, implementation of different policy interventions that target various behavioural profiles of transit riders has the potential to be more successful at public transit crowding management, as opposed to singular policies developed for all riders.

1.3 Theoretical background and research gaps

This thesis draws on the existing knowledge from several academic fields – transportation demand management, market segmentation, and behavioural science. Informed by developments in these fields and addressing the existing gaps, it seeks to enrich effective transportation demand management practices.

1.3.1 Public transit demand management programs

The first transportation demand management (TDM) programs were deployed in the 1970s, primarily to affect traffic congestion through incentives or penalties, and examples of this can now be found all over the world (Ma and Koutsopoulos 2019). Their application to public transit crowding is less common, with only a handful of real-world cases and studies with thorough evaluation (Halvorsen et al. 2016).

Existing PTDM approaches include pre-peak hour free fares, discounts at off-peak hours, and fee increases during rush hours (e.g. in Washington D.C. Melbourne, Sydney, Tokyo, and Hong Kong). TransLink uses a similar financial tool by charging higher prices on light rail and ferries for the travel between each of its three zones at peak hours (TransLink, n.d.-b). Singapore Land Transport Authority (LTA) can be considered a trailblazer of PTDM, as, on top of penalizing rush-hour commuters with higher fares and incentivizing off-peak travel for its riders, it also cooperates with employers to develop targeted programs that allow for their workers to travel outside rush-hour times, and runs a point-based reward system (Halvorsen et al. 2016). Moreover, an evaluation of PTDM efforts in Singapore led to the discovery that a $0.50 discount is almost as appealing to riders as a free pass (Currie and Yan Leong 2020). These findings were identified through the analysis of smartcard data, however, the limitation of this approach is that we do not know the reasoning behind those riders' choices.

Chapter 2 of this thesis systematically evaluates the existing knowledge about PTDM programs. It shows that past research attempts oftentimes cannot be directly compared due to the differences in program details, local contexts, and research methodologies. This thesis enriches the existing literature by exploring avenues for broader engagement of transit riders by appealing to their preferences, as well as assessing the effect of different incentives on the riders' responses to public transit crowding in Metro Vancouver. It also goes beyond existing knowledge based on studies that examined the programs that intended to shift riders only outside of peak-hour travel by investigating policies that facilitate riders' decision to change their route. Chapter 5 shows that while fare-based incentives have a higher influence on the choice to change travel time, other incentives (like a raffle, or coupon for a drink or meal) are more likely to influence the choice of a route. On the other hand, Chapter 6 found that information about crowding levels provided through a transit navigation smartphone application influenced the route choice of the app users.

1.3.2 Market Segmentation of Transit Users

In order to appeal to riders' attitudes and norms, it is important to identify the behavioural profiles of public transit users who may respond to behavioural nudges. Acknowledgment of this necessity engages this research with the field of marketing, and particularly the notion of segmentation, i.e. identification of user preferences and development of products based on those, rather than the introduction of unique features to stand out amongst the competitors (Smith 1956). Transit services compete for users against other modes (like bicycles, or cars), however, the price, capacity, timetable, speed, and environmental impact already make public transit a product that is significantly differentiated from the other travel options. This said, segmentation allows identification of the groups of existing and potential riders through deliberate marketing campaigns that introduce or emphasize the features that appeal to those groups of riders and ensure their patronage. Segmentation has been successfully used by manufacturers to increase consumers' spending on specific brands and by politicians to tailor messaging to and increase the support of and donations from specific groups of voters (e.g. Barack Obama's 2012 campaign) (O'Neil 2016), and by transport researchers to recommend transit service improvements that would benefit specific groups of riders (Grisé and El-Geneidy 2018). Unsurprisingly, interest in segmentation in the field of transportation has been steadily growing (Elmore-Yalch 1998; Molander et al. 2012).

Chapter 3 provides a broader overview of existing approaches to market segmentation of transit riders. Overall it is clear that existing literature has established the benefits of market segmentation applications in transportation and explored various classification methods. Traditional applications of segmentation in public transit studies focus on the distinction between the groups of riders based on their access to forms of transportation other than public transit and their demographics. An increase in the understanding of the prominence of personal attitudes and preferences on mode choice (Bohte, Maat, and van Wee 2009) facilitated efforts towards the inclusion of preferences in segmentation as well, especially during the COVID-19 pandemic. Likewise, the proliferation of smart card payment systems on transit networks and access to the data they collect allowed researchers to classify transit riders based on the spatio-temporal characteristics of their trips, though these data rarely have information on who travels (demographics) and why. While each of the aforementioned approaches to segmentation is capable of providing useful insights for analysts and agencies, they all come with the limitation of being deterministic. This is because they assume that if a person falls into one category, they do not have any associations with the others. In simple terms, it means that if a person's favorite ice cream is vanilla, they never consider other tastes. Such static treatment of preferences is a common limitation in all social sciences (Grüne-Yanoff and Hansson 2009), and in the past some transport researchers suggested that the classification of transit users should also account for the possibility of belonging to multiple classes and that membership to fluctuate (Jacques, Manaugh, and El-Geneidy 2013). In response, this thesis employs probabilistic segmentation of transit riders to capture their preferences more accurately and to identify the policies that might better resonate with respective groups to encourage their travel at less crowded times or routes.

1.3.3 Behavioural Insights

This thesis also explored ways of affecting the motivation of transit riders to change their travel behaviour using insights from behavioural science. The emergence of behavioural science as a field can be traced back to the advances Kahneman and Tversky (1979) made in understanding how people make choices. Labelled as the prospect theory, it attempts to explain the behaviour of real humans, as opposed to ideally rational actors. For example, their theory is based on empirical evidence that there is an asymmetry in human perceptions of losses and gains, as well as decisions made based on these perceptions. Specifically, they found evidence that people emphasize loss more than gains (Kahneman and Tversky 1979). Over the years, findings such as this formed the basis of behavioural science - a discipline that seeks to employ knowledge of mechanisms that guide human decision-making to increase the public good. There are many examples of behavioural science informing public policymaking, with special units found at all levels of government around the world, including in Canada (Afif et al. 2019).

Despite the success behavioural insights achieved in some areas, they do not guarantee an effective change in every realm applied. For example, appealing to social norms in energy conservation and sustainable transportation was found to have no effect in comparison to incentives that facilitated more sustainable choices (Gravert and Olsson Collentine 2021; Ito 2015). On the other hand, there is evidence that combining incentives and behavioural insights can effectively increase the effect of both (Center for Advanced Hindsight, 2020). The multitude of behavioural insights techniques and their potential in transportation remains to be investigated. While the use of pricing to manage transport demand has many examples (e.g. toll roads, dynamic and fixed parking fees, time-specific transit fares), none of them was designed to appeal to personal preferences. Furthermore, only a handful of examples exist of the use of non-financial means (e.g. provision of additional information on route crowding level) to affect travel patterns. Agencies that share information on transit vehicles' location and their crowding levels present researchers with opportunities to evaluate the effect of behavioural nudges on public transit.

Metcalfe and Dolan (2012) review major advances in behavioural science and how these could apply to the promotion of sustainable modes of transportation (e.g. public transit or biking). They bring up Kahneman and Tversky's idea on the asymmetry in perceptions of losses and gains (1979), hypothesizing that for a rider, a sense of dissatisfaction from a ten-minute loss of time on a commute might be far greater than the increase in satisfaction from a ten-minute shorter travel time (Metcalfe and Dolan 2012). In addition, individuals tend to overestimate small probabilities, like the odds of winning a lottery, and are more likely to pay extra for insurance when presented with vivid examples of calamity (Johnson et al. 1993). The latter phenomenon is especially relevant to the context of the COVID-19 pandemic and transit use, as, despite no scientific evidence of outbreaks connected to public transit, the media's and public's perception of safety on transit has been generally hostile (Palm et al. 2021), while clear communication with customers was found critical to combat those perceptions (Kapatsila and Grise 2021).

Metcalfe and Dolan (2012) conclude that behavioural science offers a more realistic approach to understanding human behaviour than traditional theories (e.g. the theory of interpersonal behaviour, the theory of planned behaviour, value belief norm theory), as it is more likely that individual actions are context-specific and differ from intentions expressed in advance

(Metcalfe and Dolan 2012). This research uses the aforementioned knowledge from psychology, behavioural insights, and economics to improve understanding the drivers of riders' actions in response to crowding, and how these can be engaged when designing interventions to nudge behaviours. Specifically, it employs probabilistic market segmentation to identify accurate behavioural profiles of transit riders in Chapter 3, to evaluate the effects of crowding on the choices of those profiles in Chapter 4, to identify how preferences for incentives have a higher potential to nudge individuals to opt for a socially and personally beneficial course of action in Chapter 5, and to examine how information about crowding provided on a smartphone impacts the route choices of travellers in Chapter 6.

Overall, this thesis increases knowledge about the approaches to transit demand management that can lead to positive outcomes for operators, riders, and society as a whole. Reductions in the level of crowding result in fewer disruptions (e.g. delays, bunching) that transit agencies have to tackle on their systems. On the other hand, the personal benefit of higher comfort that a less-crowded transit vehicle brings has the potential to produce social value as well. People who have a higher level of satisfaction with public transit tend to ride it more (De Vos, Singleton, and Dill 2020), bringing in financial revenue to transit agencies with their fares, and producing fewer emissions when compared to the use of private vehicles. All in all, the use of behavioural insights for transportation demand management has the potential to deliver numerous personal and societal benefits, which demands more attention from researchers and policy-makers.

1.4 Research objectives

This thesis was executed as a series of consecutive research papers, each informing the design and analysis of the next phase of research. An overview of the four research objectives that this study addresses, as well as the methods used, is presented in Figure 1. A systematic literature review was conducted to identify the state of knowledge about public transit demand management programs and position this thesis in the existing research. Next, to develop the framework that would allow the attitudes of transit riders to be engaged by policy interventions rooted in behavioural insights, it was necessary to classify individuals into accurate behavioural groups. This was achieved using a probabilistic segmentation approach based on the Direct Categorization Latent Variable (DCLV) approach that realistically represents the likelihood of an individual belonging to a certain behavioural group, unlike traditional deterministic methods. The knowledge generated at this stage laid the foundation for the studies that followed. The third study looked at the effect of crowding on the decision to board a bus and feel comfortable on it among different behavioural profiles. The fourth study assessed the effect of preferences for incentives on transit riders' actions using a stated preference survey. The last study analyzed the revealed behaviour of transit users when presented with information on the level of crowding of the alternative routes in the trip planning smartphone application.

Research Question	How can knowledge about the preferences of different behavioural profiles be leveraged to develop policy interventions that affect the travel patterns of transit riders?			
Primary objective	To identify policy interventions that engage different behavioural profiles of transit riders and evaluate their effects			
Literature Review	To investigate the state of knowledge & practice on the application of demand management strategies on public transit			
Research Objectives	To identify distinct behavioural groups of transit users	To investigate the stated choices of distinct behavioural profiles of transit users	To investigate the effect of incentives on the stated choices of transit riders	To investigate the effect of accessible information on the revealed choices of transit riders
Data	Metro Vancouver transit riders survey (Primary data)			Transit app vehicle occupancy prediction and riders' route choice
Methods	Direct Categorization Latent Variable segmentation	Direct Categorization Latent Variable modelling	Integrated Choice Latent Variable modelling	Mixed Logit Modelling
Outcomes	Demographics of identified behavioural profiles, and potential policy interventions that can engage them	Knowledge on the attitudes of distinct behavioural profiles to crowding	Information on the potential of incentives to affect the choices transit riders make	Evidence of the effectiveness of information about crowding & route alternatives in affecting the choices transit riders make
Area of contribution	Transit market segmentation	Behavioural science and public transit demand management		

Figure 1 Research objectives and methods

Three out of four research objectives of this thesis were achieved by analyzing data collected through a survey with specific questions on transit riders' attitudes towards crowding, safety, personal flexibility, and attitudes towards incentives (collected in Metro Vancouver in December 2020 and May 2021). A deliberate effort was made to ensure that the collected sample was representative of frequent transit riders in the region through the use of gender and age quotas, as well as filtering questions on the main mode used for commuting, and when it was used last. The questions used in the survey were the basis for the behavioural classification of respondents and analysis of their choices and actions. Conversely, the data for the last study are secondary and were procured from a trip-planning smartphone application Transit. Both the survey and the Transit app dataset were approved by the University of Alberta Research Ethics Office.

Addressing the first research objective allowed the identification of the specific behavioural groups of public transit users and their attitudinal preferences that can be used for policy interventions based on behavioural insights. By appealing to riders' perceptions, these policy interventions can be more effective at engaging a larger share of users as well as increase the likelihood of a long-term change in their travel behaviour.

Satisfying the second objective required taking the classification developed previously and employing it to understand the effect of crowding on the decision of different groups to board and the level of comfort of riding a bus at various crowding levels. The findings of this stage can be used for the calibration of regional travel behaviour models, 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, and accurate evaluation of such tailored interventions.

The third research objective of this thesis was achieved by exploring the actions riders may take, if any, in response to crowding, like changing travel time or switching to another transit route, and how those can be influenced by various incentives (like fare discounts, free meals, etc.). Addressing this objective created a body of knowledge on the changes transit riders considered making in response to crowding before and during the COVID-19 pandemic, provided insights into the factors that should be considered when introducing the policies that intend to manage crowding on public transit with financial instruments, and how specific preferences can be used to guide the development and introduction of such incentives.

The fourth and final stage of this research examined the effect of crowding information provision on the revealed route choices of transit riders. Using archived data on the choices transit users made and alternatives they faced using a trip-planning smartphone application Transit, it evaluated the differences in how riders traded off travel time and vehicle occupancy when planning their trips. Specifically, this stage assessed the efficacy of a behavioural nudge in the form of information on crowding levels – i.e. whether and how people made choices when presented with real-time information on crowding levels of various transit routes. The outcomes of this stage advanced the understanding of facilitating factors (like real-time information) and constraining aspects (like trip time) that motivate transit riders to change their travel patterns in response to crowding.

Overall, this research sought to systematically assess the effectiveness of programmatic interventions in public transit crowding that use behavioural insights. Its main contributions to academic knowledge can be summarized as follows:

- Systematic review and evaluation of existing policy approaches to public transit demand management based on ex-post studies;
- Identification of behavioural profiles of transit riders using a probabilistic market segmentation technique that allows for policy interventions to engage a significant share of users and to increase the likelihood of long-term changes in their travel behaviour;
- Systematic evaluation of the potential that monetary and behavioural insights-based incentives have on changing the transit riders' travel time or route to avoid crowding;
- Empirical evidence on the effects of public transit demand management programs that use improved access to information (e.g., real-time information on crowding levels of available routes for the selected pair of origin and destination);
- A framework of how behavioural insights can systematically inform transport policy planning.

At the same time, relevant lessons and conclusions can be drawn for the findings to be applied to planning practice and policy-making. Transit agencies that face crowding challenges can improve their operations by applying the findings of this thesis and potentially save costs by retaining and attracting riders, reducing system disruptions, and postponing infrastructure expansions. Recommendations developed in this thesis better equip TransLink, and similar agencies, to manage crowding on their systems effectively. Policies based on the recommendations from this study could lead to higher rider satisfaction, loyalty, and a larger customer base through the attraction of users of other modes, like private cars, who will no longer be repelled by overcrowded vehicles. Moreover, the latter effect may lead to lowering societal public health costs that result from driving, as well as reducing emissions in the transportation sector.

1.5 Thesis structure and overview of chapters

This thesis is based on five original research articles, all dealing with the topic of public transit demand management using policy instruments and appealing to the preferences of transit riders. An overview of the thesis chapters is provided below.

Chapter 2 provides a systematic literature review of the ex-post studies that evaluated the impact of transit demand management strategies. The chapter synthesized the findings from 13 different programs analyzed in 20 studies. It is concluded that the practice of alternative work schedules that allow employees greater freedom when travelling is the demand management approach that brings the most significant crowding reduction. Once that flexibility is expanded, the effect of the other strategies (e.g. incentives and behavioural nudges) that appeal to riders' preferences might go up as well. The findings of this chapter aim to encourage transit agencies to develop collaborations with large employers that can introduce alternative work schedules, as well as provide guidance to interested researchers for future research.

Chapter 3 involved creating a probabilistic classification of transit users in Metro Vancouver that could be used to develop a set of policy interventions aimed at distributing the peak hour use of transit services to other times, or less crowded routes. Principal Component Analysis was employed to explore the underlying relationships between the attitudinal indicators that informed the specification of the classification model based on the Hybrid Choice Model framework. Such socio-demographic factors as being a female, of working age or a senior, having children, having a bachelor's degree or higher, having low income, or travelling during morning peak hours were found to influence the latent variables in the classification. The final model produced six probabilistic classes based on the estimates for two latent variables that accounted for respondents' concerns regarding crowding and safety, as well as personal flexibility to travel to and from work via public transit. Based on the results, a policy framework was developed which suggests that Metro Vancouver's transit agency might already be affecting the travel choices of those riders who are most concerned and flexible through the provision of information on crowding levels.

Chapter 4 aimed to understand the factors that affected the decision to board a bus and the level of comfort of riding it for different behavioural classes of transit riders before and during the COVID-19 pandemic. It employed a classification of transit riders developed in Chapter 3 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 chapter 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.

Chapter 5 identified the differences in preferences for various incentive schemes on public transit and assessed the relationship between the riders' eagerness to modify their travel patterns in response to crowding and the likelihood of responding to incentives that influence them to do the same. The findings suggest that people who favour incentives tend to be more likely to change their travel behaviour in response to crowding and that incentives that reduce the cost of travel on public transit have more potential to shift riders' travel time, while other incentives (like participation in a raffle, or smartphone game points) have a more pronounced effect on the decision to travel via a less crowded public transit route. Demographic-specific preferences for various incentive schemes were also identified; for example, individuals in the 20-34 age group were found to be more likely to respond to incentives, while full-time workers had a lower propensity to do that. This chapter provides public transit agencies with insights about policy instruments' ability to manage transit crowding and advances knowledge about the influence of personal preferences on travel behaviour.

Chapter 6 provided evidence that information about crowding has a meaningful effect on the travel decisions trip planning smartphone application users make, with the increase in crowding lowering the chances of a route being selected. It also allowed for the effects of crowding to be quantified using time and money as units of measure. While the findings are comparable to the estimates that the other sources of revealed preferences on transit (like smart card records) provide, coming from a revealed preference dataset (thus not subject to uncontrolled biases and potential errors) they are more accurate and reliable. Overall, this chapter informs transit agencies about the impact of crowding information provision and can potentially facilitate the possibility of expanding that effort (e.g. ensuring higher accuracy and broader availability of the data).

Lastly, **Chapter 7** concludes the thesis with a summary of the findings and their role in achieving the objectives of this research. It also discusses the implications of the findings for the development of new public transit demand management strategies by transit agencies and provides directions for future research.

The five research articles described above aimed to identify policy interventions that engage different behavioural profiles of transit riders and evaluate their effects. Nevertheless, the work conducted during the doctoral studies has led to 14 articles in total, all of which were submitted to international journals, and most presented at international conferences. These studies cover a variety of topics that promote new approaches to planning for and efficient operations of public transit, as well as better integration with land use. Table 1 provides a list of all these contributions, however only five were included in the dissertation as separate chapters to preserve a thematic focus on the topic of the use of behavioural insights for crowding management on public transit

Table 1 Overview of the contributions

Title	Published / Presented	Role / Co-authors
Measure Twice, Cut Once: Identifying Meaningful Performance Measures for On-Demand Transit Service.	Currently under review at an international journal. Presented at the 103 Transportation Research Board (TRB) Annual Meeting in Washington, D.C. USA, January 7–11, 2024.	Lead authorship, including data analysis and writing. Alex Hindle, Anson Stewart, Emily Grisé.
The Effect of Digital Crowding Level Information on the Revealed Route Choice of Transit Riders.	Currently under review at an international journal. Presented at the 103 Transportation Research Board (TRB) Annual Meeting in Washington, D.C. USA,	Lead authorship, including data analysis and writing. Emily Grisé, Dea van Lierop, Francisco Bahamonde-Birke.

Title	Published / Presented	Role / Co-authors
	January 7–11, 2024.	
Assessing Transport Affordability in a Car-centric City.	*Journal of Transport Geography* 114	Lead authorship, including survey design, analysis and writing. Damian Collins, Emily Grisé.
It Takes a Village: Using Behavioral Nudges and Incentives to Increase Affordability of Public Transit Systems	*Findings* Presented at the 103 Transportation Research Board (TRB) Annual Meeting in Washington, D.C. USA, January 7–11, 2024.	Lead authorship, including survey design, data collection, analysis and writing. Emily Grisé.
What Makes Public Transit Demand Management Programs Successful? A Systematic Review of Ex-post Evidence.	Currently under review at an international journal. Presented at the 103 Transportation Research Board (TRB) Annual Meeting in Washington, D.C. USA, January 7–11, 2024.	Lead authorship, including data collection, analysis and writing. Emily Grisé.
The Effect of Incentives on the Actions Transit Riders Make in Response to Crowding.	Currently under review at an international journal. Presented at the 11th Symposium of the European Association for Research in Transportation in Zurich, Switzerland. September 6-8, 2023.	Lead authorship, including survey design, data collection, analysis and writing. Emily Grisé, Dea van Lierop, Francisco Bahamonde-Birke

Title	Published / Presented	Role / Co-authors
Impact of the COVID-19 Pandemic on the Comfort of Riding a Crowded Bus in Metro Vancouver, Canada.	*Transport Policy* 141, 83-96. Presented at the World Conference on Transport Research 2023 in Montreal, Canada, July 17-21, 2023.	Lead authorship, including original idea, survey design, data collection, analysis and writing. Emily Grisé, Dea van Lierop, Francisco Bahamonde-Birke
Identifying behavioural profiles of transit users for demand management using a probabilistic approach.	Currently under review at an international journal. Presented at the 16th International Conference on Travel Behaviour Research in Santiago, Chile, December 11-15, 2022.	Lead authorship, including survey design, data collection, analysis and writing. Emily Grisé, Dea van Lierop, Francisco Bahamonde-Birke.
The Value of Access to Rapid Transit Among Affluent Households: Evidence from the City of Vancouver, Canada.	Proceedings of the 8th Conference on Spatial Knowledge and Information (SKI) Canada. Presented at the 8th SKI Conference in Banff, Canada, February 16-19, 2023.	Lead authorship, including data processing, modelling, analysis and writing. Katrina Villeneuve, Emily Grisé, Feng Qiu.
Going Electric: Comparing Operational Performance of Electric, Hybrid, and Diesel Buses in Portland, OR, USA.	*Transportation Research Part D: Transport and Environment* 128 Presented at the 102 Transportation Research Board (TRB) Annual Meeting	Lead authorship, including data processing, modelling, analysis and writing. Miles Crumley, Emily Grisé, Ahmed El-Geneidy.

Title	Published / Presented	Role / Co-authors
	in Washington, D.C. USA, January 7–11, 2023.	
Resolving the accessibility dilemma: Comparing cumulative and gravity-based measures of accessibility in eight Canadian cities.	*Journal of Transport Geography* 107 Presented at the 16th International NECTAR Conference in Toronto, Canada, July 20-22, 2022.	Lead authorship, including data processing, modelling, analysis and writing. Manuel Santana Palacios, Emily Grisé, Ahmed El-Geneidy.
If you build it, who will come? Exploring the effects of rapid transit on residential movements in Metro Vancouver.	*Journal of Transport and Land Use 17 (1), 163–185* Presented online at the 2021 World Symposium on Transport and Land Use Research (WSTLUR), August 9-11, 2021.	Lead authorship, including data processing, analysis and writing. Jordan Rea, Emily Grisé.
From Riding to Driving: the Effects of the COVID-19 Pandemic on Public Transit in Metro Vancouver.	*Findings.*	Lead authorship, including data analysis, and writing. Emily Grisé, Dea van Lierop, Francisco Bahamonde-Birke.
Public Transit Riders' Perceptions and Experience of Safety: COVID-19 Lessons from Edmonton.	*Findings.* Presented online at the 2021 University of Alberta ATLAS Symposium, April 12-15, 2021.	Lead authorship, including modelling, analysis and writing. Emily Grisé.

Chapter 2[1]: A systematic review of ex-post evidence on the impacts of public transit demand management programs

2.1 Chapter overview

Transit crowding results in negative experiences and mode change for transit riders and operational challenges for operators. The COVID-19 pandemic initiated an ongoing transformation of how, when, and where people travel, yet the challenge of balancing demand and supply in transportation remained topical. The pandemic has also exposed the traditional approach of infrastructure expansion for being too slow to respond to the challenges of crowding in a timely manner. As such, this chapter provides a systematic literature review of the ex-post studies that evaluated the impact of transit demand management strategies. Using the insights from the literature, I conceptually defined the phenomenon of crowding on public transit and systematized the possible approaches to its reduction. I synthesized the findings from 13 different programs analyzed in 20 studies. I found that the practice of alternative work schedules that allow employees greater freedom when travelling is the demand management approach that brings the most significant crowding reduction. Once that flexibility is expanded, other strategies that appeal to riders' preferences might have a larger effect as well. The findings of this review aim to encourage transit agencies to develop collaborations with large employers that can introduce alternative work schedules, as well as provide guidance to interested researchers for future research.

2.2 Introduction

Overcrowding on public transit (PT) can be disruptive to the system's operations and the travel experience of transit riders. Crowding tolerance varies by trip purpose and time and size of the city, with larger elasticities for smaller communities and at off-peak non-commute trips (Litman 2004; Taylor, Garrett, and Iseki 2000), making it one of the reasons for ridership loss. For example, according to customer satisfaction surveys, crowding was among the factors that impacted the ridership decline on the Bay Area Rapid Transit (BART) system in the 2010s (Wasserman and Taylor 2023). While the COVID-19 pandemic dramatically reduced the

[1] This chapter is based on the article: Kapatsila, B., Grisé, E. (Under Review). What Makes Public Transit Demand Management Programs Successful? A Systematic Review of Ex-post Evidence.

demand for travel due to the mix of government restrictions and work-from-home policies (Singh, Hörcher, and Graham 2023), that decline proved to be mainly temporary. For example, 8% of buses in Metro Vancouver, Canada were already overcrowded in 2022 (compared to 9% in 2019), though ridership was only at 82% of the pre-pandemic levels (TransLink 2023c). Despite the ongoing transformation of how, when, and where people travel, the challenge of balancing demand and supply in transportation remains topical.

In this study, I review existing empirical evidence on the effect of public transit demand management (PTDM) strategies without limiting the period when they were executed. Admittedly, this is not the first review on the topic. Cervero (1986) reviewed time-of-day pricing approaches from the US and around the globe to conclude that they had limited success in shifting ridership to off-peak periods. Similarly, McCollom & Pratt (2004) summarized the findings of US pilot studies of discounted or free off-peak bus service published since the 1970s which also produced mixed results, as reported declines in peak ridership ranged at 3-20 percentage points, depending on the city. Liu & Charles (2013) focused exclusively on rail transit studies, however, their selection of papers included several simulations and only one real-world application. Ma et al. (2021) provided a broad overview of theories and factors that play a role in PTDM strategies, but their empirical component included only three studies of the same PTDM program in Hong Kong. Lastly, Hörcher et al. (2022) reviewed the literature on potential demand management strategies suitable for ensuring occupancy levels required by social distancing measures during the COVID-19 pandemic, like inflow control and advanced booking, but no empirical evidence on the effects on public transit was presented. In contrast, this study takes a comprehensive look at ex-post evaluations of PTDM programs across all transit modes and synthesizes the findings to identify the factors that make them successful, as well as pointing out the gaps for future research. The issue of peak overcrowding on transit has been dampening patronage for years (Wasserman and Taylor 2023), and it is likely to continue being a serious obstacle to ridership recovery in the post-pandemic world. By systematically reviewing existing knowledge and suggesting avenues for future research, I aim to facilitate the process of the proliferation of effective PTDM strategies.

2.2.1 Overview of crowding on public transit

The preconditions for congestion in the transport system emerge out of unbalanced land use mixes that force many people to travel across the region instead of living close to where they work. Lindsey & de Palma (2015) differentiate between three manifestations of congestion, namely delay (longer trips), loss (denied boarding), and crowding, which encompasses the attributes of the first two. Crowding is most common on mass transportation, when too many passengers may setback the departure time of a transit vehicle, while a packed vehicle lowers the comfort of riders onboard, or even forces some potential riders to wait for the next vehicle. This definition of crowding is broader than the meaning attributed to the term in psychology, where it is used to describe the only person-specific feeling that an individual experiences from sharing the same space with a large number of people (Cox, Houdmont, and Griffiths 2006). The definition used by Lindsey & de Palma (2015) also include the consequences of crowding to the rider (delay and loss) on top of the individual perception. In the thesis, I employ this comprehensive meaning since the focus of the study is not on the individual perception of vehicle occupancy, but rather on the state when a high density of riders becomes both an emotional nuisance and a physical barrier for an average traveler. To avoid any confusion, I rely on the term congestion when discussing the phenomena in general, use the term traffic or vehicular congestion when discussing it for cars, and crowding as it applies to transit for the rest of the study.

It is highly unlikely for a transportation system to be always congested, but if the temporal component of congestion is set aside, the imbalance of demand and supply in transportation can be easily illustrated. I use a discussion of vehicular traffic congestion in Lindsey & de Palma (2015) and PT crowding in Hörcher et al. (2022) to overview the imbalance and illustrate the effects of various crowding interventions in Figure 2. The cost borne by an average rider (AC) includes the fare, the cost of time, and the value they place on travel comfort, which includes both physical (e.g. presence of a seat) and psychological (e.g. available space between riders) domains (Cox, Houdmont, and Griffiths 2006). A marginal social cost (MSC) remains equal to AC until the number of passengers is below U, as no operational or individual downsides are observed, and it goes up steeper than AC at point B when the two curves bifurcate as the free flow of passengers and their comfort are disrupted. Point M, where MSC crosses the demand, is the socially optimal cost of transit travel, as it represents some level of crowding that does not cause significant disutility, meaning that the infrastructure is well utilized. Passenger volume S represents the level of crowding of a transit line or route that is successful at connecting many people to the places where they want to go while minimizing the costs of service delivery per each rider for the operator. On the contrary, passenger volume A stands for the level of crowding that slows movement through the system and prohibitively delays or even precludes some of the trips, as well as causes inefficiencies to transit operators.

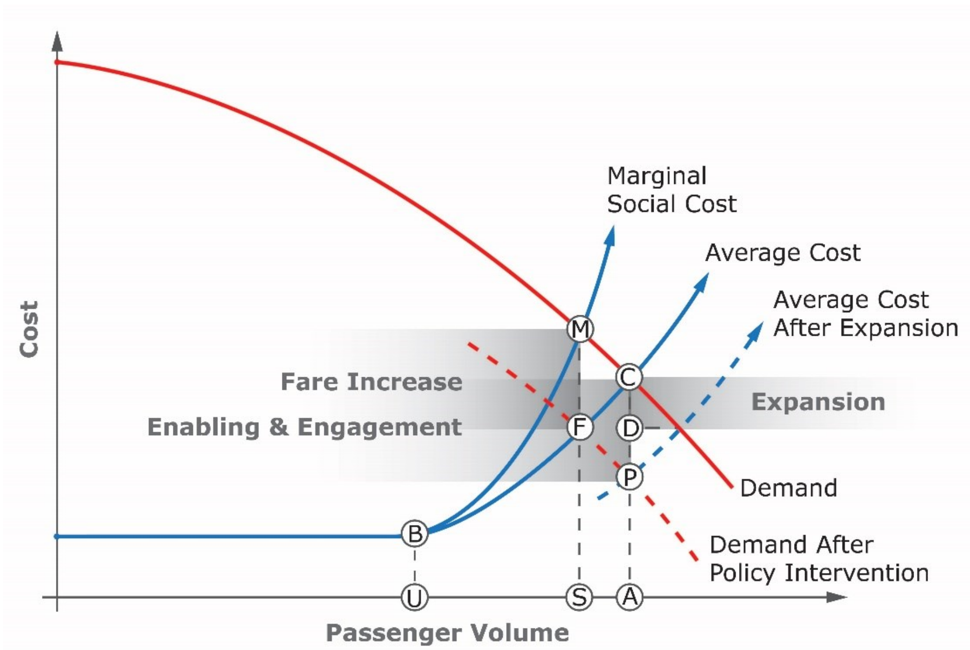

Figure 2 The relationship between supply and demand on public transit

Tackling crowding on PT benefits both operators (who do not have to troubleshoot system performance and do not lose riders) and users (who have a better travel experience, and do not have to seek alternatives). Multiple strategies can be considered to alleviate transit crowding, and it is likely that similar to the traffic congestion context, no single solution is capable of resolving it alone (Downs 2004). Three broad categories of interventions can be identified, including increased capacity through added infrastructure, demand management through fare changes, and engagement of riders by appealing to their preferences and norms. I briefly overview each of the approaches in the respective sections.

2.2.2 Infrastructure expansion

While the focus of this study is on the effect of demand management strategies to reduce crowding on transit, the discussion of their benefits would be incomplete without a brief overview of supply approaches. Adding system capacity is a common solution, that takes significant time and resources to be implemented, although it delivers concrete results while expecting little to no behavioural change from the rider. For example, since the early 2000s the City of Toronto had been planning the building of a new subway line, labelled as Relief Line, to alleviate the growing transit crowding downtown (HDR 2018), only to be replaced with plans for a more ambitious Ontario Line anticipated to begin service by 2031 (Toigo 2023). Increasing the transit fleet that can be deployed during peak hours is another viable option volume (particularly for bus service), that, nevertheless, involves not only the operational costs (e.g. drivers' salaries) and the expense of procuring additional vehicles but also the expansion or building of new garage space for their maintenance and storage, hence potentially resulting in extensive timelines as well. Figure 1 illustrates these approaches with a rightward shift of the AC curve (blue dashed line) due to the decreased cost of travel for an average rider. In theory, the new equilibrium should take place at point P producing the lower cost for passenger flow A. However, this can not be expected in reality, as these new riders, whether they come from another mode, or route, or who shifted their travel time, now contribute to crowding as well, which means that expansion of supply shifts the average cost to only D. This phenomenon can be referred to as induced demand, i.e. attracting the trips that could not take place previously due to some obstacles, like limited supply or a high cost (Clifton and Moura 2017). In the context of intercity high-speed rail, induced demand can account for 10%-20% of ridership after 2-4 years of introduction (Givoni and Dobruszkes 2013). This temporal overcrowding that may occur after service opening or frequency increase is a testament to the system's ability to satisfy the travel needs of many users and the necessity to continuously improve transit service to accommodate even more riders. As such, accounting for the effect of induced demand and its effect on peak ridership is an important component of the supply-side approach to overcrowding.

Other supply-side strategies to tackle crowding include the amendments of operations, like timetable modifications that arrange arrival times at interchange points to prevent on-station crowding (Wong et al. 2008), stop-skipping and service frequency changes (Gkiotsalitis and Cats 2021), vehicle holding or speed control (Wu, Liu, and Jin 2017) or the provision of viable alternatives, including shared modes (like cars, bicycles, or e-scooters that can be rented), among the others. The latter approach, however, can hardly be considered a preferable solution for a transit agency due to the possible loss of ridership. While not always the main reason, crowding reduction is one of the arguments for transit capacity expansion, and the economic valuation of crowding relief is sometimes included in the benefit-cost analysis of transit projects (Cats, West, and Eliasson 2016).

2.2.3 Financial tools

Expansion of the transit system is not the only approach to tackle crowding. From the point of basic economics, high demand should be reflected in a price increase that would restore a desired equilibrium. Looking at Figure 2, it means that the difference between the average and marginal social costs (MF) should be bridged with an equal fare increase imposed on the users. This higher price will decrease the flow of riders to the socially optimal level S. While Figure 2 does not have a temporal component, if we assume that it illustrates only a certain moment of the peak demand for infrastructure (e.g. the rush hours), a cost increase is necessary only when that takes place. Similarly, the higher cost can be imposed on critical links (e.g. stations or routes), or a combination of both. As a result, overall better utilization of the system capacity occurs, as the measure redistributes the demand across time and space. This also means that the agency gets a bigger bang for its buck, as increasing ridership at the off-peak time or on a less-utilized route increases the operator's revenue and brings down the cost of service delivery per rider. I illustrate the concept in Figure 3.

The discussion of varying fares dates back to the 1960s when Vickrey argued for their use to manage crowding on the subway (Vickrey 1963). Since then several studies performed a theoretical analysis of dynamic fare pricing schemes to show their impact on queuing and crowding (Yoshida 2008; de Palma, Lindsey, and Monchambert 2017) and their ability to remove overcrowding altogether (Tian et al. 2009). Time-of-day pricing is fairly easy to introduce on PT, but political will has usually been the main obstacle (Henn, Douglas, and Sloan 2011). Moreover, transit agencies often have to compromise between different, or even conflicting goals (e.g. financial solvency vs. equity), pushing fare-based approaches outside of the demand management equation. Another likely reason is the agencies' desire to simplify fare structures, as over the years, the number of cities where fares would vary by the time of the day went down (Multisystems, Mundle & Associates, and Simon & Simon Research and Associates 2003). These days, differential fare pricing can be found in Hong Kong, Melbourne, Singapore, Sydney, Tokyo, Vancouver, and Washington D.C., among others. The proliferation of electronic payment systems and smart cards that simplify the introduction of fare-based crowding management policies and their evaluation, as well as the reinvigorated interest in crowding that the COVID-19 pandemic brought in (Gkiotsalitis and Cats 2021), will likely facilitate the emergence of more programs and studies on the effects of pricing on PT in the near future.

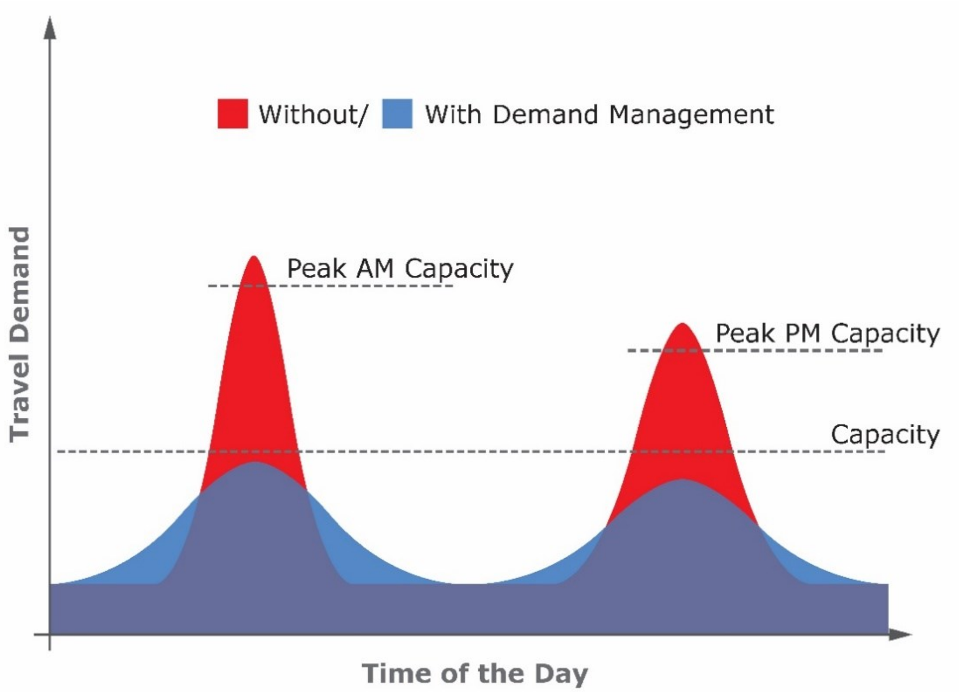

Figure 3 Temporal redistribution of demand for transport infrastructure

2.2.4 Behavioural insights

Unlike the structural methods, like adding infrastructure and changing fares that modify the physical or financial attributes of the transit service, the other approach involves interventions that either increase riders' awareness about the alternatives/consequences of their usual choice or appeal to their attitudes and norms to change their travel behaviour (Steg 2003). The approach falls under the umbrella of behavioural science tools that acknowledge the limitations of rational assumptions used to predict human behaviour and instead, seek insights into the motivation for human actions. This knowledge is then applied to inform the design of policies that increase societal benefits. Areas, where behavioural science was successful in advancing the public good, include personal finance, healthcare, and development policy (Metcalfe and Dolan 2012). In transportation, this approach has been mainly studied from the traffic congestion angle, remaining fairly under the radar in the PT context (de Palma, Lindsey, and Monchambert 2017). For example, several studies have found information on traffic conditions to influence the time and route commuters choose to drive (Ben-Elia and Ettema 2011; Srinivasan and Mahmassani 2003). In the PT context, behavioural insights have a similar potential to encourage the use of transit systems at off-peak times, resulting in the temporal redistribution of ridership as illustrated in Figure 3 in blue. For the peak hour period, this constitutes the leftward shift of the demand curve (red dashed line) in Figure 2 that establishes a new system equilibrium at point F through the more efficient use of existing resources, rather than an increase in their supply.

Examples of behavioural science applications in transportation include the provision of personalized routing options, custom-tailored messaging aimed at introducing behavioural change, or sharing of information about vehicle arrival time at the stop, all pursuing the idea of encouraging more transit use. While there is a consensus regarding the untapped potential of behavioural insights in transportation (Kormos, Sussman, and Rosenberg 2021), empirical results vary depending on the scale and quality of evaluations, ranging from null results in randomized controlled trial studies (Arnott et al. 2014) to moderate improvements under more relaxed study conditions that looked at the effect of interventions only within subjects without comparing to control (untreated) groups (Semenescu, Gavreliuc, and Sârbescu 2020). In practice, programs that combine incentives with behavioural science approaches are more common, oftentimes engaging users through the elements of gamification via smartphone technology, or offering points that can be exchanged for rewards (Whillans et al. 2021). A thought experiment that illustrates the benefit of a policy aimed at behavioural change combined with infrastructure expansion can be discussed using Figure 2. A slight temporal reduction in demand could further decrease the cost of travel for the remaining transit riders from point C to P, as opposed to just the point D which would be the result of just added capacity. All in all, as more opportunities for the use of behavioural insights in transportation are explored (Whillans et al. 2021), it is likely that they will percolate to crowding management as well.

It would be unfair to compare the benefits of different categories of approaches to reduce crowding on transit, as they differ in the amount of resources required (e.g. new bridge vs.

informational campaign), time for planning, implementation, and effect, as well as the scale of influence (increase in frequency on a crowded line vs. system-wide discount), and likely, an array of strategies should be considered to effectively reduce transit crowding. Nevertheless, one clear advantage that demand strategies have over the supply approach is that they can be deployed simultaneously, providing relief to the system, rather than just on a particular link that may shift overcrowding upstream or downstream of the link where the capacity was added. On the other hand, any demand policy can only be successful at changing travel behaviour to the extent the riders have that flexibility. I discuss the effects of alternative work schedules and initiatives that tried to increase travel time flexibility in the findings as well.

2.2.5 Literature review scope

As it stems from the introduction, this chapter's objective is to provide a systematic overview of existing ex-post studies on the impacts of various approaches to PT crowding management and draw relevant lessons for transit agencies. While acknowledging the benefits that riders experience from reduced crowding, it does not engage studies on riders' perception of crowding, the impact of congested transit on travel behaviour, or the broad impact of crowding on the value of travel time, as this knowledge and associated elasticities are well understood and structured. Instead, I concentrate on the empirical evidence of the effect that travel demand strategies have on PT crowding reduction, and the factors that allow those strategies to succeed, so that the agencies and researchers seeking guidance on such approaches could use it as guidance for their planning.

2.3 Methodology

Following the best practices for systematic literature review, this study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) Statement. Several eligibility criteria were considered in the paper selection process. First, in terms of the study context, I only selected papers that performed an ex-post evaluation of a pilot or permanent crowding management/reduction program and did not consider theoretical discussions, hypothetical scenarios, or evaluations that did not have base measurements from before the intervention, or studies that used synthetic datasets. Likewise, the objective of the program that the study discussed had to be explicitly dedicated to crowding management on PT, which meant that findings on changes in transit use because of a shift from driving were not considered. Due to the modest number of available studies on the topic, no limitations were set regarding the study design, participants involved, or whether the publication was peer-reviewed. The same reasoning was applied to the decision not to restrict the time period of the review. Studies also had to present quantitative outcomes to be eligible for the analysis, and only articles in English were retained. The full process for paper screening and selection is presented in Figure 4.

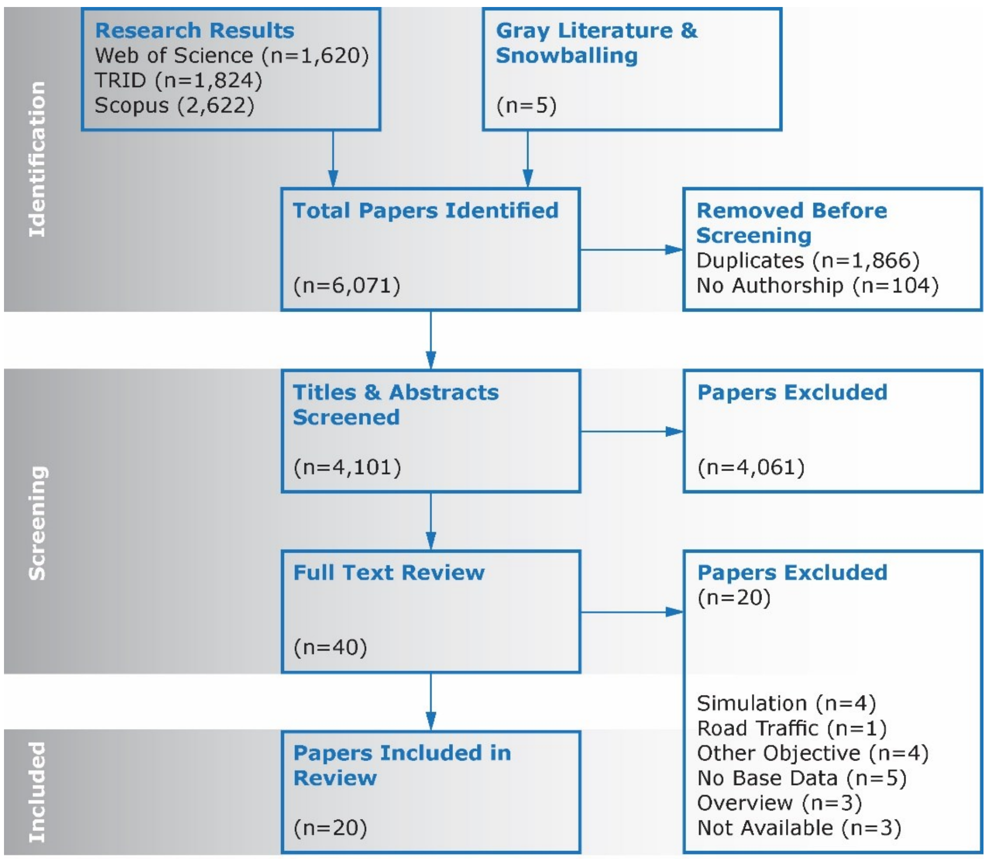

Figure 4 PRISMA diagram

Three academic databases were searched in May 2023: Web of Science, Transport Research International Documentation (TRID), and Scopus using the same combination of search terms in each ("*crowd*" OR "congested" OR "*peak" AND "pricing" OR "discount" OR "incentives" OR "reward" OR "free" OR "schedul*" AND "public transport*" OR "transit" OR "bus" OR "metro" OR "subway" OR "streetcar" OR "rail" OR “train”). Two academic papers and 3 professional reports were identified via a snowballing effect. Titles and abstracts from the databases were imported into Zotero for screening which resulted in 20 studies that were included in the final review. Given that all studies present empirical evidence, I considered the idea of literature findings to be assessed using meta-analysis techniques, however, the diversity of program contexts, as well as evaluation techniques prevented me from pursuing that option. Instead, the results were reviewed using the critical lens, like assessing the sample size, robustness of analysis methods, and other contextual factors, in an attempt to highlight the factors that speak to the reliability of findings.

2.4 Findings

The systematic search identified 20 sources – 13 papers and 7 reports that cover 13 distinct programs. I divide them into three separate groups that characterize their mechanism best, namely discounts, behavioural insights, and alternative work schedules. The summary of the main findings on the programs is presented in Table 2, and I discuss them in the respective subsections.

2.4.1 The effect of discounts

Overall, a decrease of 0.8%-6.1% in peak-time riders can be attributed to discounts and free fares, with the average hovering somewhere between 2%-3%. The Mercer Metro study was a year-long off-peak free fare pilot in the US in the 1980s, and Yang & Lim (2017) provide details of a randomized controlled trial of pre-peak free fares in Singapore. The remaining 3 programs launched around the 2010s remained in place. The level of discount in those programs ranged from a completely free fare to a 25% discount at off-peak times. In discussing the relatively modest results observed, the authors acknowledged the limitations of using a blanket approach such as pricing, as it mostly rewards the existing behaviour of riders who already travel off-peak. In this regard, the findings offered by Currie (2010) are particularly interesting, as his analysis of the Early Bird Train Travel program, a free fare offered to all rail users who completed their journeys before 7 a.m. in Melbourne, estimated that even the observed decrease of 1.2%-1.5% in peak hour demand allowed the agency to break even with regard to the revenue foregone. If not for the program, the agency would have to provide from 2.5 to 5 additional trains during peak hours to satisfy the growing demand (approx. AUD $20 million of capital costs per train and additional AUD $1 million for operations annually) - an investment far greater than the revenue lost due to foregone fare collection (AUD $6 million annually) (Currie 2010). Back-of-the-envelope calculations offered by Yang & Lim (2017) in their evaluation of the pre-peak free transit field trial in Singapore provide similar evidence about savings from crowding demand management through fare discounts being larger than the loss of revenue.

The Early Bird Discount Promotion of the Hong Kong Mass Transit Railway (MTR) has been evaluated by three groups of authors since its launch in 2014. It is interesting that it has not only a temporal component, as a 25% discount is offered to the riders who egress before the rush hour but also spatial, as the discount only applies to the 29 highly utilized MTR stations. While the average effect of discounts on peak hour travel was on par with other places (~3% decline), Halvorsen et al. (2020; 2016) and Ma et al. (2020) found in their respective studies that the biggest shift was observed for the riders who travel infrequently during the weekdays. Peak-hour ridership for those groups went down by 6.1% in Halvorsen et al. (2016) and by 3.8% in Ma et al. (2020), with the latter study reporting that 35%-40% of those who started travelling off-peak since the beginning of the program reverted over two years. The variance in changes for infrequent riders between the two studies can be explained by the differences in sampling approaches and variables used for segmentation, however, it also exposes the limitations of the before-after methodology that does not account for ridership growth, service disruption, or other confounders. Anupriya et al. (2020) controlled for confounding factors based on temporal changes (e.g. change in demand) using a difference-in-difference approach, making their assessment more robust compared to the simple before-after approach used by Halvorsen et al. (2016) or Ma et al. (2020) among the others. Controlling for confounders, Anupriya et al. (2020) found just a modest 25-second aggregate shift of arrival time that could be attributed to the Early Bird Discount Promotion on MTR in their sample of Hong Kong riders.

The program in Beijing has all of the components of the Early Bird Discount Promotion in Hong Kong, as it is also limited to only 24 stations, although the discount has been offered at 50% for tapping in before 7:00 am since 2017, an expansion and a bigger price reduction from the initial pilot of 16 stations and 30% discount that was found ineffective (Zou et al. 2019). In this latest iteration, the riders who travelled the first 10 minutes of the peak period before the program were those who most likely shifted their travel time to pre-peak due to the discount, and it was found very unlikely for someone to travel more than 30 minutes earlier because of the discount (Zou et al. 2019). The authors also found that after six months, retiming elasticity went up, meaning that with time riders were able to adjust their behaviour and became more responsive to the discount, with the elasticities being the highest for the riders who travelled least frequently.

Overall, all the programs identified so far were successful at reducing peak-hour ridership using fare discounts, however, they consistently showed the limited effect of such an approach that also varied depending on the methodology used. It is also possible that such strategies require time to take effect, as some riders need to adjust their schedules. Likely, some of the pilots discussed had been too short to allow all of the interested riders to benefit from them. Evaluations presented also lacked data on the demographics and motivating factors that facilitated the change, something that is a common challenge for large-scale travel behaviour research in general.

2.4.2 The effect of riders' engagement and information provision (Behavioural Insights)

So far, I have reviewed programs that assumed rational economic behaviour in their design and expected the change in travel costs to modify the riders' travel patterns. However, as discussed in the conceptualization part of this chapter, this assumption does not always hold true. Three initiatives, in the Netherlands, Singapore, and the US used behavioural science principles to introduce commitment mechanisms (i.e. the requirement to sign up for the program) and elements of gamification into their crowding management programs. As Table 2 shows, their effect was far more palpable, ranging from an 8% to 22% reduction in peak ridership, however, it should be acknowledged that their provision was associated with participants receiving incentives as well - i.e. engagement was used to facilitate the effect financial tools, rather than a standalone approach. On the other hand, a pilot that aimed to redistribute passengers more evenly across train cars through the provision of information on crowding levels at the subway station in Stockholm resulted in an approximately 4% drop in the number of passengers in the first two cars of the train (Y. Zhang, Jenelius, and Kottenhoff 2017). While a relatively modest result, its low opportunity cost should be acknowledged, as the operator lost no farebox revenue, while it also indicates that online services and apps displaying crowding levels of transit vehicles, like Google and Transit app, might actually have an effect on riders' choices to avoid crowding (i.e. travelling at other time, or via a different route).

The pilot evaluation of rail commuters' departure time change in response to rewards in the Netherlands performed by Peer et al. (2016) is not that different from the programs that rely solely on price change. What makes it more unique is volunteer recruitment, which meant that only people who saw the flexibility to change their travel time enrolled in that pilot for 25 weeks, and, I argue, the commitment and engagement that enrollment in the program instituted, establishing a behavioural anchor for the participants (not discussed in the chapter). A conscious choice to sign up for the program is the expression of commitment that has been shown to influence outcomes (Baca-Motes et al. 2013), and combined with the self-selection sorting that the recruitment mechanism provided, the rather impressive result of 22% of pilot participants shifting their travel times to off-peak periods looks less surprising. The authors acknowledge that volunteer enrollment could have been a cause of bias, which makes it impossible to decompose the effect of commitment to the program in that study. Moreover, the absence of a control group tightens the limitations of the findings even further.

The only initiative in this subsection that is a permanent program (not a pilot or experiment) is the Incentives for Singapore Commuters (INSINC) launched by the Singapore Land Transport Authority (LTA) in January 2012. It was a platform that offered participating users credits for travelling during shoulder hours before and after the morning peak, 6:15 am – 7:15 am and 8:45 am - 9.45 am (Fwa 2016). Riders could receive additional credits through friend referrals, learning "INSINC facts", or achieving personalized behavioural goals. The credits that a user earned could be exchanged for cash or be used to participate in online games or a raffle. The analysis of the first six months of the program concluded that on average peak-hour demand fell by 8% among program subscribers, and was almost twice as low (-15%) among active participants in the raffle and those who interacted with other users (Christopher Pluntke and Prabhakar 2013; Siow, Prabhakar, and Fong 2013). The program experienced tremendous expansion, growing to 103,000 participants in 16 months, and since all of them had to provide demographic information, it showed that more men were shifting their travel to off-peak than women, 17% v. 11% respectively (Siow, Prabhakar, and Fong 2013). With all these findings INSINC creators were able to confirm hypotheses that commuters prefer to gamble on higher rewards than receive a lower payout with certainty, and that social interactions and peer motivation increase the effect of monetary rewards. The program was rebranded as Travel Smart Rewards in 2014, and significantly modified in 2017 when only the direct exchange of credits and online games were kept in place, and it was changed again in 2020 under the new brand of Travel Smart Journeys that only rewards riders for taking selected bus routes during weekday rush hours (“Travel Smart Journeys Schemes” 2023). Unfortunately, no evaluations of these program modifications are publicly available.

Using the INSINC program as a model, BART ran a six-month reward program Perks in 2016-2017. Its overall goal was to reduce the rush-hour congestion on the Transbay heavy rail corridor, and it allowed users to redeem earned points either through an automatic raffle, a Spin-to-Win game, or a cash buyout (Greene-Roesel et al. 2018). As in Singapore, where almost 87% of participants preferred the raffle (Christopher Pluntke and Prabhakar 2013), 86% went with the raffle in San Francisco (Greene-Roesel et al. 2018). Overall, the BART Perks pilot resulted in 10% of participants shifting their travel to times outside of the morning peak hour, although it was not able to achieve the main goal of the pilot - alleviate the congestion on the Transbay corridor - an overcrowded BART link that will not see an increase in physical capacity until at least 2030 (BART, n.d.). Only 13% of all pilot participants were commuters on that link – a share too small to bring in a meaningful change (Greene-Roesel et al. 2018).

Studies reviewed in this subsection support the overall notion of the benefits that the use of behavioural science tools brings into transportation. They show both the positive effect of information provision and how the effect of rewards can be facilitated with commitment and engagement. The main limitation of the studies that looked at the programs in this subsection is the lack of information on the difference (or lack of) in effects among the control and treatment groups, that would allow for causality to be established. Nevertheless, setting that limitation aside, I see the potential for demand management policies informed by behavioural insights to have a bigger impact than just incentives. It is still limited though, as these soft interventions can only appeal to people’s preferences, but as discounts, they cannot address the structural obstacles that influence riders’ flexibility. Programs that aimed to do that are discussed next.

Table 2 Summary of the effects of identified public transit demand management programs

Source	Stakeholder / Location	Program Details / Timeline	Evaluation Design	Data / Sample Size	Effect
Discounts					
Anupriya et al. (2020)	Mass Transit Railway / Hong Kong	Early Bird Discount Promotion (25% fare discount for trips ending before 7:15 am) / Since 2014	Difference-in-difference analysis	Smart card records / 1704 OD pairs	Aggregate time reduction of 25 seconds
Ma et al. (2020)			Before-after analysis of rider segments	Smart card records / 500,000 IDs	2.9% short-term decrease (1.4%-3.8% for various groups), ~40% reversed in the long run
Halvorsen et al. (2020; 2016)			Before-after analysis of rider segments	Smart card records / 400,000 IDs	2.5% short-term decrease (0.8%-6.1% for various groups)
Zou et al. (2019)	Beijing Subway / Beijing	50% fare discount for those who tapped in before 7:00 am at 24 stations / Pilot in 2016, updated in 2017	Before-after analysis of rider segments	Smart card records / ~ 3M IDs	Middle-term elasticity is 2x more than the short-term (more so for infrequent riders), 30 min is a max

Source	Stakeholder / Location	Program Details / Timeline	Evaluation Design	Data / Sample Size	Effect
Yang & Lim (2017)	Land Transport Authority / Singapore	Early treatment group: free fare before 7:45 am, 25% discount before 8:00 am; Late treatment group: free fare before 8:00 am, 25% discount before 8:15 am / September 22 – November 28, 2016	Randomized controlled trial	Smart card records / 348 IDs	Treatment groups were 2% and 5.5% more likely to travel before 7:45 am and 8:00 am respectively; changed to 2.1% and 4% during post-treatment (30 weeks)
Currie (2010)	Public Transport Victoria / Melbourne	Early Bird Train Travel (free fares before 7 a.m.) / Since 2009	Before-after analysis	Train boardings / -	1.2%-1.5% decrease in peak riders
Studenmund & Connor (1982), Connor (1982), Dommasch & Hollinger (1979)	Mercer Metro / Mercer County, NJ	Free off-peak fare pilot (10:00 am – 2:00 pm, 6:00 pm – 10:00 pm, and weekend) / March 1978 – March 1979	Before-after analysis	Estimates based on ridership counts and surveys / ~5,000 respondents before and ~5,000 after	3.4%-5.4% decrease in peak riders[2]

[2] The study provides two figures based on estimates from ridership counts and surveys, with the second being more moderate. Connor (1982) believed the moderate decline estimated using surveys to be more accurate.

Source	Stakeholder / Location	Program Details / Timeline	Evaluation Design	Data / Sample Size	Effect
Behavioural Insights					
Greene-Roesel et al. (2018)	Bay Area Rapid Transit / San Francisco	BART Perks (riders who shifted to off-peak earned points to be exchanged for rewards) / 2018	Before-after analysis	Smart card records / 5,788 IDs	10% decrease in peak-hour riders (among participants)
Zhang et al. (2017)	Stockholm metro / Stockholm	Real-time crowding information pilot (audio and visual announcements) / 6 days of May 2015	Observations / Surveys / Before-after analysis of passenger loads	Train boardings / -	~4% decrease in passengers in the most crowded cars at Tekniska Högskolan station
Peer et al. (2016)	Dutch National Railways / -	Peak avoidance experiment (distance-based reward for travelling outside am and pm peaks) / Summer 2012 - Spring 2013	Before-after analysis	Smartphone app tracking, logbooks / 1009 participants	22% decrease (reward period), 10% decrease (post-measurement) among participants
Pluntke & Prabhakar (2013), Siow et al. (2013)	Land Transport Authority / Singapore	INSINC (riders who shifted to off-peak earned points that could be exchanged for rewards) / 2014	Before-after analysis	Smart card records connected to an online account / ~103,000 IDs	8-15% decrease in peak hour riders among participants

Source	Stakeholder / Location	Program Details / Timeline	Evaluation Design	Data / Sample Size	Effect
Alternative Work Schedules					
Charles River Associates (1984)	Duluth Transit Authority / Duluth, MN	Phase 1: Employers were encouraged to introduce variable work hours. Phase 2: Riders could purchase a discounted pass (20%) that could not be used between 7:30 am – 8:00 am / 1980-1982	Before-after analysis	Passenger counts / -	No effect. Only 1 employer introduced variable work hours (30 employees); random sales and the impact of discounted passes were insignificant
O'Malley (1975), Port Authority (1977)	Port Authority / New York - New Jersey region	Staggered Work Hours Program (SWHP) for 220,000 of 400 companies in Manhattan / 1970-1977	Before-after analysis	Passenger counts at the 3 the busiest subway stations / -	26% decrease in passengers during the 15-min. am peak, and an 18% decline during the 15-min. pm peak
Greenberg & Wright (1975), as referenced in Copas & Pennock (1980)	Government employees / Toronto-Queen's Park /	Change to staggered and flexible work hours / Started in October 1973	Before-after analysis	Passenger counts on the Yonge subway line / -	51% decrease in passengers during the 15-min. am peak line, 53% decline in the peak am hour

Source	Stakeholder / Location	Program Details / Timeline	Evaluation Design	Data / Sample Size	Effect
Safavian & McLean (1974), as referenced in Copas & Pennock (1980)	Federal employees / Ottawa	Change to staggered and flexible work hours / Started in March 1974	Before-after analysis	Counts of transit riders crossing the Ottawa central business district screen line / -	50% decrease in passengers during the 15-min. am peak, and a 57% decline during the 15-min. pm peak, 16.9% and 23.7% for am and pm peak hours

2.4.3 *The effect of alternative work schedules*

This section covers the programs that introduced either flexible work arrangements or staggered work schedules with large employers in the locations that regularly experienced significant overcrowding at transit lines and stations. I acknowledge that alternative work schedules are commonly introduced and may reduce transit crowding – but only studies that explicitly examined the benefits for transit were included in this review. Four such programs with rigorous evaluation were identified through the search, in the US and Canada. All these programs date back to the 1970s and 1980s, and while similar ideas were proposed later on, like the call for more flexible and remote work arrangements in the 2018 Manchester congestion plan (Burnham, Greater Manchester Combined Authority, and Transport for Greater Manchester 2018), or the idea of adjusting school and university start times so that students could travel after the morning rush hour in Europe and Australia (Daniels and Mulley 2013; UITP Marketing Committee 2020), none were implemented. The program in Duluth, was largely unsuccessful, as only one employer with 30 workers introduced an alternative work schedule, while sales of discounted passes without the increased flexibility from employers did not have a noticeable impact on peak ridership (Charles River Associates 1984). The other three programs displayed impressive results - a 42% to 51% decline during the morning peak-of-the-peaks (the busiest 15 minutes of the am rush hour) at the segments of the system that served participating employers, and a 17% to 53% drop during the am peak hour. Of the four studies identified in this subsection, the one in New York is the most extensive and well documented, with more than 400 employers participating with their combined workforce of about 220,000 people at the time when O'Malley (1975) reported it. The effect of that program displayed in Table 2 covers the staggered hours approach when employers were encouraged to shift the regular 9 am to 5 pm schedule by a 0.5-1-hour window earlier or later. As a result, peak-hour ridership at the three most crowded subway stations fell by 26% (O'Malley 1975). The flextime arrangement, meaning that workers had "core" hours when they were required to be in the office, and "flexible" 1.5-hour slots at the beginning and end of the day so that they could adjust their presence while still fulfilling the 8-hour work commitment, was tested at the Port Authority's office in 1974-1975. The experiment reported having a positive, but relatively small effect, as it was operating in an environment where staggered work hours were already implemented, so only a marginal reduction of peak hour change (as captured by Port Authority employees entering the lobby) was observed (Port Authority 1977). The experiment that involved federal employees opting into flex and staggered hours schedule reported a slightly smaller effect of almost 17% peak-hour transit demand decline in downtown Ottawa in the morning (Safavian & McLean (1974), as referenced in Copas & Pennock (1980)), while the busy Yonge subway line in Toronto saw a 51% decline in ridership during the busiest 15 minutes of the morning rush hours a result of a similar experiment (Greenberg & Wright (1975), as referenced in Copas & Pennock (1980)). Based on the studies above, it seems that a larger effect size could be observed at the transit system links of extreme crowding. The effect size went down as the geographic scale of analysis increased to include areas of different levels of crowding. Still, even in the most moderate scenarios, they show more promise than the other demand approaches, and thus likely have the potential to make a meaningful impact in the post-pandemic reality of more flexible work arrangements. Nevertheless, work schedule modification is potentially the hardest strategy to implement, as it requires the involvement of numerous stakeholders outside of the transport sector.

2.5 Synthesis

Transit crowding is a multilayered phenomenon that stems from the decisions made at the individual, societal, agency, and infrastructural levels. As such, it should be tackled at each of the respective levels to be effectively mitigated using both the supply and demand approaches as I illustrate in Figure 5. Moreover, the infrastructural and agency levels are intertwined which I illustrate with a dashed line, especially in the case where one regional body is in charge of both the planning and operations of transit, like TransLink in Vancouver, Canada, or Metropolitan Council in the Twin Cities region in the US. Demand management programs discussed in this chapter are primarily available to the agencies, although equally engaging the personal and societal levels of crowding in their influence. In Figure 5 I highlight those demand approaches and their effect on travel choices in blue. Although they range in the magnitude of their impact (as I illustrate in Figure 5 with the grey arrows), identifying their most successful applications allowed us to synthesize the factors that bring the biggest return on investment.

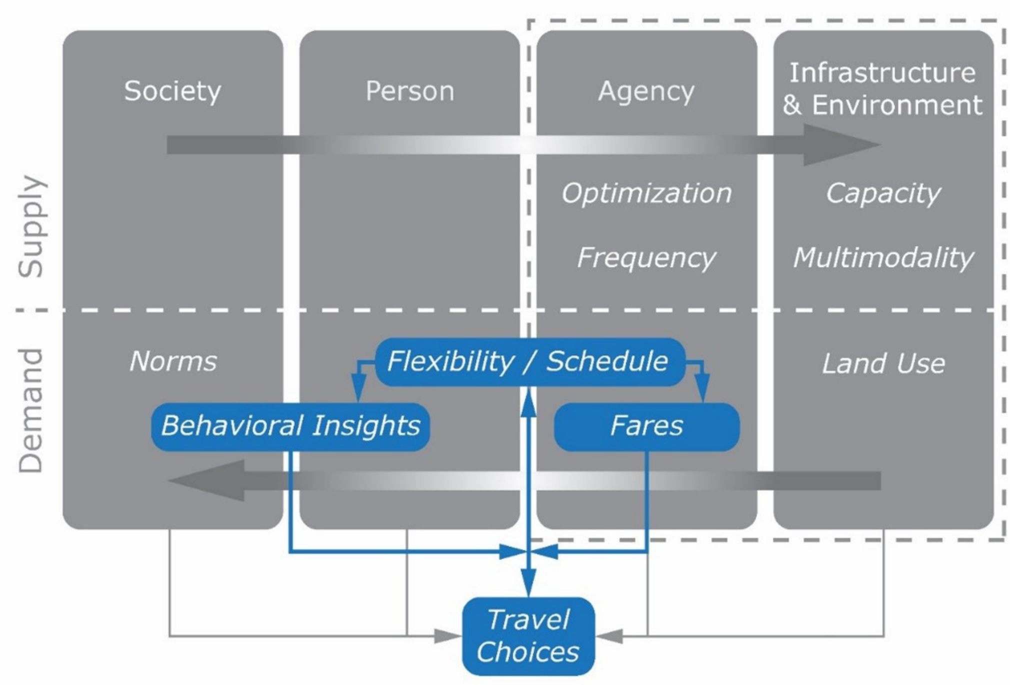

Figure 5 Conceptual framework of crowding reduction approaches

I acknowledge that in the current fiscal climate, the concern for riders' experience might be just one of many competing priorities for a transit agency However, it is possible that a successful demand management strategy may redistribute peak-hour ridership to the extent that will allow some of the service to be redeployed at other places. To set the basis for the operator's perspective in these recommendations, I use the Chicago Transit Authority's (CTA) estimate that at least a 5% shift of ridership from morning and evening 45-minute peak periods would be necessary to allow the agency to deploy fewer vehicles to serve rush hours (Zimring 1975). While Currie (2010) and Yang & Lim (2017) suggest that any reduction in crowding on rail rapid transit can be translated into operational savings for the agency, their argument is grounded in back-of-the-envelope calculations specific to the local context. With this reasoning in mind, I assume that a 5% bar still holds ground, meaning that based on this review, none of the programs that offer fare discounts in a blanket fashion offer sufficient change as a single-strategy policy to manage crowding peak-period and peak-direction. Moreover, scenarios considered by Zimring (1975) for CTA evaluated the feasibility of staggered work hours, which meant no foregone revenue for the agency that a discount would have brought. This should not undermine the positive outcomes that probably took place – an increase in riders' comfort and more stable operations due to fewer disruptions during boarding and egress. Nevertheless, Ma et al. (2021) posit that even for passengers a 5% decrease in crowding is too small to improve passengers' comfort noticeably. Moreover, it is likely that for the free fare or discount programs to be at least cost-neutral, the shift should be even larger. This suggests that the effect of rewards with gamification and engagement elements is reasonable enough for the agencies to consider as a viable solution. However, neither BART Perks, nor INSINC survived to this day, despite their encouraging results, and a potential qualitative study might shed light on the reasons for their fleeting success and adoption.

The punchline of this review is that the defining factor for the success of a PTDM program is the degree of personal flexibility stemming from the daily schedule imposed by either an employer or an educational institution. At least within the scope of the limited number of identified ex-post studies, changes to work schedules produce the largest declines in rush hour ridership among the programs reviewed. The other approaches, whether it is a discount or the use of a mechanism that facilitates a positive behavioural response, can only moderate the effect of the level of travel flexibility a person has. This is explicitly stated in the analysis of alternative work schedules and discounted fares in Duluth (Charles River Associates 1984). Some evidence to support this hypothesis can also be sourced from newer studies. Halvorsen et al. (2020) and Ma et al. (2020) identified segments that had the highest share of riders who shifted their travel time to off-peak (6.1% and 3.8% respectively) as having the biggest flexibility based on the spatial and temporal attributes of their travel, although the absence of any demographic or attitudinal information prevents us from getting deeper insights.

The mechanisms for a transit agency's engagement with employers can be based on existing frameworks. Singapore Land Transport Authority's Travel Smart Network supports companies that enable employees' flexibility to travel at off-peak times and earn rewards through the Travel Smart Program (Land Transport Authority 2015). Another option is to partner with existing mobility platforms, like Commutifi, which is offered to large employers in Metro Vancouver through a partnership with TransLink, allowing them to study and reward socially optimal travel choices of employees (TransLink 2023d; n.d.-a). Potential incentives for employers can also be explored, like discounted prices for agency-supported transit passes, lower charges for advertising on transit, or public recognition of the employers' efforts.

I should also acknowledge the other factors that play an important role in the success of a PTDM program. Local context has to be properly studied to identify the types of provisions and/or incentives, as well as the geographic scale at which they apply (e.g. particular links of the system, whole city, or region) (Eriksson, Nordlund, and Garvill 2010; Gärling and Fujii 2009; Richter, Friman, and Gärling 2011). Likewise, local political support and public acceptance of particular measures may play an important role in the program's success, and effective communication of the objectives and the forming of a positive brand can improve public acceptance of the change (Gärling and Schuitema 2007; Ma et al. 2021). Identification of target groups for crowding interventions and tailoring them to their preferences is another way the effect of a PTDM program can be facilitated (Kapatsila et al. 2023; Ma et al. 2021), though it is important that implementation and logic remain simple to grasp for the average user, even if more complicated program designs have a theoretical promise of better efficiency (Maruyama and Sumalee 2007). Overall, given that the ultimate goal of a PTDM intervention is behavioural change, its successful adoption is contingent upon the proper inclusion of social norms, values, and preferences in the program design (Schade and Schlag 2003).

The flexible and staggered work hours arrangements tested in the 1970s should not be mixed with the derivative of work-from-home policies prevalent now. While taking such riders out of the system on some days, it still ensures that they will be travelling at the peak time when they have to get to and from the office if it operates in a 9 to 5 fashion. As such, working with large employers to develop schedules that allow for regular peak hours to be avoided should be considered by transit agencies as a demand management strategy with the biggest return. Once that flexibility is more prevailing, other moderating factors can be explored, like alternative pricing schemes for off-peak times (e.g. peak price increase, ladder pricing, a combination of pre-peak increase with peak surcharge), identification of the most appropriate time windows for the discounts, and behavioural mechanisms that might facilitate the uptake. On the other hand, ensuring workers' flexibility has broader societal benefits that go beyond PT. A study from the same period that most of the findings on alternative work hours came from found that flexible schedules had also a positive impact on the odds of ridesharing (Wegmann and Stokey 1983). More recent studies arrive at the same conclusion (Tahmasseby, Kattan, and Barbour 2016), which suggests that flexibility is generally conducive to more sustainable travel patterns. The reduction of cars on the road is more palpable for commuters, as it results in lower congestion levels and travel time savings. Nevertheless, transit riders receive significant comfort improvements as crowding goes down, ensuring their continuous use of the service.

Nevertheless, it does not mean that the introduction of work flexibility alone will have a significant effect on peak crowding. When He (2013) studied the effect of flexible work arrangements on travel behaviour in two Californian regions - San Francisco and Los Angeles using the 2009 US National Household Travel Survey (NHTS), they found that transit riders were less likely to travel after peak time than during it, hypothesizing that the reason might have been in the less frequent service at off-peak times. Improvements in off-peak service are known to increase transit use (Hansson et al. 2022), so when riders are encouraged to shift their travel, those other times should have a level of service supportive of such a choice, potentially provided through reallocation of service from the peak time. Nevertheless, the amount of service reallocation should be limited to the extent that does not cancel out the benefits that emerged from the initial crowding reduction.

2.6 Conclusions

This chapter reported on a systematic literature review of the ex-post studies that evaluated the impact of PTDM strategies. As a result, a recommendation is developed for transit agencies to partner with large employers and introduce flextime and staggered work schedules that allow workers greater freedom when travelling. Once that flexibility is expanded, other strategies that appeal to riders’ preferences might have a larger effect as well. Transit agencies are equally encouraged to deploy PTDM strategies in combination with the planned expansion of infrastructure, both to deliver faster relief and to accommodate the induced demand that will likely emerge because of the added capacity (in other words, to achieve the full decline of travel costs from point C to P for an average rider as conceptualized in Figure 2). At the same time, relieving the strain on service provision at the peak time might allow for some resource reallocation to off-peak periods, leading to stimulation of ridership increase at those times. Such improvements will have multiple equity benefits, as fewer people will be denied boarding, while more non-rush hour service will improve travel flexibility.

On the other hand, the estimates of the effects of flextime and staggered work hours developed almost half a century ago need to be updated using the advances that have occurred since then, like automatic counters and smart cards. At the same time, it should be acknowledged that even that information comes with limitations (limited or absent demographics) and does not provide insights into the motivations of riders. It is recommended that agencies explore ways of engaging with riders and gathering their insights through social networks and a continuous rider census. Collecting this information will allow us to know more about the riders' needs to develop tailored interventions as well as evaluate the effectiveness of such initiatives. While the operational benefits of reduced overcrowding are fairly easy to detect for an agency, only getting riders' feedback can shed light on the effect of crowding interventions on riders' satisfaction. Moreover, this knowledge would also allow us to address the main limitation of this review. The studies and the recommendations based on them focus on a typical downtown-bounded office worker and thus can be challenged for their rather narrow perspective, excluding people who travel on transit elsewhere but still experience crowding. While Yuh-Jye Lin et al. (2023) did not identify equity concerns in terms of crowding exposure across different income groups in their Stockholm study, their use of demographics of the nearby areas rather than the riders as a proxy left a degree of uncertainty to the findings. Moreover, as the pandemic has shown, the most vulnerable groups have the least flexibility in when and how they can travel (Q. He et al. 2022), which means that both the facilitators and strategies to change their travel choices might differ from those identified in this review. Overall, more quality data on local transit users will result in better policies that satisfy their needs.

I should acknowledge another limitation of this review. With the focus on ex-post evaluations, the pool of information consisted only of 13 papers and 7 reports to draw insights from. Nevertheless, my findings suggest that the actual effects of demand management programs are likely more modest than modelling attempts suggest. For example, I saw that among the studies reviewed, on average inventive programs resulted in a 0.8%-6.1% decline in peak ridership, while modelling based on stated preference surveys pointed in the direction of 17.2-64% of study participants supporting the idea of changing their travel behaviour in response to incentives (Wang et al. 2018; Z. Zhang, Fujii, and Managi 2014). The bias and lack of realism in survey-based methods are commonly acknowledged (Dixit et al. 2017), and this review brings in one more argument for the broader move towards more ex-post evaluations.

I also encourage researchers to turn their attention to more rigorous research methods in the evaluation of travel behaviour change. In research on behavioral insights' effect on transportation mode change, more robust methods of experimental design usually produced modest, or even null results (Arnott et al. 2014). As such, I call for thought leaders and leading journals to also institute a standard for experimental design and evaluation in transportation, similar to those that exist in the medical and business research communities. In the existing environment of fiscal austerity and the Cambrian explosion of information production, it is necessary that research provides defensible evidence on the presence or absence of the effect of an intervention that can be comparable in systematic and meta-analyses.

Chapter 3[3]: Probabilistic segmentation of transit riders

3.1 Chapter overview

Before the COVID-19 pandemic, Metro Vancouver was the North American leader in transit ridership growth, with its most popular routes being severely crowded during peak travel times. As the region gradually recovers from the effects of the pandemic, it is expected that the crowding will also return to the transit system and will have to be tackled. This study performed a probabilistic classification of transit users in Metro Vancouver that could be used to develop a set of policy interventions aimed at distributing the peak hour use of transit services to other times, or less crowded routes. Principal Component Analysis was employed to explore the underlying relationships between the attitudinal indicators that informed the specification of the classification model based on the Hybrid Choice Model framework. Such socio-demographic factors as being a female, of working age or a senior, having children, having a bachelor's degree or higher, having low income, or travelling during morning peak hours were found to influence the latent variables in the classification. The final model produced six probabilistic classes based on the estimates for two latent variables that accounted for respondents' concerns regarding crowding and safety, as well as personal flexibility to travel to and from work via public transit. Based on the results, a policy framework is developed that suggests that Metro Vancouver's transit agency might already be affecting the travel choices of those riders who are most concerned and flexible through the provision of information on crowding levels. On the other hand, to affect the choices of those riders who are least flexible, it is recommended that the agency develop partnerships with large regional employers.

3.2 Introduction

Transit crowding has been found to have a major impact on the feeling of safety, customer satisfaction, and loyalty for public transit users (Cho and Park 2021; Haywood, Koning, and Monchambert 2017; de Oña and de Oña 2015; dell'Olio, Ibeas, and Cecin 2011; Eboli and Mazzulla 2007). As one of the densest Canadian urban regions and the economic center

[3] This chapter is based on the article: Bahamonde Birke, F., van Lierop, D., Grisé, E. (Under Review). Identifying behavioural profiles of transit users for demand management using a probabilistic approach.

of the province of British Columbia (BC), Metro Vancouver's public transport agency, TransLink, was the leader among North American peers before the COVID-19 pandemic in terms of transit ridership growth, resulting in some of its routes experiencing significant station and in-vehicle congestion (TransLink 2019). In March 2020, the high demand for transit was dramatically reduced due to government interventions. The first COVID-19 case in BC was reported on January 28, 2020 (Government of British Columbia 2020), and a province-wide state of emergency was announced on March 17 of the same year, which resulted in the closing of the educational and public service institutions (like courthouses, but also recreation centers and libraries), limiting public gatherings (including dining at restaurants) and institution of social distancing, postponement of non-urgent operations at the hospitals, and beginning of work-from-home arrangements when possible (CBC 2020). These actions inadvertently reduced people's need for travel, while fulfillment of the social distancing guidelines reduced the available space on transit to 30% of the full capacity (TransLink 2020b). Altogether, this led ridership to decrease to 17% of the pre-pandemic level in April 2020 (TransLink 2020b). Nevertheless, by Spring 2021 ridership recovered to almost half of what it was before the pandemic (TransLink 2021c), and reached 80% by the Fall of 2022 (TransLink 2023a), more than a year after the pandemic state of emergency was lifted (CBC 2021). Given the historically high share of transit users in the region (Statistics Canada 2017b), ridership can be expected to rebound, bringing back the limited capacity and crowding issues from the past. Moreover, over the course of the pandemic, the continuous promotion of physical distancing measures has challenged the agency's ability to provide transportation services in a manner that allowed for vehicle occupancy that was accepted as safe among current users and did not force them to opt for other modes of transportation. All in all, the COVID-19 pandemic has exacerbated the need for TransLink to accommodate peak demand in ways that are faster and more economical than traditional infrastructure expansion.

With a focus on the opportunities for effective public transit demand management (PTDM) policies to reduce in-vehicle crowding, this study applies a probabilistic market segmentation technique to identify distinct behavioural profiles of transit riders in Metro Vancouver. The results can be used to develop targeted policy interventions to influence travel patterns, specifically to nudge certain riders to travel using less-congested routes or at off-peak times. PTDM policies can influence travellers' mode choices, and, more importantly, retain existing transit riders, having a positive impact on their well-being and the sustainability of the cities where they live in turn (Jacobson, King, and Yuan 2011; Wasfi, Ross, and El-Geneidy 2013). Policies that promote the use of public transit have been well documented (R. Cervero, Ferrell, and Murphy 2002), however more recently researchers have started paying attention to the effects of personal attitudes and preferences on the mode choice (Bohte, Maat, and van Wee 2009). Moreover, the potential to engage transportation system users based on knowledge of their preferences has not been fully realized (Metcalfe and Dolan 2012), and this study aims to bridge this gap.

Probabilistic segmentation employed in this study allows the preferences and attitudes of transit riders to be represented more accurately when compared to other techniques. Unlike a traditional deterministic classification, this segmentation approach allows for a user to be a member of different classes simultaneously with a certain degree of assurance. Such a technique is more appropriate for analyzing behavioural profiles, as, for example, a person can be both environmentally minded and concerned for their safety, and capturing this nuance will allow designing policy interventions that engage a larger share of users as well as increase the likelihood of a long-term change in their travel behaviour. The probabilistic segmentation applied in this study also accounts for the non-linear impact of preferences, something that has been argued for the effect of sociodemographic variables as well, adding another level of conceptual robustness to the study, which better reflects real-life situations (Bahamonde-Birke et al. 2017). Given that the programmatic transportation demand management approach is believed to be a cost-effective and expeditious solution to spread riders' demand in time while offering a feasible alternative to expensive and protracted expansion of fleet and/or infrastructure (Victoria Transport Institute, n.d.), accurate identification of distinct groups of transit riders is an important first step in developing such interventions.

The remainder of this chapter is structured as follows. An overview of existing approaches to market segmentation of transit riders establishes the argument for this study. Data and methodology reviews offer the details on the study sample and modelling approach used for classification. Discussion of the identified behavioural classes forms the main body of this work, while policy recommendations and suggestions for future research wrap up this chapter.

3.3 Literature review

This study builds on previous research that argued for the benefits of market segmentation applications in transportation and developed previous classification approaches. Segmentation was first discussed in the 1950s in the field of marketing as a way to increase the appeal of products based on the varying preferences of consumers, as opposed to differentiation, i.e. varying product features to stand out amongst the competitors (Smith 1956). Since then, empirical studies have shown a positive effect of market segmentation in traditional retail (Foedermayr and Diamantopoulos 2008), online sales (Xingyu Chen, Tang, and Ling 2019), and public health policy (Czaplicki et al. 2023; Gomez, Loar, and England Kramer 2018). In the field of transportation, interest in the potential of segmentation has been steadily growing (Elmore-Yalch 1998; Molander et al. 2012). Most of the segmentation studies focused on the differences between captive riders, which represent those who use a specific transportation mode because they have no other alternatives, and choice riders, including those individuals who make their transportation decisions based on preferences and lifestyle, but not the financial constraints they face. Wilson et al. (1984) used specific survey questions to assign an individual to a transportation class in Ottawa, ON, forming four market segments for cars and the same number for transit users. These included functional captive mode users - those who have no alternatives, marginal captive mode users, i.e. those whose mode choice is constrained for a set time, but not indefinitely, marginal choice mode users - those who have multiple options and would respond to policy change, and free choice users - individuals with access to multiple transportation modes and low responsiveness to policy changes. McLaughlin and Boyle (1997) used car availability and income to differentiate riders dependent on transit in LA County, CA, and to develop a targeted transit-incentive program. While the concept is still fairly common in professional and academic literature, it should be noted that the transit choice and dependence dichotomy in riders' classification has been criticized for its limited theoretical base and empirical proof, with studies pointing out that complete transit dependence is rare and is likely to occur in the areas with good transit service (Guerra 2022).

More recent studies effectively took advantage of the proliferation of smart card payment systems on transit and information about the riders' trips they collect (see Halvorsen et al. (2020), and Cats and Ferranti (Cats and Ferranti 2022) for examples of applications). Kieu et al. (2015) used smart card data to distinguish between those who use transit just for commuting, travel for different purposes via transit regularly, passengers who are habitual (i.e. travel repeatedly at the same time), as well as irregular passengers, while Deschaintres et al. (2019) identified 12 different classes of transit users based on the level of heterogeneity of their transit use recorded via smart cards. Such classification of riders based on the spatial-temporal characteristics of transit trips has a theoretical grounding in the Theory of Planned Behavior (Ajzen 1985) as suggested by Chen & Chao (2011), but it does not provide a lot of information for policy-making that targets travel behaviour. While a source of a large amount of spatial-temporal records and a clear ability to distinguish between the habitual and occasional transit users, analysis and segmentation based on smart card data is usually limited due to the absence of information about the demographics of the riders, and, more importantly, their preferences and attitudes, that were shown to influence travel behaviour (Molander et al. 2012). In other words, while smart card data provides a detailed snapshot of where and when people travel and allows us to classify them based on those attributes, they lack information on who and why does that.

Some researchers accounted for the effect of the COVID-19 pandemic in their classification of transit riders. For example, Shelat et al. (2022) estimated two classes of transit riders, namely COVID Conscious Travelers and Infection Indifferent Travelers, using a latent class choice model. They found a higher likelihood for younger and frequent riders to belong to the Infection Indifferent Travelers class who had higher tolerance to the level of crowding onboard and infection rate in the community. Nevertheless, their classification was not informed by the preferences of the respondents, but by their mode choices, making the behavioural component of the classes and labels rather hypothetical.

The inclusion of personal attitudes and preferences in classification offers additional insights into the travel behaviour of identified classes. Focusing on access to modes and modal preferences, Beimborn et al. (2003) classified transit users into captive and choice riders in Portland, OR, while Krizek and El-Geneidy (2007) built on these findings and included habits and preferences to classify both transit users and non-users in the Minneapolis-St. Paul, MN region. This approach extended the broad categorization into captive and choice riders of the papers mentioned above to also include the potential users as a separate group. Van Lierop and El-Geneidy (2017) explored that direction even further and used data from Montreal, QC, and Vancouver, BC to develop samples specific to the context and then classified transit users using the information on income and car availability. Their motivation to use segmentation came from the identified gap in research efforts that target retention of existing transit riders, instead of encouraging car users to switch to using transit. They focused on satisfaction as a means for ridership retention and used information on demographics, preferences, and satisfaction of transit riders to better differentiate between the existing user groups. As a result, they proposed adding a new broad group to the captive and choice riders categorization - captive-by-choice riders. Importantly, their focus on user preferences and motivations goes in line with the previous studies that have also found those factors to impact travel satisfaction and mode choice (Gountas and Gountas 2007; Lai and Chen 2011; Şimşekoğlu, Nordfjærn, and Rundmo 2015; St-Louis et al. 2014).

Molander et al. (2012) have argued for the use of social background, values, and attitudes to improve the understanding of travellers' choices. This has become of interest for transit and shared mobility operators as an avenue to increase their knowledge about riders' comfort and decision-making (Chou, Lu, and Chang 2014; Elmore-Yalch 1998; van Lierop, Badami, and El-Geneidy 2018). Considerations for these factors impose a set of new requirements on the approaches to the categorization of transportation users, as it has been acknowledged that preferences are not static – something that is oftentimes overlooked in social sciences (Grüne-Yanoff and Hansson 2009). Jacques et al. (2013) did not address this directly, but acknowledged the potential implications of such considerations. They developed four segments of transit users using the concept of choice and captive riders: "convenience," covering traditional choice riders; "true captivity," meaning captive riders; as well as "utilitarian" and "dedication," which were not included in the previous two groups. Most importantly, the authors suggested that group membership can fluctuate, and should not be deterministic. That assumption is where this study fits into the historical context of transit riders classification, as it moves away from the traditional deterministic approach, and identifies market segments probabilistically, paving the way to a more realistic representation of transit riders' preferences. The chapter also offers a set of policy recommendations that might engage riders from identified classes to change their travel behaviour and reduce peak-hour crowding.

3.4 Data

In this study, I performed a probabilistic classification of transit riders who participated in two waves of the survey distributed in December 2020 and May 2021 by a marketing research company that used hard age and gender quotas to represent the population of Metro Vancouver. Compared to the pre-pandemic trends, there is evidence that more people began working from home and switched from transit to private vehicles in Metro Vancouver (Kapatsila et al. 2022), though there were no significant changes to the official pandemic-related restrictions between the survey waves. A total of 2,397 complete records was collected; however, this study aimed at capturing the established transportation behaviour of respondents, which is why the sample was narrowed to those who travelled regularly for work or education purposes via public transit before March 2020. This step produced a final sample of 1,201 respondents for the analysis, where participants identified as frequent transit users and had either never stopped riding TransLink or had not used it since March 2020 but did ride frequently before the start of the pandemic.

The study area, Metro Vancouver, is displayed in Figure 6. It encompasses 21 municipalities, a Treaty First Nation, and an Electoral Area, with a population of almost 2.5 million people in 2016, placing it third among other Canadian Census Metropolitan Areas (CMA) by size (Statistics Canada 2017b). The principal public transport agency of the region is TransLink, which provides service to an area of more than 1,800 square kilometres through 245 bus routes and three light rail transit (LRT) lines that span 79 kilometres (TransLink 2021b). In 2017, only 11.6% of trips were by public transit in the region (Metro Vancouver 2017), however, its share was significantly higher in the City of Vancouver – the CMA's main urban center with a population of 631,486 people (Statistics Canada 2017a), where 28% of work trips were made by public transit in 2019 (McElhanney and Mustel Group 2021).

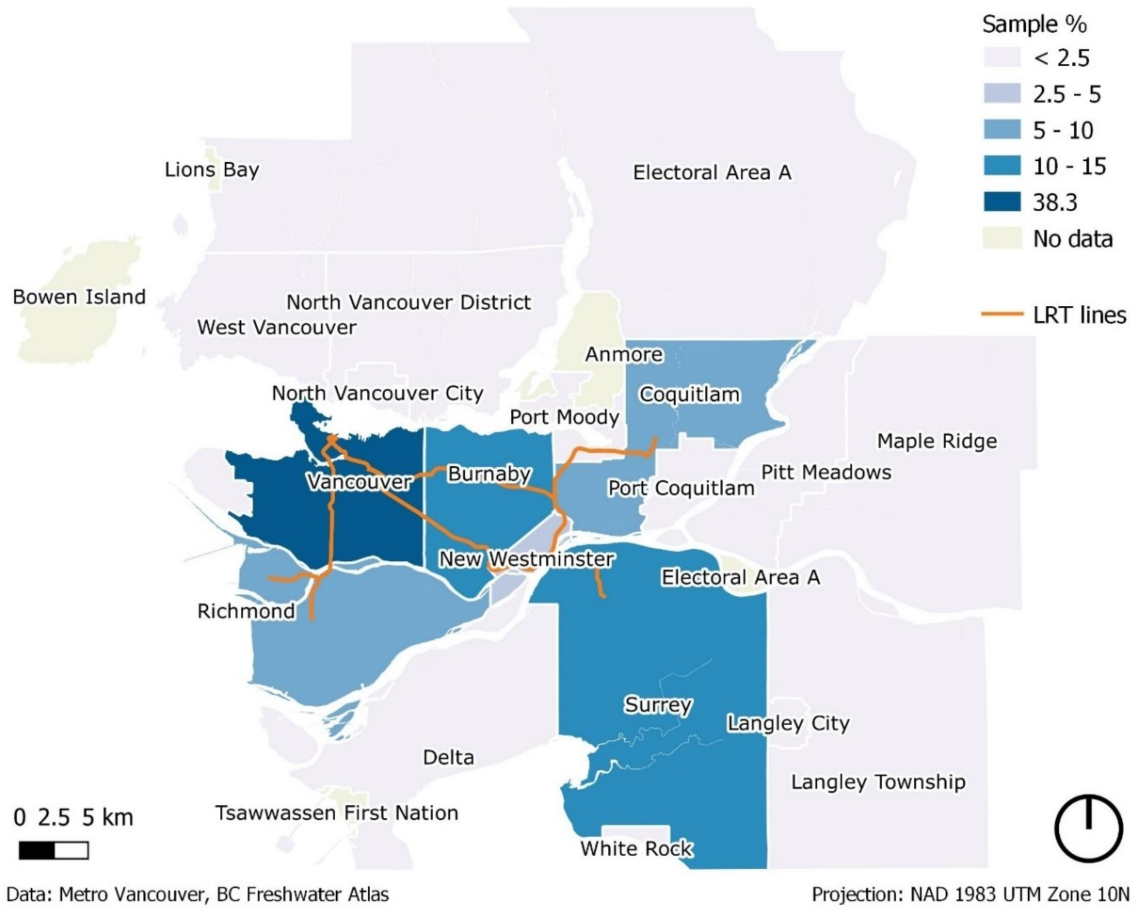

Figure 6 Geographic representation of survey respondents in the study sample

Almost two-fifths of respondents came from the City of Vancouver, with nearby Burnaby and Surrey accounting for 13.8% and 10.5% of the sample respectively. These are the areas served by the region's LRT system (SkyTrain) with high transit ridership, so it is not surprising that most of the survey respondents came from those municipalities. Figure 6 does not include those 0.58% of respondents who identified their home postal code that is outside Metro Vancouver, while another 1.75% of the sample did not provide their home location at all. The summary statistics for the study sample are presented in Table 3 where they are compared to the Statistics Canada 2016 Census.

Table 3 Study sample summary statistics

		Respondents in the study sample (%)	Vancouver CMA (%)
N		1201 respondents	2,463,430 people
Gender	Female	50.9	48.8
	Male	49.1	51.2
Age	18-19	5	N/A[4]
	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

[4] 2016 Census has information for the 15-19 age group that accounts for 5.8% of Metro Vancouver population

		Respondents in the study sample (%)	Vancouver CMA (%)
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	
	Contract employee	2.7	
	Homemaker / Stay-at-home	1.3	
	Other	2.5	N/A[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	
	1	19.6	N/A[6]
	2 and more	14.3	

As Table 3 shows, the gender representation of Vancouver CMA has been roughly preserved, however, despite the hard age quotas used there are significant discrepancies in nearly all age groups. For example, the 25–34-year-olds were oversampled by almost a third, while the seniors (65+ age group) were undersampled. The disparity in age and other demographics between the sample and the Census can also be attributed to the focus that this study introduces, as it surveyed the adult population who used public transit, and who are not the dominant cohort in the region, as previously mentioned. Other noticeable observations from Table 3 are that the sample has significantly fewer residents who earn

[5] 2016 Census has information only on full-time and part-time employment for those who worked a full year

[6] 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)

less than $29,999 annually than there are according to the Census, while there are two times more respondents with at least an undergraduate degree (61.6%) compared to 30.6% of the population in Vancouver CMA. These are most likely to be the result of the online nature of the survey, which has been reported to limit the participation of less-educated respondents and households with low income (Jang and Vorderstrasse 2019). This is an important limitation as it might have an impact on the classification results that are discussed in the findings section. Similarly, there are almost two times more fully employed individuals in this study's sample (likely due to the focus of the study on transit commuters), while there are significantly fewer respondents from single-person households than there are in Metro Vancouver.

The survey also captured participants' attitudes towards crowding, safety, transit use, flexibility, and actions they took to avoid crowding on transit before the pandemic, as well as sentiment towards TransLink's actions and policies during the COVID-19 using 5-point Likert scales, ranging from strong disagreement (1) to strong agreement (5) with the statements. This study primarily focused on the attitudes towards safety and flexibility as they showed the highest potential for the classification. Safety-related statements captured the sentiment towards the concern for unsafe transit environment before the COVID-19 pandemic (e.g. "*Prior to the pandemic I felt concerned for my personal safety aboard crowded transit vehicles"*), dissatisfaction with crowding and preferences to use other modes or travel at off-peak times to avoid it, and the pandemic-related anxiety regarding the agency response (as captured by the statement *"I am concerned that the health measures put in place by TransLink are not sufficient or will not be followed on public transit"*). The latter had the highest average response on the 5-point Likert scale of the studied indicators (3.56, with a standard deviation of 1.15), while the preference to use modes alternative to transit to avoid crowding before the pandemic had the lowest average value (2.45, with a standard deviation of 1.42). The flexibility-related indicators captured the respondents' stated ability to change the start time for their trips to and from work or study before the COVID-19 pandemic. I provide additional details on the attitudinal statements of the survey when discussing the results of the study.

3.5 Methodology

The categorization of respondents into behavioural classes was performed using unobserved latent variables (LV) as proposed by Bahamonde-Birke and Ortúzar (2020). This approach is based upon the Hybrid Choice Model (HCM) framework (Ben-Akiva, Mcfadden, et al. 2002) and, unlike other methods for probabilistic segmentation of individuals, it aims at the identification of latent classes (LC) based on underlying unobserved attitudinal traits. Along these lines, this approach allows identifying how observed characteristics of the individuals affect the likelihood of exhibiting a given underlying trait, which, in turn, results in a likelihood of belonging to a given population segment (Bahamonde-Birke and Ortúzar 2020). The main benefit of this categorization approach is that it does not lead to an introduction of new error terms, unlike the other methods. For example, latent variable latent class (LVLC) models add variability of the categorization function to the error term of the LV, while direct categorization based on latent variables applied in this study avoids that by associating individuals to the classes using an LV's position between the estimated thresholds (Bahamonde-Birke and Ortúzar 2020). However, as with any other model using the HCM framework, it does not have a closed-form solution, so to estimate the model's parameters by maximizing it, the likelihood is computed via simulation (Ben-Akiva, Mcfadden, et al. 2002; Bierlaire 2003). As far as I know, no other academic studies (with the exception of the initial application in Bahamonde-Birke and Ortúzar (2020)) combined HCM and LC frameworks in a fashion that avoided adding new error terms. This was discussed as a possibility in Walker and Ben-Akiva (2002), but not implemented. At the same time, both Hess et al. (2013) and Motoaki and Daziano (2015) applied the LVLC approach in their studies.

Within the HCM framework, it is assumed that all individuals may be characterized in terms of unobserved LVs (η_q). These underlying LVs can be modelled by means of structural equations taking the following form:

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

where X_q enumerates observed characteristics of a respondent q, α_X is a vector of parameters to be estimated, while υ_q is an error term that follows an assumed distribution (e.g. normal, or logistic), based on the theoretical considerations for the model.

Within this framework, it is assumed that the unobserved LVs are the reason behind the variability observed in the attitudinal indicators collected by the analyst. A subset of the attitudinal indicators is considered to be a direct expression of the underlying LVs. Assuming a linear specification, a given indicator *I* that is directly expressed by an LV for an individual q may be represented as:

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

where X_q again enumerates explanatory variables, ς_q is an error term that follows a given distribution with a mean of zero, while γ_X and γ_η are the parameters to be estimated. When answers to an indicator are recorded on a Likert scale, it can be treated using its ordinal nature through an Ordinal Logit specification (i.e. by assuming that the error term follows a Logistic distribution with mean zero), where a set of thresholds are introduced to account for every possible level of the indicator. The value of the observed answer then depends on whether a threshold for a particular level has been crossed. Within this framework, the probability of the answer *I* for a person q observing a given indicator *n* can be expressed as follows:

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

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

The remaining indicators are thought to be an expression of unobserved LCs. These LCs are, in turn, explained by the underlying LVs. In other words, all indicators are affected by the underlying attitudinal traits, however, for some of them, a continuous impact is considered while for the remaining ones, the effect is the result of belonging or not to the aforementioned LCs.

The individual probability of belonging to a given LC is associated with the value of the LV being larger or smaller than a given set of thresholds $\underline{\psi}$ to be estimated (note that it implies that the different LCs group together all individuals scoring at a similar level in the underlying LVs, e.g. having a low level or high level of flexibility, as considered in this study). This probability can be expressed as:

$$P_{qk} = P\left(\psi_B < \eta_q < \psi_T \middle| X_q, \alpha, \Sigma_\eta\right)$$
$$P_{qk} = P\left(X_q \cdot \alpha_X + \upsilon_q < \psi_T\right) - P(X_q \cdot \alpha_X + \upsilon_q < \psi_B) \tag{4}$$

where ψ_B is the bottom class threshold and ψ_T is the top one, X_q enumerates explanatory variables, α_X is the vector of parameters to be estimated for the individual characteristics and LVs used for categorization. It should be noted, that, using this framework, a probability of being smaller or larger than a set of thresholds can also be estimated for a combination of two LVs.

Finally, the probability of observing a certain outcome D (an indicator that is considered to be a direct expression of an LC) can be expressed as the outcome of latent-class specific utility function:

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

where β_{Xc} is a vector of latent-class specific parameters to be estimated, while ε_q is an error term whose distribution is assumed to be i.i.d. EV1 with a mean of zero. As a result, the likelihood function for this framework includes the discrete choice part (where the latent variable is utilized categorically), the component of measurement indicators, and the distribution of the latent variable used for the integration of the function. It can be expressed as:

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

Like other models using the HCM framework, Equation (6) does not have a closed-form expression. Consequentially, it is considered by simulating the LV η_q based on a finite series of random realizations. This generates a discontinuity in Equation (4) and the algorithm's convergence and successful identification of thresholds cannot be guaranteed (Bahamonde-Birke and Ortúzar 2020). This can be overcome by introducing an auxiliary LV η_q^a that has the exact same specification as η_q. If both η_q^a and η_q follow an i.i.d. Logistic distribution with a mean of zero, Equation (4) can be expressed as a closed-form expression (i.e. an Ordered Logit probability kernel), overcoming the discontinuity issues that arise when Equation (6) is integrated numerically.

A schematic representation of the model is displayed in Figure 7. To be able to employ the attitudinal indicators for classification, their relationships with each other were first explored using Principal Component Analysis (PCA). This approach creates new variables (principal components) that are not correlated with each other and captures the existing variability in the dataset, reducing the number of dimensions and optimizing the data for analysis. These new latent variables can be then used for categorization in the subsequent steps of the analysis. This stage of the analysis was performed using the generic functionality of R statistical software (R Core Team 2013).

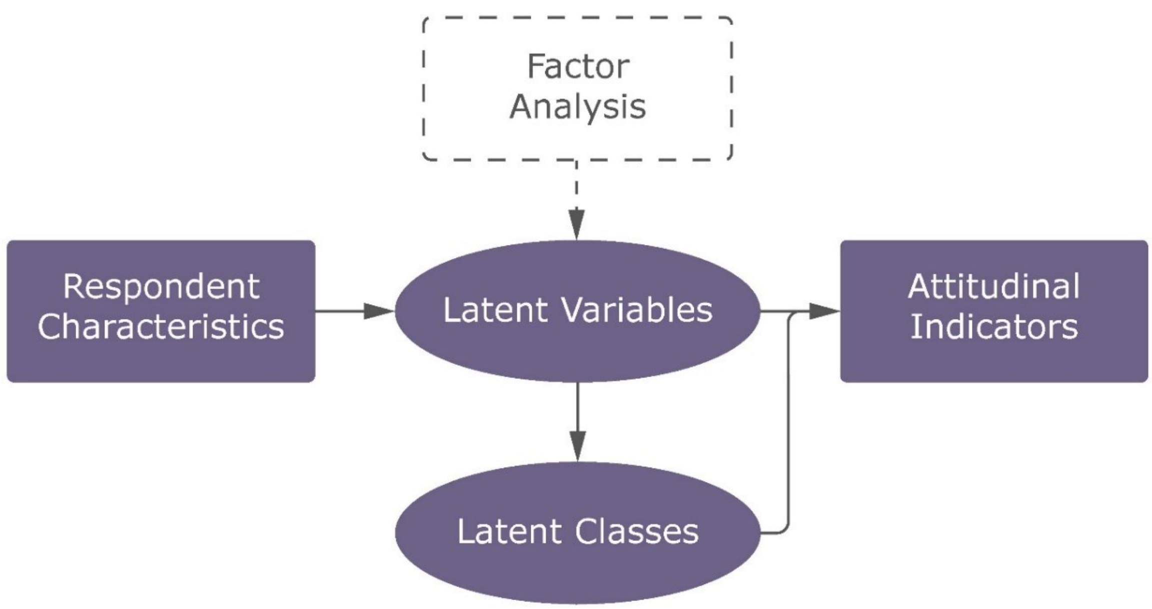

Figure 7 Schematic representation of the methodological approach to classification

PCA was performed on the questions that captured attitudes towards crowding and personal safety before the pandemic, health safety during the pandemic, flexibility to travel to and from work/education purposes, experience with mobile technologies, and TransLink transportation services. The attitudinal statements were captured in the survey using 5-point Likert scales, with 1 accounting for the strongest disagreement and 5 for the highest agreement, while Varimax rotation for Eigenvalues larger than one was used to ensure the maximum of squared loadings' variance. Following the guidance from Hair et al. (1995), only indicators with loadings larger than 0.3 were retained for the final analysis.

Once latent variables were identified, indicators for every LV were first explored continuously (i.e. without the categorization). These measurement equations were estimated using the Ordered Logit specification to establish the baseline log-likelihood for each LV. I then sequentially tested each indicator for classification using the HCM framework described above and retained those for the next step of classification if an improvement in log-likelihood was observed. Following this approach, the estimation of probabilities was performed using Binary and Ordered Logit specifications for 2 and 3 classes respectively.

The final likelihood function was calculated using the Apollo package (Hess and Palma 2019) in the R statistical software (R Core Team 2013). Estimation was performed using maximum simulated likelihood, where 1000 Sobol draws (Sobol' 1967) approximated the distribution for the integration. Furthermore, as with other latent class methodologies, it was acknowledged that the outcomes of this analysis depended on the starting values used for estimation. To ensure that the categorization process produced reliable estimates, multiple values were tested to confirm that the model didn't arrive at a local optimum as a result of the non-monotonous categorization function. The final model that combined both latent variables for simultaneous estimation had 52 parameters and a log-likelihood of -14213.46.

3.6 Results

The focus of this study was to perform a probabilistic classification of transit users in Metro Vancouver that could be used to develop a set of policy interventions aimed at distributing the peak hour use of TransLink services to other times, or less crowded routes. Principal Component Analysis (PCA) was employed to explore the underlying relationships between the attitudinal indicators that informed the specification of the classification model based on the HCM framework. The final model produced six probabilistic classes based on the estimates for two latent variables that accounted for respondents' concerns regarding crowding and safety, as well as personal flexibility to travel to and from work via public transit.

3.6.1 Factor analysis

Performing PCA resulted in the four internally consistent groupings presented in Table 4, each representing a latent variable that captured a certain attitude, namely concern regarding crowding and safety on transit, flexibility to travel by transit, technical aptitude to use smartphone applications, and favourable view of the transit. I highlight the highest factor loadings in bold. The first LV captured sentiment about congested transit vehicles before the COVID-19 outbreak, like the statements "I felt concerned for my personal safety aboard crowded transit vehicles" and "I chose to travel at off-peak (less busy) hours to avoid crowding on transit", as well as during the pandemic, like "I am concerned that the health measures put in place by TransLink are not sufficient or will not be followed on public transit". As Table 4 shows, the last indicator had a relatively low loading (0.351) but was retained to preserve the observed link between the attitudes towards comfort and personal safety before the pandemic and health safety in the course of it. Given the strong presence of the concern for personal and health safety in the statements associated with this LV (either directly, or reflected through the actions taken out of that concern), I applied the "Concerned" label to this LV. The second latent variable captured a strong positive relationship between the perceived flexibility of outward and inward travel, indicating that individuals in the sample are consistent in perceiving their general travel flexibility, and not separate parts of it. This aspect of the travel behaviour was utilized to label the second latent variable as "Flexible". Results for the tech-savvy LV follow the general logic that individuals used to paying with a smartphone are also comfortable with app-based navigation systems. Finally, the fourth latent variable indicates that respondents who have good accessibility via public transit also emphasize the environmental effect of their transportation choices, while having higher trust in the transit and other governmental agencies.

Overall, this stage of the analysis resulted in the underlying relationship between the indicators in the dataset and allowed us to establish the relationships between the measurement equations of the hybrid choice model used for classification.

Table 4 Summary statistics of attitudinal statements and factor analysis results

Survey Question	**Sample Avg. (SD)**	**Factor loadings**			
		Concerned	**Flexible**	**Tech-Savvy**	**Transit-Friendly**
Prior to the pandemic I felt concerned for my personal safety aboard crowded transit vehicles	3.06 (1.39)	**0.756**			
Prior to the pandemic I was bothered by the crowding which I experienced on transit	3.76 (1.2)	**0.629**	-0.102		-0.101
Prior to the pandemic I needed a seat to feel comfortable onboard transit	3.19 (1.35)	**0.542**			
Prior to the pandemic, if travelling 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)	**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	3.17 (1.35)	**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	3.56 (1.15)	**0.351**		0.107	

Survey Question	Sample Avg. (SD)	Factor loadings			
		Concerned	Flexible	Tech-Savvy	Transit-Friendly
transit					
Flexible in time to travel to work via public transit	2.39 (1.4)		**0.839**		0.114
Flexible in time to travel from work via public transit	2.92 (1.47)		**0.763**		
I feel comfortable using mobile payment systems	3.54 (1.3)			**0.788**	0.207
I feel comfortable downloading and using new smart-phone travel applications	3.79 (1.22)			**0.767**	0.19
TransLink can get me anywhere I need to go	3.14 (1.21)		0.123		**0.579**
I am aware of the measures put in place by TransLink to keep customers safe while riding public transit	3.72 (1.05)			0.133	**0.507**
I make an effort to travel using environmentally sustainable modes of transport	3.48 (1.14)			0.177	**0.49**
I feel comfortable sharing my personally identifiable information with companies and government agencies	2.79 (1.24)		0.102	0.162	**0.408**
Variance: 41.2%					

3.6.2 Classification

Following the described methodological approach, it was determined that half of the LVs identified in the Principal Component Analysis, namely tech-savvy and transit-friendly, were not suitable for categorization as the resulting classes were divided into most of the sample and extreme cases, while such specifications had inferior log-likelihood compared to continuous representation. As a result, two latent variables were used for the final classification, including those that reflected respondents' attitudes towards crowding (LV1 concerned) and their flexibility to use transit going to and from work and education (LV2 flexible).

Indicators Safety aboard when crowded, Bothered by crowding on transit, Needed a seat for comfort, and Traveled off-peak to avoid crowding were considered to be a direct expression of the LV1 concerned, and indicators Chose alternative during peak, and Safety measures insufficient were chosen to be an expression of the LCs for LV1 concerned based on the log-likelihood tests. On the other hand, indicator Travel from work via transit was deemed as a direct expression of the LV2 flexible, while indicator Travel to work via transit was considered to be an expression of the LCs for LV2 flexible. A correlation parameter between LV1 and LV2 was introduced in the model to capture potential relationship, while the first thresholds for indicators of the LCs for both LVs were fixed at 0 to avoid correlations with the constants.

The number of LCs for each LV was sequentially tested and only retained after the increase if an improvement in log-likelihood was observed. Using this experimental approach, LV1 concerned was categorized into three classes (low concern, medium concern, and high concern), while two classes were found to be optimal for LV2 flexible (low flexibility, high flexibility). All available socio-demographic factors were tested for their influence on the LVs in the classification. Importantly, the variable that evaluated the effect of change in attitudes towards crowding throughout the pandemic was found to be insignificant, suggesting no shift in those perceptions between the two waves of the survey. These steps are illustrated in Figure 8.

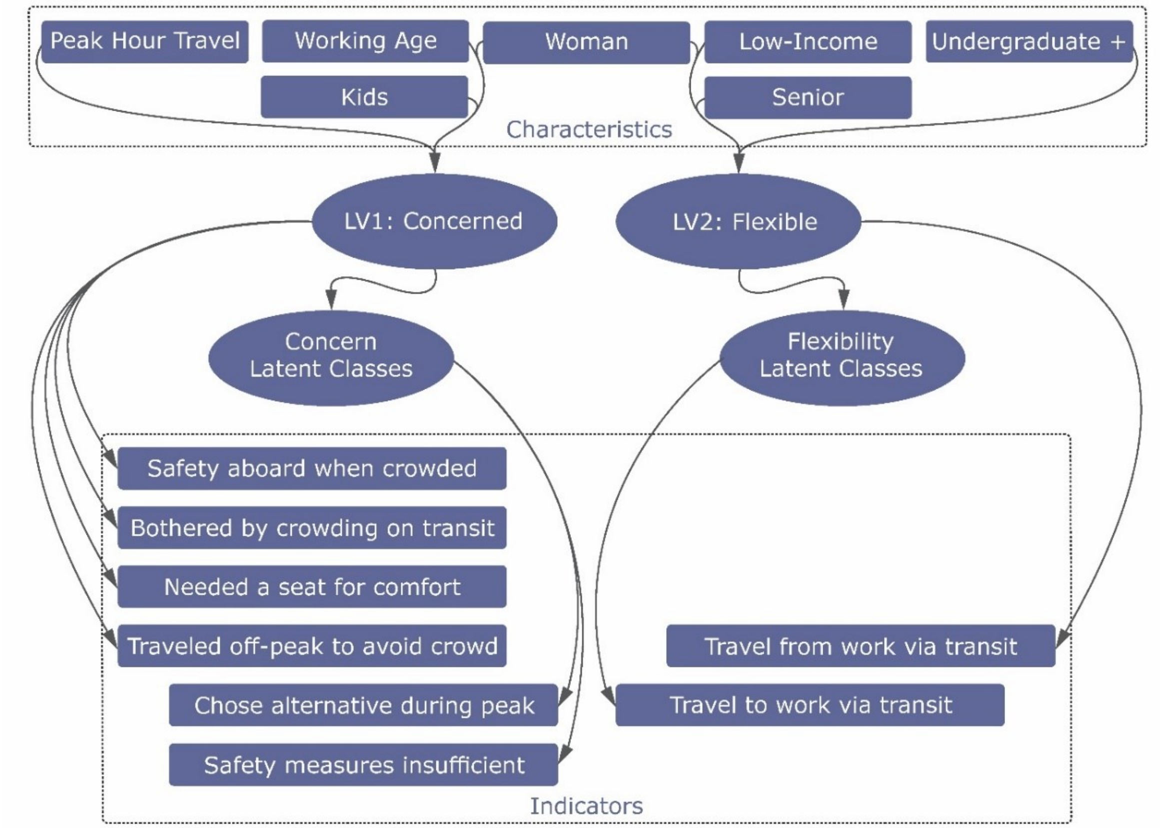

Figure 8 Diagrammatic representation of the final classification model

The estimates of the structural and measurement equations of the model can be found in Table 5. The concerned LV had an impact of a respondent being a woman, of working age (25-44 group), having kids, and travelling during the morning peak hour (6-9 am in Metro Vancouver). It was found that women were more likely to be concerned about crowding and safety, as were riders with children, and those in the 25-44 age group (work age). The former two categories were expected to display a higher propensity to be concerned about crowding, as past research suggests that women feel less safe on transit in general, not only when it is crowded (Ouali et al. 2020; Börjesson and Rubensson 2019), while the same considerations affect the travel mode choices for households with children (McCarthy et al. 2017). Börjesson and Rubensson (2019) posit that women view crowding more negatively than men because of the history of harassment and assaults that took place on public transit which can be exacerbated by the high level of crowding.

Table 5 Structural and measurement equations estimates

Variable	Equation	Estimate	SD	t-test
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 traveller		-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[7] 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	-	-

[7] ASC stands for alternative specific constant.

Variable	Equation	Estimate	SD	t-test
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	-
Log-likelihood (final, whole model): -14213.46				
AIC: 28530.92				
BIC: 28903.78				

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.

When it comes to the morning and work-age commuters, it is intuitive to assume an overlap between the two factors (people travelling to work early in the morning). Nevertheless, that was not the case for the sample, as low correlation and unmeaningful interactions showed. That can also explain the opposite direction of estimates for the parameters. The 25-44 age cohort can be considered a prime workforce group, and their higher likelihood to be concerned about crowding can be explained by the potential decline in the reliability of crowded transit (due to longer boarding and egress times, or the need to wait for the next transit vehicle) and thus inability to meet professional obligations, as well as the decline in productivity during the commute (inability to read or work) (Haywood, Koning, and Monchambert 2017). On the contrary, morning peak travellers were less likely to be concerned about crowding and safety on transit. This finding can be explained by the mere exposure effect, a concept developed in psychology that suggests the human preponderance to favour objects or situations that they are more familiar with. It is believed that the attitudes towards crowding follow the same trend – those who travelled between 6 am and 9 am in Metro Vancouver, and most likely experienced the highest level of crowding on transit regularly, developed a tolerance for it high enough to be less concerned about it. This also suggests that the definition of a crowded vehicle should not be the same throughout the day and that a more crowded route during the morning rush hour can have a lower effect on riders' satisfaction, than the same level of crowding at other times (van Lierop and El-Geneidy 2017).

On the other hand, the LV that captured the statements on flexibility revealed that women and seniors were less likely to consider themselves flexible, as opposed to low-income and highly educated (with an undergraduate degree, or professional schools, like medicine, master's, or Ph.D. degree) individuals. Highly educated individuals tend to be more flexible as has been previously documented in numerous studies (Alexander, Dijst, and Ettema 2010; Hamermesh 1996; Golden 2001). What comes as a surprise is the similarly high flexibility of individuals earning less than $50,000 annually (which is considered to be a low income given the high cost of living in the region (Metro Vancouver 2016)) who are most likely to be employed in sectors with fixed shift schedules and have limited flexibility in when they can travel to and from work. The observed effect is believed to be the result of the composition of the sample used in this classification, where those with an undergraduate degree and higher account for 61.6% of respondents compared to only 30.6% of highly educated individuals who are in Metro Vancouver in reality. The share of highly educated individuals in the low-income subsample is slightly lower than in the full study group (50.8%), but it is still significantly above the regional share, which probably drives the similar effect on the flexibility LV as being highly educated does. Moreover, the low-income cohort has a higher share of students when compared to non-low-income workers (those earning more than $50,000 annually) – 15% versus 6% respectively, and more from the former group live alone (30% compared to 15% for non-low-income respondents) while being younger (24.1% are in the 18-24 age group compared to 12%). The low-income cohort may have many young and highly educated professionals who are in the early stages of their careers that place them in the lower income bin, but who work in occupations that allow them to be flexible. The confluence of these factors most likely produced the effect observed during the classification.

The finding that women are less flexible can be explained by the fact that females are more likely to work part-time (Patterson 2018), as well as shoulder a larger share of care-based responsibilities (Loyser 2017). The absence of a rigid work schedule and the necessity to multitask throughout the day are likely to negatively impact opportunities for personal transportation flexibility for this demographic group. Similarly, senior respondents display diminished travel flexibility as an age group known for their aversion to change (National Research Council 2006).

Lastly, the estimates for the explanatory variables and thresholds for 3 LCs that represent concern and 2 LCs that capture attitudes towards flexibility were used to calculate final cross-probabilities for 6 LCs for every individual (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). This step required the generation of another 10,000 normally distributed error terms and integration over the entire domain to take correlation into account. These results are presented in Table 6. The class that encompasses high concern and high flexibility was found to have the largest average class allocation probability of 28.11%, while the two other classes that account for high flexibility (low concern, high flexibility; medium concern, high flexibility) had average allocation probabilities of 6.26% and 16.99%

respectively. This is an important finding, as it suggests that an average respondent in the survey has a 51.36% chance of being in a highly flexible behavioural class. This means that a large share of the sample can change their travel start time to and from work, and thus can potentially respond to policy interventions that nudge them to travel at off-peak hours. Moreover, it should be expected that for the high concern, high flexibility class the considerations for personal safety might be already a reason good enough to travel at less crowded times, while the high concern, low flexibility class members might opt for other modes if they have access and ability to. On the other hand, it seems that there is a large share of transit riders who are concerned with crowding and safety on transit – something that reflects the heightened attention to those matters during the COVID-19 pandemic when the data for this study was collected. This cohort might respond to additional information on crowding levels and safety measures on the transit system as an argument good enough to modify their travel time, route, or mode.

Table 6 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%

Overall, these findings suggest that the probabilistic classification can be operationalized for the identification of different classes of transit users. The obtained distinct behavioural classes and their demographics can be targeted with specific programs emphasizing crowding and flexibility in their messaging to influence transit riders' choice to travel outside of the peak hours, as well as allow decision-makers to better plan for necessary timelines and resources for their implementation.

3.7 Policy implications

This study has applied a probabilistic approach to the classification of transit riders using the underlying LVs that represented respondents' sentiment towards crowding and safety on public transport vehicles and their flexibility to travel to and from work and/or education purposes. In practical terms, the knowledge generated through the application of probabilistic segmentation increases the chances for the transit agency to engage more transit riders. As discussed in the literature review, the major limitation of deterministic classification is that a person is associated with only one class at a time, which significantly reduces the options for messages and interventions a transit agency would consider to target individuals. This is overcome in the probabilistic framework where we estimate the likelihood of a respondent belonging to all classes based on the measured preferences, meaning that we get a richer base to understand the preferences of transit users. This accuracy opens up opportunities for more nuanced messaging and interventions, as now users can be targeted from the angle of multiple classes that they have a significant probability of belonging to. In a hypothetical example, a rider who has a relatively high likelihood of belonging to both high concern, high flexibility class and high concern, medium flexibility class can be targeted with a campaign that emphasizes the benefits of travelling at off-peak times (due to fewer people travelling) and clearly outlining alternative routes to the most crowded links of the transit system for those who have less freedom in changing their travel time. As a result, this tailored campaign based on a nuanced understanding of people's preferences has a higher chance of improving the behavioural outcomes of transit riders, as it has been found for custom messaging in public health preventive care (J. Jensen et al. 2012) and advertising (Olsen and Pracejus 2020). Moreover, from the marketing perspective, as Olsen & Pracejus (2020) state, higher customization of advertising campaigns improves the customer experience with and trust in the brand, which in the case of transit agencies can lead to higher ridership and loyalty. Given the ridership losses that agencies experienced due to the COVID-19 pandemic, such an opportunity to maintain more users can not be overlooked.

Our findings bolster the argument for the application of probabilistic classification in transportation planning by introducing a more accurate representation of commuters' behavioural profiles and socio-demographic factors that increase the likelihood of a person belonging to a certain group. This study was supported by TransLink to develop such insights and the influence of these findings can be traced in the TransLink's 2022-2027 Customer Experience Engagement Plan, where the agency recognized the multidimensionality of their customers, and classified them according to five mindsets riders might have when travelling – accessible, practical, advantageous, flexible, and cautious (TransLink 2022a). According to the plan, TransLink intends to improve the experience for the last two mindsets (which this study also identified) by increasing the ways (e.g. bus stop information screens) and accuracy of the information (i.e. real-time updates) on crowding levels and distribution within the vehicle (to point out areas for easier boarding), as well as explores the ways for being more transparent and responsive about the cleaning and maintenance efforts using QR codes. At the same time, the plan outlines numerous strategies to engage the other mindsets of transit riders as well.

Nevertheless, this classification offers even more opportunities for TransLink and other agencies alike to be more successful at engaging transit riders. Average class allocation probabilities estimated in this study and a proposed course of interventions are presented in Figure 9. These probabilities should be used by transit providers as a basis for policy interventions, though the exact class-specific impacts would have to be evaluated.

In the logic model for the application of the proposed classification in Figure 9, the behavioural classes are overlayed with the timeline and resources that might be necessary for the agency to implement it and respective profiles to change their travel behaviour. The potential interventions range from relatively low-cost and quick-to-adopt programs that allow riders to adjust their travel plans based on the levels of crowding or knowledge about the feasible alternatives, to monetary incentives and employer-based programs that modify workers' flexibility. It is hypothesized that riders in the high concern, high flexibility class are the group most ripe for programmatic interventions that provide additional information. TransLink might already be engaging this class through the service provided in partnership with a technology company Transit. Since August 2021 Transit app users have been able to access information on the available capacity of incoming buses and LRT trains in Metro Vancouver (Chan 2021). The effect of such a provision on riders' actual actions and choices is yet to be determined, however, existing evidence supports this assumption. A study in Stockholm reported a 4% decline in the boardings of the first two cars of the train as a result of crowding information communication via audio (Y. Zhang, Jenelius, and Kottenhoff 2017). Similarly, past modelling attempts indicated a possible increase in travellers' utility and alleviation of overcrowding as a result of such service (Drabicki et al. 2021). Being a fairly low-hanging fruit, it is only natural that the aspiration to continue expanding such interventions was included the Translink's 2022-2027 Customer Experience Engagement Plan. At the same time, the authors are working closely with TransLink to evaluate their effect and share the learnings with the other agencies as well.

Along the same lines, the high concern, high flexibility class might respond to a program that provides information on personalized travel alternatives to the usually crowded routes. An informational service like that was fairly successful in nudging private vehicle drivers to start using transit for their daily commute in the City of Durham, NC, reducing the share of motor vehicle commuters by 8.2 percentage points (Center for Advanced Hindsight 2020). Moreover, by advertising the health and safety benefits of using the programs mentioned above, TransLink can appeal to the concerned side of that class and further facilitate its behavioural change.

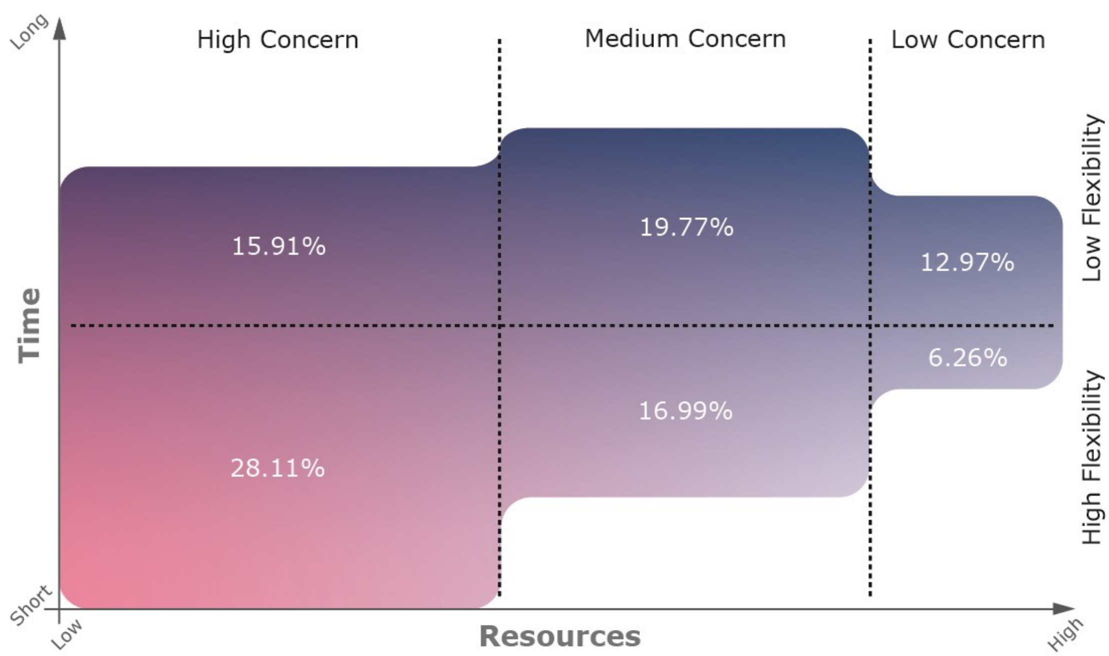

Figure 9 Average class allocation and proposed course for interventions

The other two classes that are less concerned with crowding and safety, but still view their travel schedules as flexible can be targeted with programs that incentivize the change in transportation behavior. This approach can be modelled by the reward program Perks that Bay Area Rapid Transit (BART) ran as a study pilot for six months in 2016-2017. Its overall goal was to reduce the rush-hour congestion on the Transbay corridor, and it allowed users to earn points for travelling outside of morning peak hours and redeem them either through an automatic raffle, a Spin-to-Win game, or a cash buyout. Overall, the BART Perks pilot resulted in 10% of participants shifting their travel to times outside of the morning peak hour (Greene-Roesel et al. 2018). This, like the other two information technology-based programs, can be adopted by the classes that have a higher degree of flexibility.

As for the classes that have low flexibility, the ones with the high concern should become the primary target group for policymakers, as it is possible that these individuals would prefer to travel at other times or use other means but are unable to do so due to the lack of access to diverse transportation options. It is also evident that for the policy interventions to be successful at changing the travel behaviour of commuters with low flexibility, they should target not only individuals but also their employers. The mechanism for such formal engagement can be based on the Singapore Land Transport Authority's Travel Smart Network. Designed as a pool of resources that encourage large employers to provide their workers with schedule accommodations that allow them to travel at off-peak times and earn rewards through the Travel Smart Program – an incentive-based initiative that BART's Perk was inspired by, it partnered with 60 organizations employing 160,000 workers just in the first year of its existence (Land Transport Authority 2015). It is important to mention that an evaluation of the Travel Smart Program concluded that on average peak-hour demand fell by 7.5% during the first six months of the program (C. Pluntke and Prabhakar 2013). Figure 9 suggests that targeting appropriate classes with these programs will require more resources and additional time, and thus should be considered a far-off strategy. Moreover, it is important to distinguish between the partial remote work arrangements that allow employees to work from home on some days of the week now and the flexible or staggered hours programs that proved to be effective in reducing peak hour crowding on transit in the 1970s and 1980s. The former reduces transit demand when they work from home, while still pushing people to travel during the regular peak hours on the days when they commute to work. In the case of the latter, the change in regular work hours or institution of the daily work start/end flexibility allowed commuters to avoid travelling at the times when transit was most crowded (Copas and Pennock 1980; O'Malley 1975).

Targeting the less concerned and less flexible classes is also getting a footing in Metro Vancouver. As a part of the strategy to employ gamification and collaborate with employers in the region to steer travel behavior toward socially optimal choices, TransLink started a partnership with a commuting platform Commutifi in 2023. The platform allows employers to understand and incentivize sustainable commuting decisions of their workers, with large institutions, like the University of British Columbia, taking advantage of the offering (TransLink 2023d; n.d.-a). Another area of collaboration is the promotion of the Transit-Friendly Employer Certification that appeals to employees' desire to contribute to making commutes in the region more sustainable (TransLink, n.d.-d). Although these strategies have larger objectives that go beyond crowding management, they likely influence the spatial and temporal distribution of demand for transit services as well.

Overall, the findings of this study indicate that transit riders in Metro Vancouver can be classified into behavioural classes susceptible to responding to programmatic interventions that might shift their travel to off-peak times. While the study investigated the classification based on two dimensions only, it should be noted that there are more behavioural dimensions in practice that remain to be explored. Future work should also further investigate the effect of time on the classification. This study found no impact of time on the attitudes of transit riders, which is most likely the result of the timing of the survey waves when no major changes in the pandemic course and restrictions related to it took place. It is also possible that the results were influenced by the heightened level of concern during the COVID-19 pandemic, as well as by the fact that the pre-pandemic attitudinal indicators were collected retroactively and could be unreliable due to respondents recalling their experiences inaccurately. A dedicated effort should be considered towards investigating the change in attitudes over time and under the regular state of public health conditions. Additional work also should be done to understand how the identified behavioural classes respond to crowded transit vehicles, what actions they take in response to crowding, and what is their sensitivity to different programs and incentives. At the same time, it is recommended that TransLink continues piloting and experimenting with services like information on crowding offered through the Transit app. Existing research suggests that even short-term disruption, like a two-day strike on the London subway system, is capable of changing the transport behaviour of commuters (Larcom, Rauch, and Willems 2017). That is why the COVID-19 pandemic is believed to be a unique opportunity to introduce lasting change in the choices and habits of transit riders that shifts some part of the peak hour demand to other times.

3.8 Conclusions

The findings of this study are expected to enrich the existing knowledge and practice on market segmentation of transit users by using probabilistic classification that allows for a rider to be assigned to several profiles with a degree of certitude, rather than deterministically to a single profile. Besides being a more accurate representation of reality, this approach also allows the evaluation of the temporal effect on class membership. This improved segmentation provides better opportunities for public policy interventions to achieve the results they intend and introduce the change in transportation behaviour that benefits the system as a whole, increasing the safety and appeal of transit as a safe and comfortable transportation mode. Research shows that tailored messaging is more successful than generic campaigns at influencing individual travel choices (Gärling and Fujii 2009), while successful marketing campaigns could indeed increase the use of more sustainable transport modes and discourage car use (de Oña, de Oña, and López 2016). Similar targeted communication strategies can be expected to be successful in managing the demand of transit users. Informational campaigns that emphasize the benefits and safety of a less crowded vehicle during off-peak times to females, young professionals, or riders with kids, have a higher chance of shifting travel patterns of those groups to before or after rush-hour periods. Furthermore, segmenting those demographic groups based on their preferences will only increase the likelihood of engagement. On the other hand, encouraging employers to shift their traditional schedules or initiate programs that allow for variable work hours can affect the perception of personal flexibility and choice to travel to and from work outside of peak hours.

There are limitations to this study that need to be mentioned. The data collection took place during the period of stringent COVID-19 restrictions and was influenced by their effects, as well as a heightened level of cautiousness for personal safety in society at that time. It is likely that the preferences and priorities of transit riders might have changed as the management of COVID-19 by authorities shifted from pandemic to endemic frameworks. It is also possible that the classes identified in this study are specific to Metro Vancouver and would be different in other contexts. Researchers are encouraged to account for that as they try to investigate classes of transit riders in other regions.

Future research should focus on applying this segmentation approach to evaluate the initiatives that some agencies already have in place, like information on crowding levels or time-varying fares. This will allow for the identification of the factors that can be facilitated for representatives of different groups and influence their choice to travel at off-peak times or routes. Similarly, new initiatives (e.g. incentives with gamification elements) should be informed, piloted, and evaluated in the context of such segmentation approaches to achieve the maximum possible effect of crowding management interventions. This is especially relevant now, as the disruption caused by the pandemic offers a unique opportunity for introducing the change and ensuring the safety and satisfaction of the riders who return to transit, while respective regions can benefit from fewer car trips that will be substituted with public transportation and reduce the manmade contribution to climate change.

Chapter 4[8]: The impact of crowding on riders' class-specific behaviour

4.1 Chapter overview

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 who 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 the level of comfort of riding it for different behavioural 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.

4.2 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 levelled 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, Avineri, and Susilo 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, Miravet, and Domènech 2021; C.

[8] This chapter is based on the article: Kapatsila, B., Bahamonde Birke, F., van Lierop, D., Grisé, E. (2023). Impact of the COVID-19 Pandemic on the Comfort of Riding a Crowded Bus in Metro Vancouver, Canada. *Transport Policy* 141, 83-96.

Sun and Zhai 2020). These trends were also true in Metro Vancouver, the third largest urban region in Canada (Statistics Canada 2022a), which 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 2022b), however, even in the best-case scenario it is expected to fully rebound no earlier than in 2025 (TransLink 2022c).

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 2017) 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 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 the level of comfort of riding it for different behavioural 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 the expansion of system capacity too slow and inflexible to respond to the rapidly changing preferences and concerns regarding the 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 the short run while growing ridership.

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

4.3 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 (Haywood, Koning, and Monchambert 2017; de Oña and de Oña 2015; dell'Olio, Ibeas, and Cecin 2011; Eboli and Mazzulla 2007). An increase in public transport crowding makes the perceived travel time longer (Yap, Cats, and van Arem 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, Koning, and Monchambert 2017). In this literature review, I 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.

4.3.1 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, Maat, and van Wee 2009), researchers introduced those factors in the classification of transport users as well. For example, van Lierop and El-Geneidy (2017) 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 those 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 study 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.

4.3.2 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, Houdmont, and Griffiths 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, Cox, and Griffiths 2012), as well as heightened concern for personal safety (Cox, Houdmont, and Griffiths 2006). Commuters who experience 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 can 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 2017).

4.3.3 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, Esmailpour, and Shiwakoti 2021) and the presence of passengers without masks (Basnak, Giesen, and Muñoz 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; D. L. Floyd, Prentice-Dunn, and Rogers 2000; M. F. 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 traveller's behaviour. 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 behaviour (Chou, Lu, and Chang 2014; Elmore-Yalch 1998; van Lierop, Badami, and El-Geneidy 2018). Shelat et al. (2022) identified two classes of transit riders using a latent class choice model based on the decisions travellers make with regard to crowding and the degree of virus spread in the community and labelled 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 Travellers, who were also less likely to be women, and more likely to be younger and frequent riders (Shelat, Cats, and van Cranenburgh 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 are 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 behaviour in general. Finally, the findings provide guidance on how information on the choices of different behavioural classes can allow for public policy interventions to better facilitate transit use.

4.4 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 travelled 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, although 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 and BC Centre for Disease Control 2022). Moreover, no COVID-19 outbreaks were linked to transit use in Metro Vancouver.

4.4.1 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 kilometre, which makes it one of the most populous and concentrated parts of Canada (Statistics Canada 2017c). 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 Figure 10. There, it is easy to notice that the most congested bus routes in Metro Vancouver serve the City of Vancouver, especially the campus of the University of British Columbia in the west, and neighbouring suburban municipalities, oftentimes overlapping with the LRT lines.

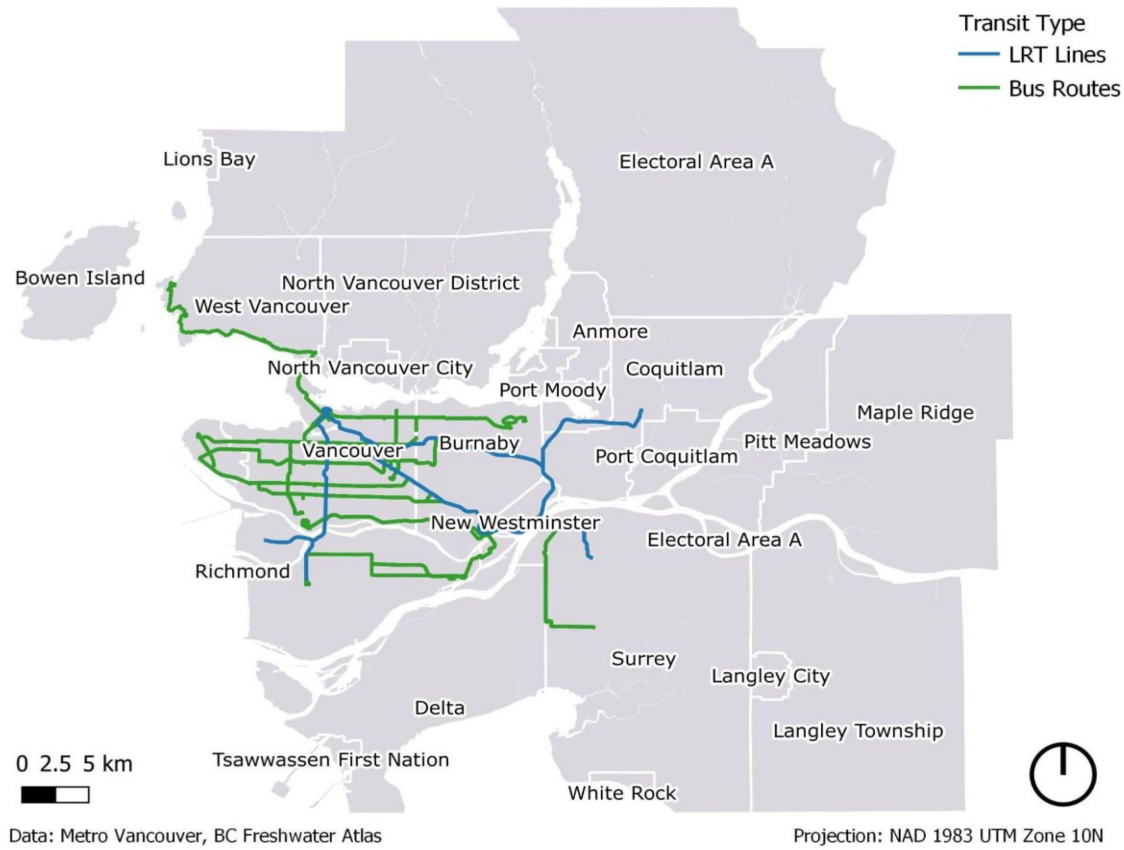

Figure 10 Geography of the studied region, its light rail train system and the 10 most overcrowded bus routes in 2019

Inspection of Table 7 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 travelled by public transport in 2016 (Statistics Canada 2017c), 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).

Table 7 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[9]
	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%

[9] 2016 Census has information for the 15-19 age group that accounts for 5.8% of Metro Vancouver population

		Respondents in the study sample	Vancouver CMA
	$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%	
	Contract employee	2.7%	
	Homemaker / Stay-at-home	1.3%	
	Other	2.5%	N/A[10]
	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%	
	1	19.6%	N/A[11]
	2 and more	14.3%	

[10] 2016 Census has information only on full-time and part-time employment for those who worked a full year

[11] 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)

4.4.2 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. Summary statistics for the indicators retained for classification are provided in Table 8.

Table 8 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 travelling 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

While the reliance on respondents' memory for the retrospective answers is a limitation of my study, I 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. In addition, 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).

The 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 Figure 11 and a 5-point Likert scale. 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).

Figure 11 Levels of crowding (low, medium, high) visualization used in the survey

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 9. 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.

Table 9 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

Demographic and non-demographic variables were iteratively tested in the estimated models and retained only if displayed statistical significance. Furthermore, I 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 modelling process.

4.5 Methodology

This chapter investigated the factors that affected the transport choices of different behavioural classes of transit riders before and during the COVID-19 pandemic. I first identified the behavioural classes of transit riders. I then modelled 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.

The behavioural 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, Mcfadden, 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 behavioural 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 the HCM framework (Ben-Akiva, Mcfadden, et al. 2002; Bierlaire 2003). To the best of my 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.

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

$$\eta_q = X_q \cdot \alpha_X + \upsilon_q \tag{7}$$

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.

The 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:

$$I_q = X_q \cdot \gamma_X + \eta_q \cdot \gamma_\eta + \varsigma_q \tag{8}$$

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:

$$P(I_{qn}) = \frac{e^{\mu_{n,I_{qn}} - \varsigma_{I_n}\eta_q}}{1 + e^{\mu_{n,I_{qn}} - \varsigma_{I_n}\eta_q}} - \frac{e^{\mu_{n,I_{qn-1}} - \varsigma_{I_n}\eta_q}}{1 + e^{\mu_{n,I_{qn-1}} - \varsigma_{I_n}\eta_q}} \tag{9}$$

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.

I 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:

$$\begin{aligned} P_{qk} &= P(\psi_B < \eta_q < \psi_T | X_q, \alpha, \Sigma_\eta) \\ P_{qk} &= P(X_q \cdot \alpha_X + \upsilon_q < \psi_T) - P(X_q \cdot \alpha_X + \upsilon_q < \psi_B) \end{aligned} \tag{10}$$

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:

$$U_q = X_q \cdot \beta_{Xc} + \varepsilon_q \tag{11}$$

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 modelled 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 modelled 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, I 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:

$$L_q = \int_\eta \begin{bmatrix} \sum_k \begin{matrix} P\left(B_q^p \middle| X_q; \alpha,\ \beta_b, \Sigma_U, \Sigma_\eta\right) \cdot P\left(C_q \middle| X_q; \alpha,\ \beta_l, \Sigma_U, \Sigma_\eta\right) \cdot \\ P\left(D_q \middle| \alpha,\ \beta_k, \Sigma_U, \Sigma_\eta\right) \cdot\ P\left(k \middle| X_q, \alpha, \Sigma_\eta\right) \end{matrix} \\ P\left(I_q \middle| X_q, \eta_q; \alpha, \gamma, \Sigma_I, \Sigma_\eta\right) \cdot f\left(\eta_q \middle| X_q, \alpha, \Sigma_\eta\right)\ \cdot d\eta \end{bmatrix}. \tag{12}$$

In the absence of a closed-form solution for (12), LV η_q is identified via simulation which leads to discontinuity in Equation (10) 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 (10) to have a closed-form expression (i.e. an Ordered Logit probability kernel), and avoid discontinuity when integrating (12) 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 (12) 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. I 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.

4.6 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. I 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 Figure 12 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.

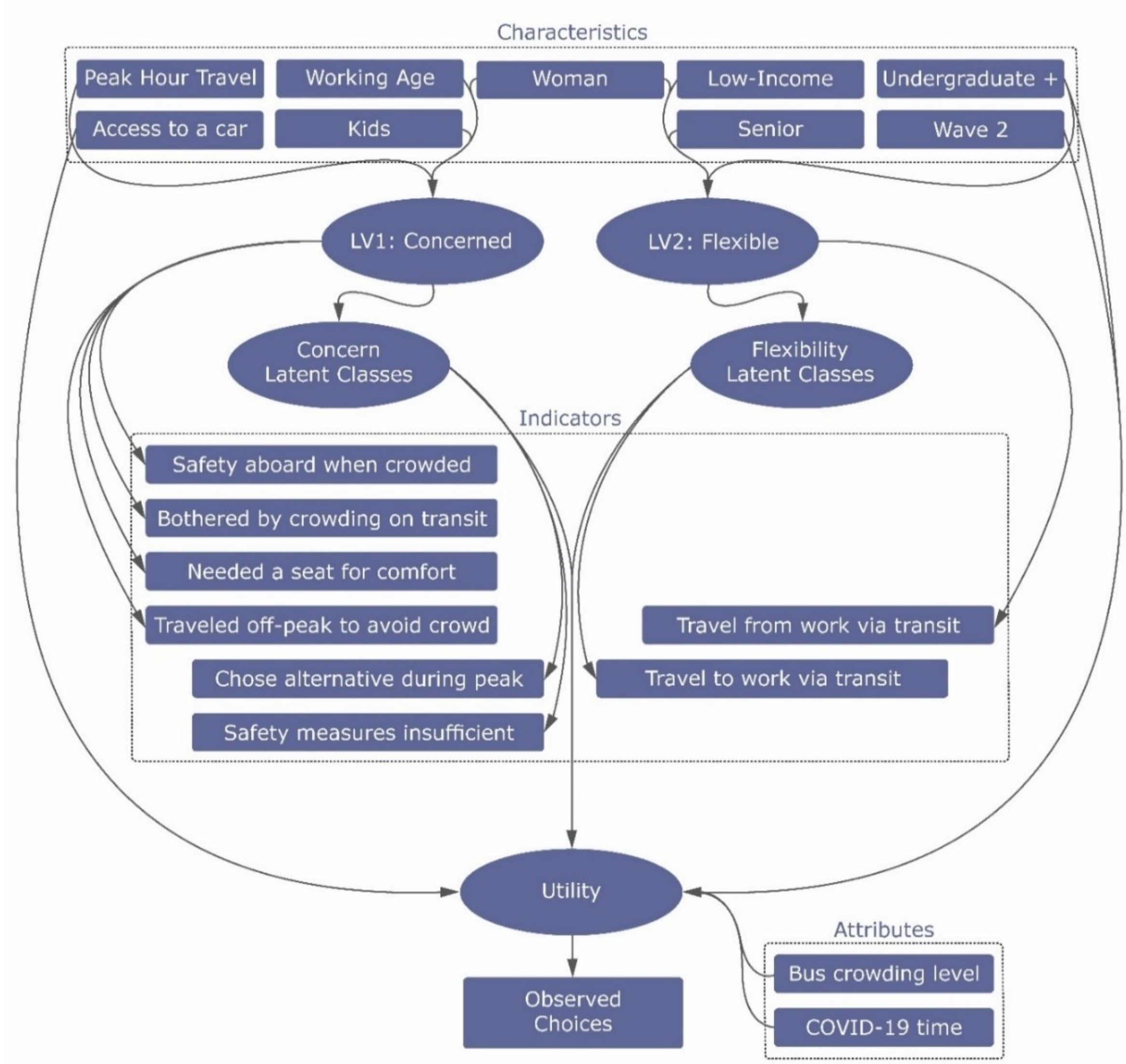

Figure 12 Diagrammatic representation of the model

4.6.1 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-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 discernable 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), which captures 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 modelling process are presented in Table 10.

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. 2020; Shelat, Cats, and van Cranenburgh 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 (Ouali et al. 2020; Börjesson and Rubensson 2019). Similarly, riders of 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, Koning, and Monchambert 2017).

Table 10 Structural and measurement equations estimates of the 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	-

Variable	Equation	Estimate	SD	t-stat.
Threshold 4		4.801	0.650	-
Threshold 1		-1.871	0.109	-
Threshold 2	M.E. Traveled off-peak	-0.811	0.091	-
Threshold 3	to avoid crowd	0.384	0.088	-
Threshold 4		1.740	0.104	-
ASC Class Low		1.156	0.422	2.741
ASC Class Medium & High		4.301	0.506	8.503
Threshold 1	M.E. Safety measures	0	-	-
Threshold 2	insufficient	1.715	0.284	-
Threshold 3		3.686	0.487	-
Threshold 4		5.116	0.504	-
ASC Class Low		-1.361	0.314	-4.341
ASC Class High		8.417	13.498	0.624
Threshold 1	M.E. Travel to work	0	-	-
Threshold 2	via transit	6.997	13.507	-
Threshold 3		8.578	13.505	-
Threshold 4		9.612	13.504	-
Threshold 1		-1.927	0.453	-
Threshold 2	M.E. Travel from work	-0.664	0.215	-
Threshold 3	via transit	0.967	0.291	-
Threshold 4		2.534	0.613	-
Log-likelihood (final, whole model): -14213.46				
AIC: 28530.92				
BIC: 28903.78				

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.

Lastly, only one sociodemographic variable indicated the negative impact on being concerned about the safety and crowding on transit - morning peak travellers. It suggests that those travelling between 6 am and 9 am in Metro Vancouver most likely experience crowding more often than the 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 2017), and this study provides another argument for that.

When it comes to the second set of LCs based on LV2 flexible, I see that women and seniors are less likely to be flexible in their travelling. I 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, Schintler, and Button 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 travelling. While it is to be expected for individuals with university degrees (Alexander, Dijst, and Ettema 2010), it comes as a surprise for low-income riders. I 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 one-third of the population in Metro Vancouver. These individuals with advanced degrees account for about half of the low-income respondents in my 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 my 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 11.

Table 11 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%

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 behaviour. 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.

4.6.2 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 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. I 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 12, it is worthwhile to discuss the final specification of the models. I 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. I 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, I 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 the Bus boarding model provides estimates in Table 12, I see that 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, I 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 had 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 and 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).

I also see that educated individuals and those who 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 positions. Driving there is complicated due to high congestion in the City of Vancouver (TomTom 2021) and scarcity of parking (Canseco 2018), facilitating the use of public transportation. On the other hand, I also know from previous research that families with kids are more likely to drive than use public transport (Kløckner 2004; Lanzendorf 2010; Prillwitz, Harms, and Lanzendorf 2006; Westman, Friman, and Olsson 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, Smith, and Walks 2016).

Table 12 Estimates of the 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
	Crowd. level	-2.174	0.271	-8.024
	COVID-19	-2.039	0.314	-6.493
	2^{nd} wave of the survey	0.246	0.134	1.833
	Low-Med Concern Class Crowd. Level * COVID-19	-1.913	0.480	-3.982
	High Concern Class Crowd. 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 Crowd. level	-1.366	0.099	-13.795
	High Concern Classes Crowd. level	-4.153	0.121	-34.381
	COVID-19	-1.684	0.096	-17.552
	Low Flexibility Classes 2^{nd} wave of the survey	-1.040	0.089	-11.629
	High Flexibility Classes 2^{nd} 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	-

Number of observations: Bus boarding model – 7206 / Level of comfort model – 5849

Number of parameters: 21

Log-likelihood of the whole model: -9765.04

AIC: 19572.08

BIC: 19716.62

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.

Lastly, the ability to access a car has a negative impact on the individual's likelihood of boarding a bus - something that follows the findings of the previous studies (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. I 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, I 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' behaviour 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 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.

4.7 Discussion

This chapter 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 behavioural classes of transit riders in Metro Vancouver. The level of crowding is the only continuous variable in the model, so I 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, I see that a person who has kids would endure an 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. I 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).[12]

The identification of behavioural classes and observed differences or absence of those between the estimates also provide guidance for nuanced policy interventions. The 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 behaviour and reduce demand for transit services during peak times. As Table 11 suggests, this could be a substantial portion of riders, as more than half of the respondents are likely to belong to a flexible behavioural class (with no regard to the level

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

of concern). It is possible that the substantial 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 is necessary both to 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 am (O'Malley 1975). 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 1975). 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; C. 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 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 an 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.

4.8 Conclusions

This study classified transit riders into probabilistic behavioural 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. I was able to confirm empirically that riders more concerned about personal safety are less likely to board a bus, that an 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' behaviour 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 chapter 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 engage proactively with large employers who can shift the commute patterns of their employees to less crowded off-peak times. Lastly, I 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, 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 local phenomena when it comes to concerns for health due to the pandemic and apply mainly to the Metro Vancouver context. It is recommended that future research 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 other contexts.

Chapter 5[13]: The effect of incentives on the actions transit riders make in response to crowding

5.1 Chapter overview

Public transit crowding has a significant influence on riders' satisfaction and needs to be tackled using both demand and supply management approaches. In this chapter, I focus on the policy response to public transit crowding using various customer incentive schemes. By analyzing data from a stated preference survey collected in Metro Vancouver, Canada, during the COVID-19 pandemic, I identified the differences in preferences for various incentive schemes on public transit and assessed the relationship between the riders' eagerness to modify their travel patterns in response to crowding and the likelihood to respond to incentives that influence them to do the same. The findings suggest that people who favour incentives tend to be more likely to change their travel behaviour in response to crowding and that incentives which reduce the cost of travel on public transit have more potential to shift riders' travel time, while other incentives (like participation in a raffle, or smartphone game points) have a more pronounced effect on the decision to travel via a less crowded public transit route. Demographic-specific preferences for various incentive schemes were also identified; for example, individuals in the 20-34 age group were found to be more likely to respond to incentives, while full-time workers had a lower propensity to do that. The findings of this study are aimed at public transit agencies interested in employing policy instruments to manage transit crowding and researchers seeking to advance the knowledge about the influence of personal preferences on travel behaviour.

5.2 Introduction

Overcrowded public transit impacts customer satisfaction and can lead some riders to opt for other modes (Cho and Park 2021; Haywood, Koning, and Monchambert 2017; de Oña and de Oña 2015; dell'Olio, Ibeas, and Cecin 2011; Eboli and Mazzulla 2007). Accordingly, effective strategies must be utilized for public transit crowding management that tackle the issue both quickly and efficiently. The traditional approach of adding system

[13] This chapter is based on the article: Kapatsila, B., van Lierop, D., Bahamonde Birke, F., Grisé, E. (Under review). The Effect of Incentives on the Actions Transit Riders Make in Response to Crowding.

capacity offers a long-term solution to the challenges of transit crowding, however, such an approach is usually a prolonged and expensive endeavour that requires years of planning and execution. For example, it has been planned to take some six to ten years to extend Vancouver's existing light rail transit line to the University of British Columbia (Clement and Abelson 2019), and relieve one of the most crowded bus corridors in North America (Chan 2022). On the other hand, managing demand on public transit using policy tools might be an equally feasible intervention, able to provide much faster and more affordable congestion relief. In the context of budget shortfalls and disinvestments that were only exacerbated by the COVID-19 pandemic (Canadian Urban Transit Association 2021), transit agencies require more guidance on policy approaches to crowding management. Nevertheless, evidence of demand management benefits in public transit is scarce, unlike in the automobile congestion context (de Palma, Lindsey, and Monchambert 2017).

The impact of rewards on general behaviour has been not only observed anecdotally but proven empirically (Knutson and Greer 2008; Schultz 2015). Some cities, including Washington D.C., Melbourne, Sydney, Tokyo, and Hong Kong, use pre-peak hour free fares, discounts at off-peak hours, and fee increases during rush hours to manage the demand among public transit riders. More elaborate approaches attempt to use the knowledge about the human tendency to gamble (Anselme and Robinson 2013) and engage riders via smartphone games that offer opportunities to win prizes more valuable than a discounted or free fare. The use of these elements of gamification in incentive schemes is less common, with Singapore and San Francisco being the cities where such approaches were tested. To better equip public transit agencies with guidance regarding the incentives schemes that can engage riders to avoid the most congested routes or travel at less congested times, this study aims to systematically assess the riders' preferences for various incentives in the context of crowding reduction and investigate whether the favourable view of incentives increases the likelihood of behavioural change necessary to reduce system crowding. Moreover, given the context under which the data for the analysis was collected, this study enriches the knowledge on the changes transit riders considered making in response to crowding during the COVID-19 pandemic and provides insights into the factors that should be considered when introducing policies that intend to manage crowding on public transit using incentive-based financial instruments.

5.3 Literature review

This study explores how the preferences for incentives (such as fare discounts, coupons for free meals, etc.) influence the actions transit riders may take in response to crowding. Specifically, I focus on passengers' likeliness to change their travel time or transit route as a response to crowding during the period of government regulations aimed at limiting the spread of the COVID-19 pandemic.

In this study, I engage the knowledge from three distinct areas of research - public transit crowding, the use of financial tools for transportation demand management, and the effect of regulatory policy on the use of public transit. The interplay between these factors is theorized in the conceptual framework presented in Figure 13, where ellipses represent latent factors that cannot be measured directly, and rectangles capture the constructs that can be quantified. Furthermore, I use white font for the aspects I have the power to control for in the process of analysis, while the grey font represents the factors that are theorized to also be influential, but that I do not have the data for. Therefore, the relationships between variables presented in a white font are discussed and measured below.

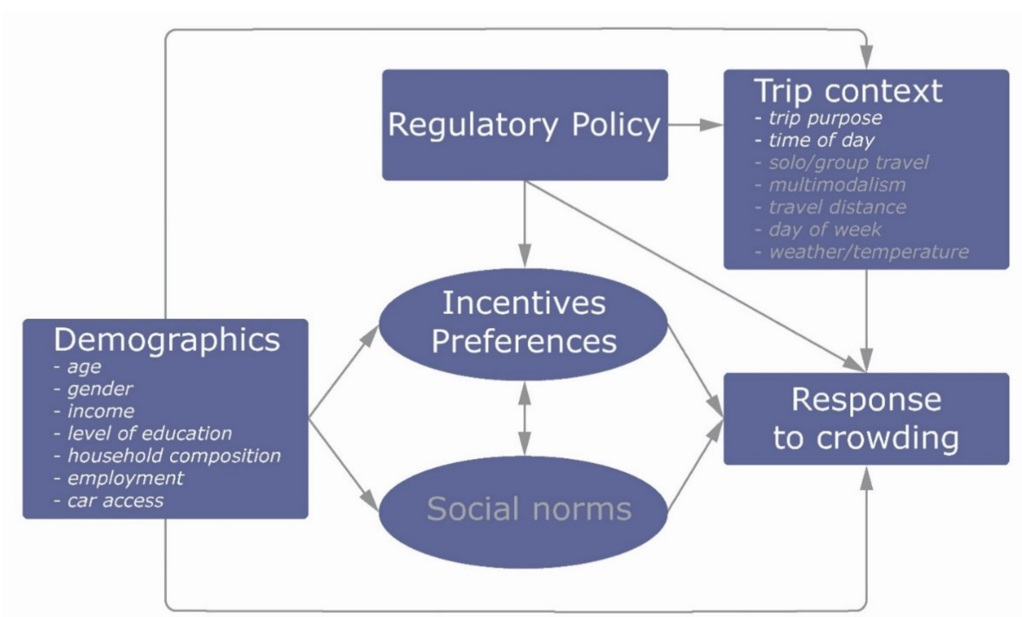

Figure 13 Conceptual framework of the factors that influence response to crowding on public transit

The conceptual framework for this study draws inspiration from the theory of planned behaviour, which explains observed people's choices and actions not only as a result of their sociodemographic characteristics but also preferences, attitudes, subjective norms, and perceived behavioural control (Ajzen 1985). Consideration of these influences puts this study in line with the previous research that found attitudes, preferences, and motivations to influence travel choices (Gountas and Gountas 2007; Lai and Chen 2011; Molander et al. 2012; Şimşekoğlu, Nordfjærn, and Rundmo 2015; St-Louis et al. 2014). In this study the choice that I focus on is the decision to change travel time or route in response to crowding, and whether preferences for incentives increase or decrease the likelihood of the resulting choice. I also believe that demographics influence that choice, both directly and indirectly, through the influence on preferences and person-dependent trip context (e.g. whether it is a work or recreational trip, or if the vehicle is boarded at a rush hour or at some other time). Similarly, regulatory policy is hypothesized to affect the response to crowding directly (i.e. if everyone is ordered to work from home then it must be very unsafe not to avoid crowding), as well as indirectly through the preferences for incentives (e.g. the utility of the incentive goes down in the face of a public health threat as communicated by the authorities) and trip context, as only the most essential trips take place. Finally, guided by the existing travel behaviour literature that points out the influence of psychological constructs other than preferences, like values and norms (M. Jensen 1999; Paulssen et al. 2014; Verplanken et al. 2008), I consider them in the conceptual framework as well. I theorize that social norms, like the acceptable distance between passengers on transit, or the work hours perceived as normal in a professional setting, also influence the response to crowding. And, while I do not possess the means to measure the influence of social norms on the responses to crowding, I believe that the relationship could be bidirectional, as riders under the influence of incentives may develop new socially acceptable norms in response to crowding. I discuss the existing literature in the three identified areas of research in the respective sections below.

5.3.1 Public transit crowding

Public transit system crowding relates to the densities of users onboard transit vehicles and at related infrastructure (i.e. stops and stations) that are higher than those were originally designed for (Li and Hensher 2013). Definitions of crowding vary across transit agencies, with many operators, especially larger ones that serve dense regions, having defined crowding standards for service (Li and Hensher 2013; Mistretta et al. 2009). For example, TransLink, a regional transit agency that serves Metro Vancouver in Canada, defines a vehicle as crowded if it is 84% to 99% full, which means that it has no empty seats and only some standing places are available, while occupancy above that is considered to be as the overcrowded state (TransLink 2018). Many agencies temporarily modified these standards during the pandemic, limiting occupancy to half of vehicle capacity, or setting it at 15 passengers (Kamga and Eickemeyer 2021).

Crowding can negatively impact both transit operations and the well-being of passengers. Studies have shown that high crowding levels increase boarding and alighting times for light rail trains (LRT) (T. Lin and Wilson 1992) and buses (Fletcher and El-Geneidy 2013; Milkovits 2008; Tirachini 2013). Longer waiting times for passengers who are not able to board the first transit vehicle that arrives due to its high occupancy (so they have to wait for the next one and spend more time on the trip) is another negative externality that can be attributed to crowding (Tirachini, Hensher, and Rose 2013). For buses, this user discomfort also translates into operational issues. If the number of passengers at the stop is larger than usual because not all of them were able to board the previous vehicle, then the next vehicle has to allow for more time for all riders to get on board, causing schedule deviation. Aggregation of these delays at the system level is defined as bus bunching (Abkowitz and Tozzi 1987), which on average leads to longer waiting times for passengers (Welding 1957).

The loss of time that transit systems and passengers experience due to crowding is not the only disadvantage that studies have identified. Riders tend to negatively view the experience of sharing a contained crowded space which can lead to stress (Mohd Mahudin, Cox, and Griffiths 2012), anxiety (Cheng 2010), concerns for safety (Katz and Rahman 2010), and invasion of privacy (Wardman and Whelan 2011). The disutility from crowding increases non-linearly (Çelebi and İmre 2020), and depends on the subjective perceptions that often differ from the objective agency standards (Li and Hensher 2013). This is particularly true for women, who are more likely to experience harassment on transit (Ceccato, Gaudelet, and Graf 2022) and tend to be more sensitive to crowding on transit due to safety concerns (Kapatsila et al. 2023; Ouali et al. 2020; Shelat, Cats, and van Cranenburgh 2022). Moreover, there is evidence that riders believe crowded transit to cause a loss of productivity onboard (Gripsrud and Hjorthol 2012) and to increase the chances of being late for work (Mohd Mahudin, Cox, and Griffiths 2011). On the other hand, crowding creates travel obstacles for some populations, effectively becoming an equity concern. These include groups that usually require more time to get on transit and more space onboard, like people who use mobility devices to assist their movement – wheelchairs, strollers, etc.; seniors, people with an injury or physical disability, or vulnerable populations such as women.

The challenges and concerns that the COVID-19 pandemic imposed on the communities translated into heightened sensitivity to crowding. Dissatisfaction with overcrowding peaked in April-November 2021 (Flügel and Hulleberg 2022), but remained above the 2018 levels even when treatments and vaccinations became widely available, and government restrictions were removed (Cho and Park 2021; Flügel and Hulleberg 2022). This higher concern was not only limited to dissatisfaction with transit crowding but also resulted in people opting for other modes, primarily private cars (Kapatsila et al. 2022; Vallejo-Borda et al. 2022) which is the behaviour that has been observed under other health-related circumstances in the past (Cahyanto et al. 2016; Lee et al. 2012; Leggat et al. 2010). If anything, public transit became stigmatized for commuters during the COVID-19 pandemic (Scorrano and Danielis, 2021).

Overall, transit crowding has an equally important influence on the satisfaction of passengers as travel time, the price, and quality of transit service (Haywood, Koning, and Monchambert 2017; de Oña and de Oña 2015; dell'Olio, Ibeas, and Cecin 2011; Eboli and Mazzulla 2007). As such, crowding challenges on public transit must be tackled quickly to prevent existing riders from opting for the other modes, which in turn will result in revenue loss for transit operators.

5.3.2 Financial tools in public transit management

The application of financial tools to crowding management on transportation systems has numerous examples, especially when it comes to attempts to manage traffic congestion. The first transportation demand management (TDM) programs for private vehicles were implemented in the 1970s in the form of incentives or penalties and spread across the world since then (Ma and Koutsopoulos 2019). In comparison, the use of fare discounts or increases to manage demand for public transit is less common (Halvorsen et al. 2016), and though some cities offer discounts at off-peak hours or fee increases during rush hours (e.g. Washington D.C., Vancouver, BC, London in the UK, Hong Kong), pre-peak hour free fares were tested only in a handful of places, including Melbourne, Australia, and Singapore. It is important to note that some studies argue the approach of increased fares produces suboptimal results at a societal level, as riders might not only change travel time but also switch to other modes (Basso et al. 2011).

Currie (2009) provided an overview of the Early Bird Train Travel program, a free fare offered to all rail users who completed their journeys before 7 a.m. in Melbourne. Launched in 2008, the program was found to be the reason for pre-peak travel for 23% of surveyed riders in the first year, while it was also the reason for taking transit for another 10% of travellers. The overall system effect of the program was estimated as a 1.2%-1.5% decrease in peak hour demand. Crowding is a significant issue in many Asian countries, so it is not surprising that many crowding demand-management programs can be found there. Using smart card data, Halvorsen et al. (2016) studied the travel patterns of 400,000 riders to understand the effect of the Early Bird Discount Promotion that was launched by the Hong Kong Mass Transit Railway (MTR) in September 2014. The program offered a 25% discount that users received when egressing at 29 highly utilized MTR stations before the rush hour. The aggregate effect of the incentive, meaning the total share of riders who shifted their travel time from the peak hour, was estimated at 2.8%.

Fare increases and discounts are among the most broadly used incentives on public transit, however, other instruments have also been explored. In this regard, the Singapore Land Transport Authority (LTA) can be considered a trailblazer. On top of penalizing rush-hour commuters with higher fares and incentivizing off-peak travel for its riders, it also ran a point-based reward system through the Incentives for Singapore Commuters (INSINC) platform (Halvorsen et al. 2016). The credits that a user earned for travelling during shoulder hours before and after the morning peak could be exchanged for cash or be used to participate in an online raffle. Additional credits could be obtained by friend referrals, learning “INSINC facts”, or achieving personalized behavioural goals. The analysis of the first six months of the program concluded that on average peak-hour demand fell by 7.5%, and it was even higher among active participants in the raffle and those who interacted with other users (C. Pluntke and Prabhakar 2013). Unfortunately, specific information on the demographics of the participants (age, gender, etc.) is not available. The Singapore LTA's INSINC program also influenced the design of a pilot reward program Perks, that Bay Area Rapid Transit (BART) ran for six months in 2016-2017. The goal of the pilot was to reduce the rush-hour congestion on the Transbay corridor, and it allowed users to redeem earned points either through an automatic raffle, a Spin-to-Win game, or a cash buyout (Greene-Roesel et al. 2018). As in Singapore, where almost 87% of participants preferred the raffle (C. Pluntke and Prabhakar 2013), 86% went with the raffle in San Francisco (Greene-Roesel et al. 2018), over the Spin-to-Win game or the cash buyout. Overall, the BART Perks pilot resulted in 10% of participants shifting their travel to times outside of the morning peak hour, though the pilot did not achieve the primary objective - to alleviate the congestion on the Transbay corridor (Greene-Roesel et al. 2018). Out of all pilot participants, only 13% regularly travelled through the Transbay corridor (Greene-Roesel et al. 2018), highlighting the importance of such programs to target populations whose decision to travel at other times or using different routes can decrease crowding at critical points on the transit system.

Wrapping up this overview of incentives, it should be noted that while existing studies shed light on the potential effectiveness of incentives in influencing travel behaviour, there is still a lack of knowledge about whether the effect remains long-term after the incentives are no longer in place, or it tapers off over time.

5.3.3 COVID-19 regulatory policy and public transit

The analysis presented in this chapter would not be complete without the acknowledgment of the context in which the data were collected and its potential long-term behavioural impacts. The COVID-19 pandemic had a profound effect on transport systems across the world (De Vos 2020). The change could be observed in fewer trips made and shorter distances covered, as well as an overall drop in travel demand, especially via public transit (Gramsch et al. 2022). While the contained nature of transit vehicles is often perceived as a place of higher risk for the spread of viruses (Basnak, Giesen, and Muñoz 2022), it is also evident that government interventions, aimed at limiting the spread of the pandemic (like lockdown and stay at home orders) had its effect as well. In Stockholm, where similarly to the rest of Sweden, authorities did not implement strict limitations as a consequence of the attempt to reach herd immunity, the decline public transit saw was about 60% in the first months of the pandemic (Jenelius and Cebecauer 2020). In the Netherlands, on the contrary, people were encouraged to leave their homes as little as possible, which led to an initial reduction of transit use by 90% (de Haas, Faber, and Hamersma 2020). Similar effects could be observed in Vancouver, Canada, where the confluence of stay-at-home orders, work-from-home policies, and travel mode substitution was the likely reason for public transit ridership going down to 17% of the pre-pandemic level in April 2020 (TransLink 2020b), and only getting back to 77% in September 2022 (Quinn 2022). Overall, while the assumed higher risk of public transit use was the main reason for the reduction in travel via transit during the pandemic (Tirachini and Cats 2020), it is also highly likely that a drop in economic activity as a result of COVID-19 regulatory policy had its effect on the demand as well.

As this literature review suggests, there is already evidence that financial tools can affect travel behavior, and potentially can decrease the congestion of transportation systems. Nevertheless, the studies reviewed in this section predominantly focused on a single type of incentive at once and only the demographics of transit users, while there is a consensus that policy interventions should appeal to attitudes and preferences as well to affect travel behaviour (Bohte, Maat, and van Wee 2009). Transit agencies lack knowledge about the engagement of different population segments of transit riders by focusing not only on their demographics but also their preferences. This study effectively bridges that gap by evaluating the effect of preferences for multiple incentives on the choices riders consider making in response to crowding. Moreover, it also investigates the effect of pandemic regulations on those preferences, effectively enriching the literature about the impact of the COVID-19 pandemic on transportation.

5.4 Data

The analysis was performed using data collected by means of two waves of a survey disseminated in December 2020 and May 2021. Hard age and gender quotas were used to recruit a sample of respondents representative of Metro Vancouver from the panel managed by a marketing research company. Given the public transit focus of the survey, I only kept respondents who frequently commuted to work or education via transit before the COVID-19 pandemic. The final sample used for the analysis includes 1,201 respondents, the majority of whom (57.1%) did not stop using public transit during the pandemic. Looking at the transit ridership trends for the region, it can be seen that the sample captured the effect of the COVID-19 pandemic. A comparison of the ridership numbers for 2019 and 2020 yields a 52% decline system-wide (TransLink 2021a). The split between the waves of the survey is almost even, with 52.7% of respondents in the sample who provided answers in May 2021. On top of the demographics of the individuals, I also recorded their preferences for incentives and actions in response to crowding using a 5-point Likert scale. Admittedly, government restrictions remained unchanged between the two waves of the survey, though the general shift towards remote employment and more private vehicle use has been observed (Kapatsila et al. 2022).

Geographically, the study covers the Vancouver Census Metropolitan Area, which has a population of more than 2.6 million (Statistics Canada 2022a). The primary transit agency of the region is TransLink which oversees local and express bus, light rail (LRT), and SeaBus (small ferry) operations. The region is notable for its significant public transit ridership, especially when compared to other communities in North America, and significant station and in-vehicle crowding levels, with some of the routes being over capacity for a third of the annual operating time pre-pandemic (TransLink 2020a). As Figure 14 shows, the most congested bus routes and LRT lines primarily serve the City of Vancouver, as well as nearby municipalities of Burnaby, New Westminster, and Richmond.

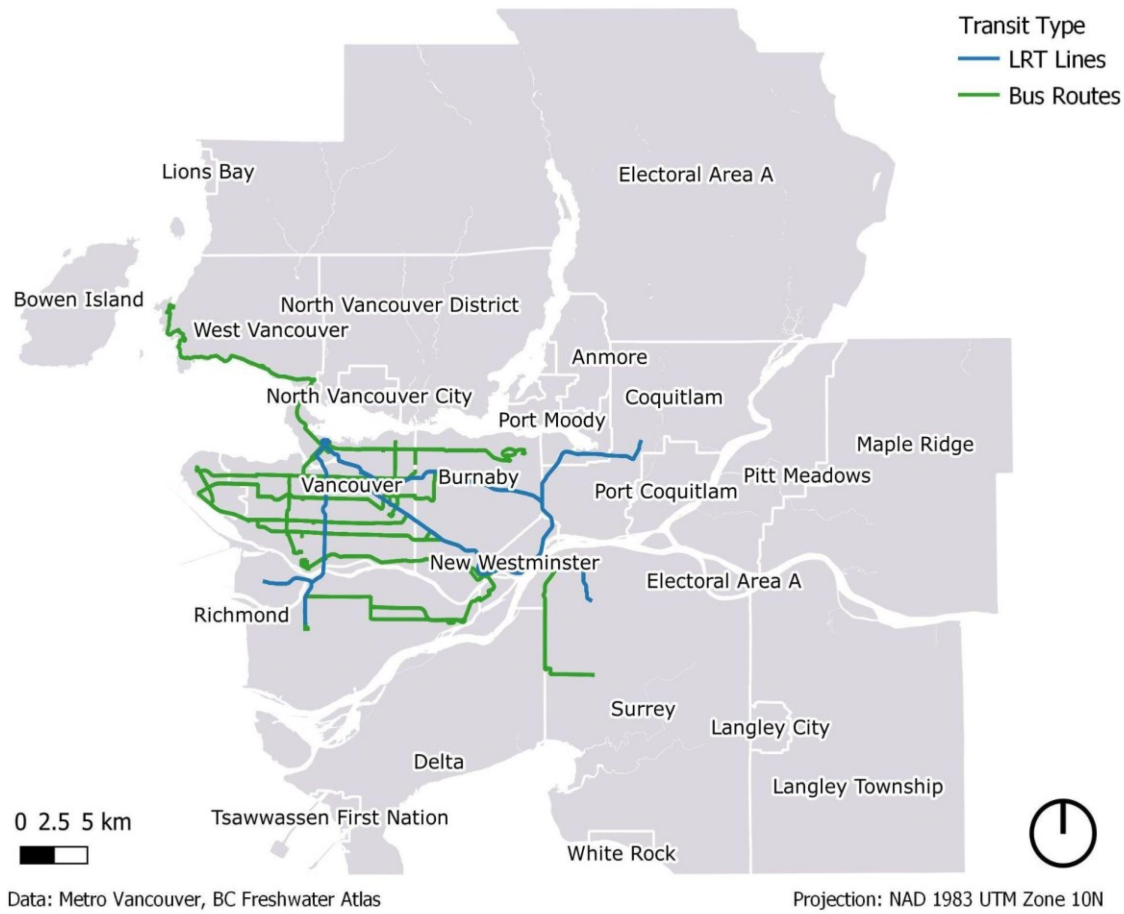

Figure 14 TransLink's light rail transit system and the 10 most overcrowded bus routes in 2019

Table 13 compares the demographics of the sample with the estimates reported by the Statistics Canada 2021 Census. While the gender ratio has been preserved, most of the age categories are noticeably off. For example, the 65+ category is less than half of what it constitutes in the 2021 Census, while the 25-34, 35-44, and 45-54 cohorts are significantly larger. Nevertheless, it should be noted that the survey targeted transit riders in Metro Vancouver, who might have demographics different from the rest of the region. Moreover, focusing on work/education commutes most likely had its effect on a large share of individuals of working age. This most likely also explains the discrepancies in the shares for each of the income groups.

Table 13 Summary statistics

		Respondents in the study sample	Vancouver CMA
N		1201	2,642,825
Gender	Female	50.9%	51%
	Male	49.1%	49%
Age	18-19	5%	N/A[14]
	20-24	9.8%	6.6%
	25-34	23.1%	15.5%
	35-44	19.5%	14.2%
	45-54	20.1%	13.4%
	55-64	14.7%	13.4%
	65+	7.8%	17.4%
Income	Less than $29,999	7.6%	12.4%
	$30,000 - $49,999	16%	12.8%
	$50,000 - $79,999	25.1%	19%
	$80,000 - $99,999	16.7%	11.2%
	$100,000 - $199,999	28.9%	31.7%
	More than $200,000	5.7%	13%
Highest education level	Elementary/grade school graduate	0.5%	12.1%
	High school graduate	16.1%	27.7%
	College/tech./voc. school	21.8%	15.2%
	Undergraduate degree	40.6%	22.9%
	Prof. school (e.g. medicine)	5.1%	0.9%
	Post-graduate (e.g. MS)	15.9%	9%
Employment type	Fully employed (30+ h/w)	59.4%	33.9%

[14] 2021 Census has information for the 15-19 age group that accounts for 5.2% of Metro Vancouver population

		Respondents in the study sample	Vancouver CMA
	Partly employed (1-30 h/w)	14.7%	30.7%
	Post-secondary student	8.5%	
	Contract employee	2.7%	
	Homemaker / Stay-at-home	1.3%	
	Other	2.5%	N/A[15]
	Permanently disabled	0.3%	
	(Temporarily) unemployed	6.2%	
	Retired	4.4%	
Household size	1	18.3%	29%
	2-4	71.5%	61.5%
	5 and more	10.2%	9.4%
Number of children	No children	66.1%	N/A[16]
	1	19.6%	
	2 and more	14.3%	

As Table 13 shows, the smallest differences between the study sample and 2021 Census estimates can be observed for the $100,000 - $199,999 income group (1.8% difference) and the largest for the category earning more than $200,000 annually (7.3% discrepancy), with the others being somewhere in the middle (4.4% difference on average). Lastly, I acknowledge that the sample is skewed towards individuals with at least a bachelor's degree, likely caused by the online nature of the survey, as well as fully employed respondents. The latter is of no surprise and can be explained by the focus on work and education commuters that this study had. Nevertheless, I controlled for this bias in my analysis.

I also provide summary statistics of preference statements in Table 14. These can be broadly divided into 3 categories, each measured using a series of 5-point Likert scale

[15] 2021 Census has information only on full-time and part-time employment for those who worked a full year
[16] 2021 Census has information on couples and children in Metro Vancouver (41.9% of all families), common law partners with children (3.2% of all families), and single-parent families (15.1%)

questions. The first one includes preferences for incentives, presented through the eight scenario options introduced with the question "*How likely would you be to travel at an earlier or later time (one hour before or after your usual travel time, keeping your travel time more or less constant) or take a different route with a similar travel time if offered any of the incentives listed below.*" All respondents evaluated their preference for those scenarios and their evaluation comprises the first half of my analysis.

The second and third groups of indicators are very similar, with the only difference in the target group that received the particular question. A little more than a half of the sample, 57.1%, continued using transit during the pandemic, so they were asked to rate their preferences for the action scenarios presented in a question "*Thinking about your use of transit over the past month in Metro Vancouver, please consider the following actions that can be taken to avoid crowding on transit, and state your level of agreement using a scale from 1 (strongly disagree) to 5 (strongly agree).*" On the other hand, 42.9% that stopped riding transit were introduced to the same scenarios in a hypothetical manner with the statement "*Reflecting on your transit experience in metro Vancouver prior to the pandemic, if your daily commute were to become busier now, please state your agreement with the following actions you would take to avoid crowding using a scale from 1 (strongly disagree) to 5 (strongly agree).*" As Table 14 indicates, there is no difference in the responses between the two categories of users to the scenario of changing the public transit route, with a median score of 3 and an interquartile range of 2 for both. At the same time, the option of changing the travel start time for the users who continued riding transit was rated lower (median=3, IQR=2) than for those who stopped (median=4, IQR=1). While statistically significant (p=0.008), I considered this deviation in 1 point acceptable for the indicators to be combined into one for subsequent modelling purposes. Furthermore, I introduced a dummy variable "No transit use (pandemic)" to control for the state of transit use by every respondent in the sample in the modelling process. While this step does not provide an explanation if the effect that the variable captured was due to the difference in samples, phrasing, or some other factors, it ensured that the estimates were unbiased. I also tested all possible interactions with the "No transit use (pandemic)" variable and did not obtain any statistically significant results.

Table 14 Summary statistics of the preference statements

	Median	IQR
Incentives (N=1,201)		
Monetary incentive towards a future monthly pass (a maximum of $20 credit for your future monthly pass	3	2
Travel at a discounted fare	4	2
Win points in a smartphone game that can be exchanged for a cash reward	2	3
Be included in a raffle to win prizes	2	2
Receive a free coffee, or a discount coupon for a meal	3	3
Make a donation to charity using earned points	2	2
Have a competitive advantage over peers on leaderboards	1	2
Receive discounts on other transportation modes (e.g. shared bikes)	2	2
Actions in response to crowding (respondents who continued using transit, N=686)		
I take routes that I know are less busy	3	2
I travel outside of the busiest times	3	2
Considerations for response to crowding (respondents who stopped using transit, N=515)		
I would change my route	3	2
I would change the time I start my trip	4	1

5.5 Methodology

This study pursued two objectives in the analysis – understanding the differences between the valuation of various incentives and establishing the causality between the stated preferences for incentives and expressed intention to change the route or time when travelling by public transit. To understand the differences in preferences between the offered incentives, I compared the values of indicators, as well as disaggregated them by age and income groups to gain further insights. Given the nonparametric nature of the preferences measured on a Likert scale, the significance of the differences was evaluated using the Wilcoxon T-test (Siegel 1956).

To achieve the second objective, I investigated the influence of the preferences for incentives on the decision to either change travel time or public transit route using an

Integrated Choice and Latent Variable (ICLV) approach (Ben-Akiva, Walker, et al. 2002). This modelling technique allows connecting the choices individuals make and preferences they express via unobservable constructs (i.e. latent variables) and understanding the strength of the effect that preferences have on the choices. While the use of the method does not always improve the model fit (Vij and Walker 2016), it offers additional insights into how unobserved traits influence the decisions of individuals.

When it comes to transport choices, it is customary to apply the discrete choice modelling framework (Ortúzar and Willumsen 2011; Train 2009) which is based on random utility theory (McFadden 1974; Thurstone 1927). Under these assumptions, the respondent q will make the choice that maximizes their utility U_q. This utility has a representative component V_q (i.e. the variables that an analyst can control for) and an error term ε_q that encompasses everything else that is either ignored or cannot be accounted for. This takes the following form:

$$\begin{aligned} U_q &= V_q + \varepsilon_q \\ V_q &= X_q \cdot \beta_X \end{aligned} \tag{13}$$

where X_q represents observed characteristics of a respondent q, and β_X is a vector of parameters obtained via estimation. The error term ε_q can be assumed to follow any distribution, however, given the ordered nature of dependent variables in this study, I assume it to have a standard Logistic distribution which leads to the Ordered Logit (OL) specification.

Having the specification of utility established, I can introduce the unobserved latent variables (LV) that explain the variation in the answers to preference questions (Bollen 1989), and are used to evaluate the impact of those preferences on the observed choices. It should be noted that LV is a distribution, so an analyst can only estimate the likelihood of an individual being related to some value of an LV. Given that, an LV η_q can be expressed via a structural equation of the following form:

$$\eta_q = Y_q \cdot \alpha_y + \upsilon_q \tag{14}$$

where Y_q represents the respondent's observed characteristics (which can differ from X_q), α_X is a vector of estimated parameters, and υ_q is an error term with a distribution suitable for the model (e.g. Normal, Logistic, Uniform, etc.). The inclusion of those unobservable latent constructs into the utility function modifies Equation (13) as follows:

$$\begin{aligned} U_q &= X_q \cdot \beta_X + \upsilon_\eta + \varepsilon_q \\ \upsilon_\eta &= \beta_\eta \cdot \eta_q \end{aligned} \tag{15}$$

where β_η is a vector of parameters to be estimated for the LV η_q. As previously stated, LVs in the ICLV framework affect both the observed choices and preference indicators, with the latter being a direct expression of the underlying LVs. In a linear fashion, the specification of indicators takes the following expression:

$$I_q = X_q \cdot \gamma_X + \eta_q \cdot \gamma_\eta + \varsigma_q \tag{16}$$

where γ_η is the estimated effect of the LV on an indicator, γ_X is a vector of estimated parameters for the observed characteristics of respondents, and ς_q is an error term. Indicators collected on an ordinal scale can be modelled via OL specification assuming that ς_q has a Logistic distribution. As such, the probability for an indicator *n* to be observed is expressed as:

$$P(I_{qn}) = \frac{e^{\mu_{n,I_{qn}} - \gamma_{I_n}\eta_q}}{1 + e^{\mu_{n,I_{qn}} - \gamma_{I_n}\eta_q}} - \frac{e^{\mu_{n,I_{qn}-1} - \gamma_{I_n}\eta_q}}{1 + e^{\mu_{n,I_{qn}-1} - \gamma_{I_n}\eta_q}} \tag{17}$$

where $\mu_{n,I_{qn}}$ stands for the parameter to be estimated.

Given everything described, the final integrated likelihood function comprises the likelihood of a selected outcome, the likelihood of observing the considered preference indicators, and the distribution of the LV. It takes the following form:

$$L_q = \int_\eta P(y|X_q, \eta_q;\ \beta_X, \varepsilon_q) \cdot P(I_q|\ \eta_q; \gamma_\eta, \varsigma_q) \cdot f(\eta_q|X_q, Y_q, \alpha_y, \upsilon_q) \cdot d\eta \tag{18}$$

There is no closed-form expression to eq. (18), so it is solved via numerical techniques, like a maximum simulated likelihood estimation (Ben-Akiva, Walker, et al.

2002). I performed the modelling using the Apollo package (Hess and Palma 2019) in the R statistical software (R Core Team 2013). A 1000 Sobol draws (Sobol' 1967) were used to approximate the integration distribution and multiple starting values were tested to avoid obtaining the results for only a local optimum.

5.6 Results

In this section, I begin by overviewing the differences in preferences for various incentives, as well as analyzing the income- and age-specific differences between those preferences. The second half of the analysis focuses on the results of the modelling process that evaluated the likelihood of incentives affecting the travel behaviour of the respondents.

5.6.1 Differences in preferences for various incentives

Figure 15 reveals that a fare discount is the type of incentive that had the highest support in the sample (median=4, IQR=2), followed by a $20 credit for a monthly pass (median=3, IQR=2) and a free coffee, or a discount coupon for a meal (median=3, IQR=3). The other options like a discount for other modes, the opportunity to participate in a raffle, or make a donation to a charity seem to be less preferable, with a median score of 2 and an equal spread. At the same time playing a smartphone game with an opportunity to win points and exchange them for a cash reward seems to be appealing at least to some respondents. Though the median score for it is also 2, the interquartile range is as high as observed for the food coupons/discounts - 3. Lastly, an advantage over peers on a leadership board was the least preferable incentive (median=1, IQR=2), though a comparable to other options spread indicates that some people might consider it as well. All differences described above were found to be statistically significant.

Comparing the preferences for incentives by different income groups provides additional insights. Although a fare discount remains the top choice across all income groups, the high-income earners (those making more than $200,000 annually) display a larger range, suggesting that some of them (most likely those at the top of the category) have a comparatively low preference for incentives in general. This, of course, is of no surprise, as it is expected that small rewards would have lower benefits for those with higher incomes. Another finding that stands out is that both medium- (making between $50,000 and $100,000 a year) and low-income (those earning less than $50,000 annually) earners have a higher preference for winning points in a smartphone game when compared to high-income ones, and that difference is statistically significant (p=0.074 and p=0.021 respectfully). Lastly, it is surprising that for low-income respondents I see an increase in preference for donations to charity and advancement over peers in households when compared to other income bins. For the former, it is statistically significant in both comparison pairs (p=0.032 for the medium-income and p=0.0003 for high-income), while for the latter the difference is insignificant when compared to medium-income participants (p=0.132) but it is meaningful in comparison to high-income respondents (p=0.0001).

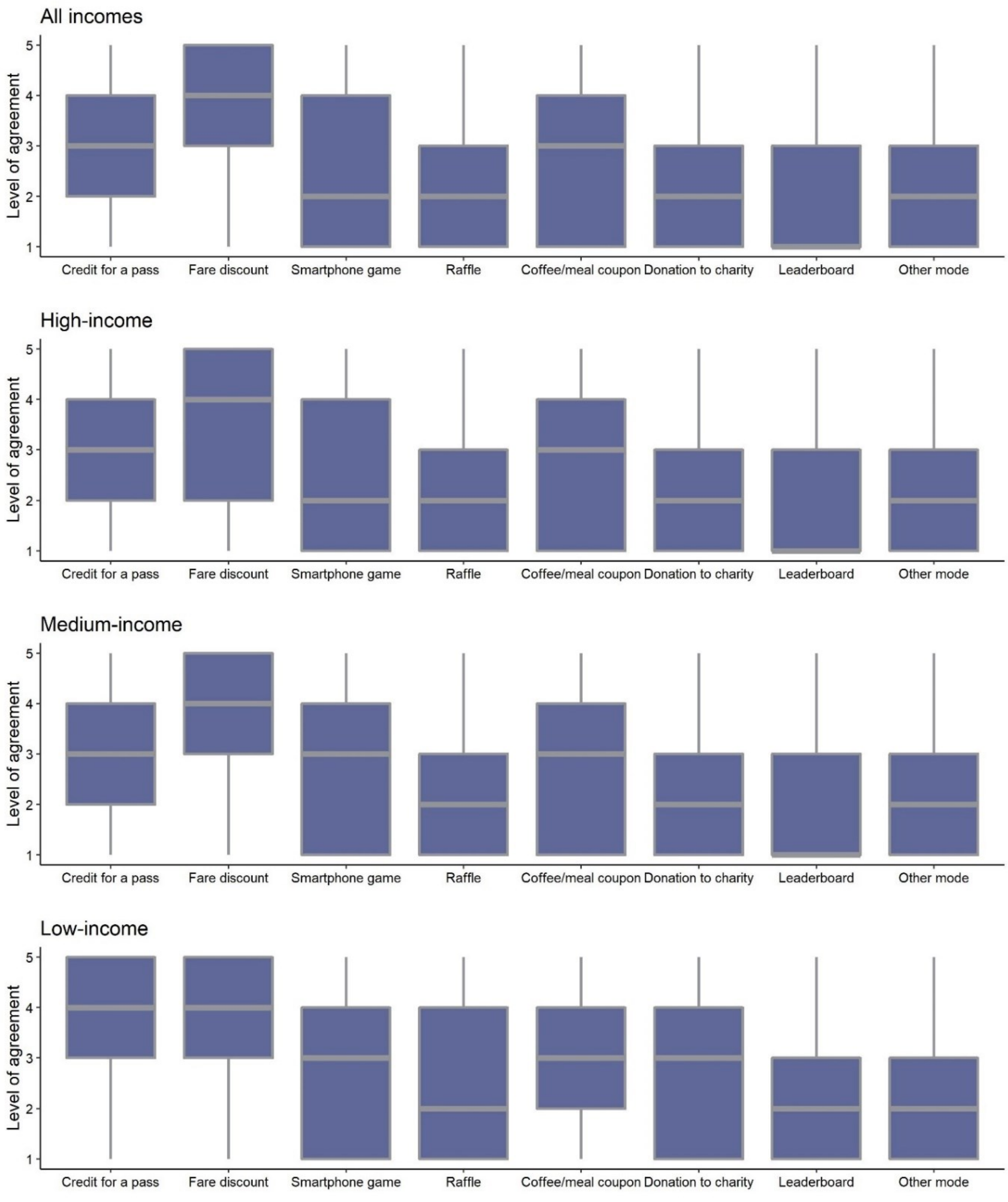

Figure 15 Preferences for incentives by income

When the preference for incentives is decomposed by age, some of the findings from the differences between income groups become clearer. For example, Figure 16 shows that the relatively high preference for donations found previously in low-income groups can be also spotted in the age 18-24 cohort. It is possible that something in the value system of Gen Z motivates them to use a reward for others. However, this difference is only statistically significant between the youngest and the 45-64 age groups (p=0.004). I return to this finding in the discussion section in greater detail. Similarly, younger respondents (18-24 and 25-44 groups) tend to be more favourable to the idea of winning points in a smartphone game, as well as having a higher standing on a leaderboard as a motivator to change behaviour in response to crowding. This is natural given the higher tech skills of people born after 1980 (Chopra and Bhilare 2020) and their general propensity to respond to activities enriched with gamification (Jain and Dutta 2019). I also see that the first two age groups drive the high level of support for fare discounts and transit pass credit observed at an aggregate level, which is likely a cause of generally lower financial security at that age due to still-evolving career paths, small children, and accumulated debt (e.g. university loans) among the others. Lastly, seniors – those aged 65+ – display a general tendency to be less likely to respond to more abstract forms of incentives like leaderboards, discounts for other modes, raffle, and playing smartphone games for points.

Several conclusions can be made based on these summary statistics. First of all, incentives that can decrease the cost of transit use can be by far the most popular offerings among riders. It is also evident that younger riders between 18 and 44 years old can potentially better respond to incentive schemes that employ elements of gamification as an engagement mechanism. Appealing to social norms and promoting the change in travel behaviour among the youngest riders as a contribution to someone else's good can nudge them to change the travel time or route to avoid crowding. And it is clear, that the group of riders who are older than 65 years seem to be less responsive to incentives in general.

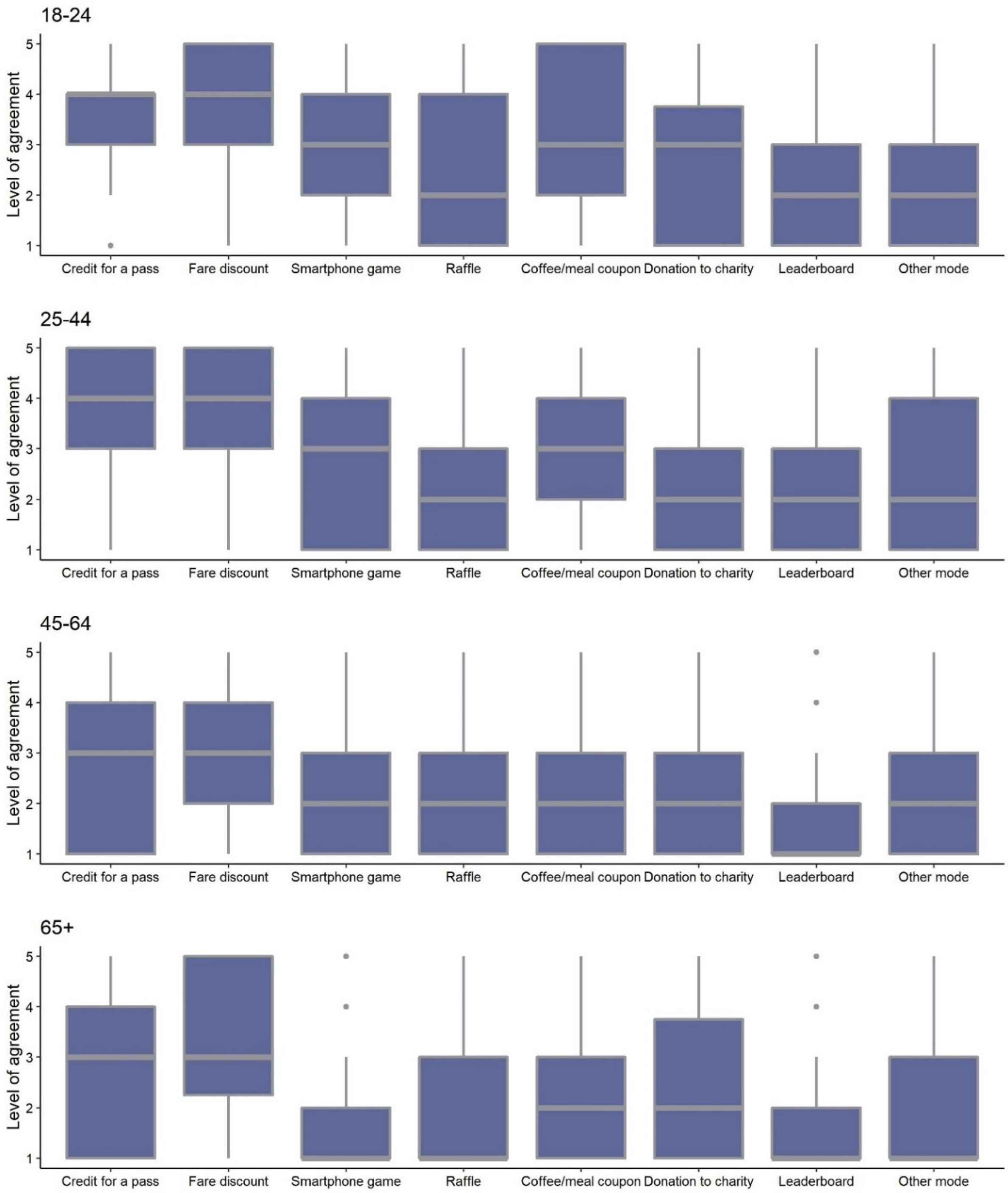

Figure 16 Preferences for incentives by age group

5.6.2 The effect of incentives on the actions transit riders make in response to crowding

In this stage of the analysis, I focus on the relationship between the preferences for incentives and the likelihood of changing travel behaviour in response to crowding on public transit. I simultaneously estimate two ICLV models, one evaluating the probability of changing the travel start time, and the other the probability of changing the public transit route, with both being subject to the influence of the identified LVs that captured preferences for incentives. Given the similar nature of the dependent variables, I introduced a normally distributed error term for both outcomes to capture the correlation effect of the parameters that could not be included in the model (e.g. social norms, trip context). The diagrammatic representation of the selected model is visualized in Figure 17.

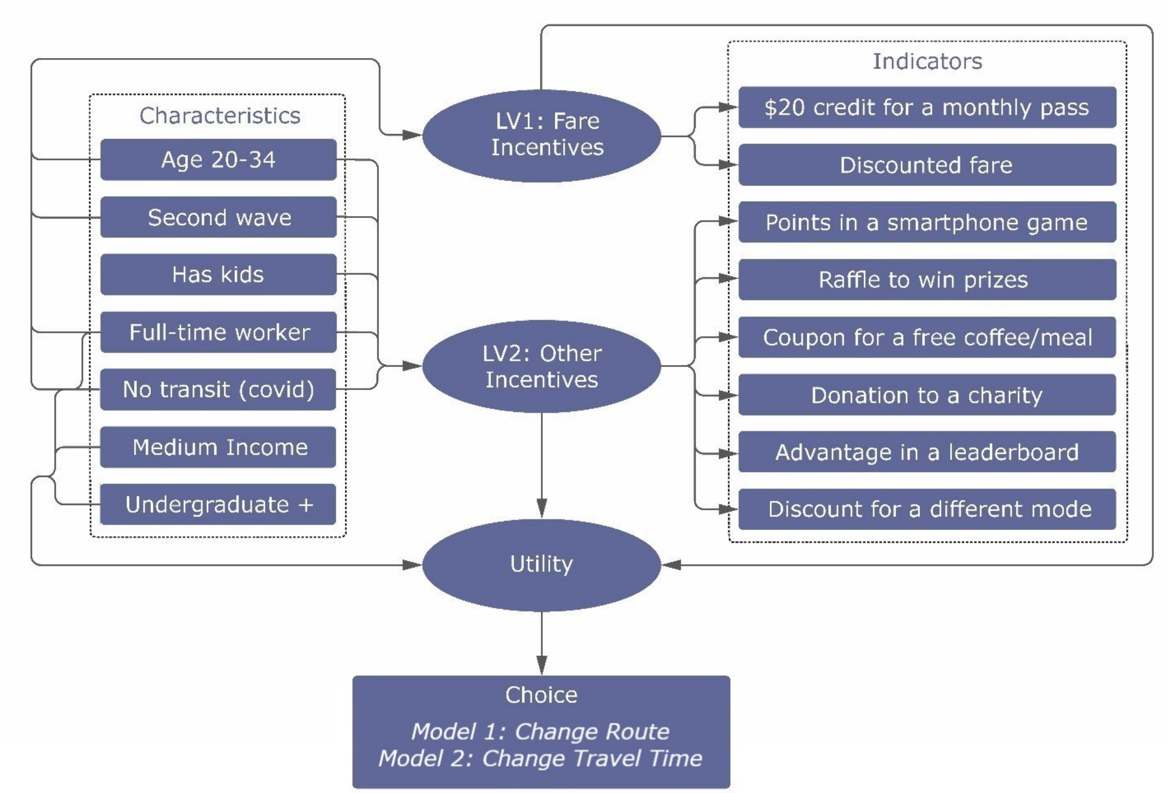

Figure 17 Diagrammatic representation of the selected Integrated choice latent variable model

Before estimating the ICLV model, I explored the relationships between the preference indicators using Factor Analysis and Principal Component Analysis (PCA) whose results aligned with each other. This stage of the analysis was exploratory and identified the groups of indicators that could be associated with respective LVs, which later informed the specification of the ICLV model, where the structure of the modelled LV resembles the one of a factor in a Factor Analysis. Using the generic functionality of statistical programming language R (R Core Team 2013), and opting for Varimax rotation for Eigenvalues larger than one, I identified two principal components (i.e. LVs) that captured the variability in the dataset but did not correlate with each other. As recommended by Hair et al. (1995), all indicators with loadings larger than 0.3 were considered for the analysis. A clear distinction can be observed between the identified LVs when examining their connections with the respective indicators as presented in Figure 17. One group encompasses the incentives that reduce the price of travel via public transit (fare discount and the monthly pass credit), while the other included the stimuli that offer other benefits (e.g. raffle, smartphone game points), hence the labels introduced for the LVs that captured variability in each of the groups of indicators. I labeled those LVs accordingly, i.e. Fare Incentives and Other Incentives. In the process of ICLV estimation, I also identified the personal characteristics of respondents that were statistically significant in predicting the probability of being associated with every LV and the likelihood of a certain choice.

In the process of model testing, I relied on the improvements in log-likelihood to select the final specification. I retained only statistically significant demographic variables in the structural equations for the LVs, while for the measurement equations of the choice component, the personal characteristics I controlled for were kept identical despite their statistical significance. Given this approach, the log-likelihood of the final model was -15422.72, and the results of estimation for the structural equations and utilities are presented in Table 15. The results of the remaining measurement equations are presented in the appendix.

Inspection of the structural equations estimates highlights the influence of several individual characteristics. Importantly, for both LVs they are nearly identical, with the only difference being individuals with kids influencing LV Other Incentives. While I do not have enough information within the dataset to confirm, I hypothesize that this may be explained by the value that individuals place on the rewards that can be shared with their family (e.g. a discount for a meal, or a potential prize from a raffle) as opposed to the discounted transit fare which is an individual reward. Past research indicated that parents who spend more time with their kids experienced an improvement in physical and emotional well-being (Musick, Meier, and Flood 2016), and an award that prompts more time with children can be a more significant factor for such individuals. The coefficients for the remaining demographics follow the common logic. Individuals in the 20-34 age group are generally more likely to favour incentives, which goes along the lines of findings from other studies that pointed to the reduction in the level of engagement with incentives with aging (Dhingra et al. 2020). It is also natural that full-time workers are less likely to respond to incentives as they are caught between professional and domestic responsibilities and have little flexibility for any changes. The fact that people who stopped using public transit during the COVID-19 pandemic are less likely to favour incentives on transit is also fairly intuitive. It is hard to imagine that people who abandoned public transit out of concern or necessity (e.g. perception of transit as an unsafe place, or decreased need to commute because of telecommuting) would see incentives to change travel behavior on public transit in the positive light. The ebb and flow of the pandemic tide can also explain the more positive view of incentives that respondents from the second wave of the survey had. In May 2021 Metro Vancouver saw a gradual increase in vaccination and a decline in COVID-19 hospitalizations (British Columbia Provincial Health Services Authority and BC Centre for Disease Control 2022), which most likely improved the uneasiness towards public transit in general, and incentives on it as well.

Shifting focus from the LVs themselves to their impact on the choices, I can see that both LVs have a positive influence on the likelihood of either changing travel time or public transit route in response to crowding. This confirmation is a piece of encouraging evidence suggesting that at least in the stated preference design setting, people who are more likely to respond to incentives and change their travel habits also tend to have a higher probability of changing travel behaviour in response to crowding. Another insight worth noting is the size of the effect each LV has on the choices. Looking at the choice to change the public transit route, I can see that it is more likely to pertain to the individuals favouring other incentives since the respective LV has a higher impact than LV Fare Incentives on that choice. On the other hand, the reverse is true for the choice to change travel time. One explanation for this difference can be the familiarity of respondents with the fare price change in Metro Vancouver where it is more expensive to travel on light rail and ferries between the three zones at peak hours (TransLink, n.d.-b). As for the higher influence of LV Other Incentives on the likelihood of changing the public transit route, several explanations can be hypothesized. There might be a correlation in the skills and preferences needed both to opt for another transit line and to play a game on a smartphone to win points, as the former can be achieved using a smartphone (e.g. getting navigation via a route planning mobile application in the case of the former), and the latter requires a smartphone. Similarly, there is potentially a positive relationship between the propensity to switch to other public transit routes and responding to a discount for the use of other modes, as both require a change in the usual means of commuting.

Lastly, the demographics that increase the likelihood of changing travel behaviour in response to crowding can be observed. Only belonging to the medium-income group has a statistically significant influence on the choice to change a public transit route, but it follows the same trend as the choice to travel at a different time. As with the positive impact of university education, these influences are not surprising, given that any change in travel behaviour requires flexibility, which is more prevalent among people in groups with higher education (Alexander, Dijst, and Ettema 2010; Hamermesh 1996; Golden 2001). As in the case of incentives, full-time workers have a lower probability of changing their travel time. Nevertheless, a dichotomy between the preferences for incentives and a choice to modify the timing of the trip can be observed. While those who stopped using public transit during the pandemic were less likely to favour incentives, they had a higher probability of considering changing travel time to avoid crowding. Most likely this is the result of survey questions appealing to different preferences. While asking a person who did not ride public transit during the pandemic about incentives on transit resulted in a less positive view of those in general, the question about a change in travel time - posed during the time of increased flexibility, the increase in telecommuting, and strong encouragement for less travel - received more support. This difference indicates the impact of government regulation on travel behaviour and elevated the importance of further investigation of the impact of preferences in crowding management, as the use of demographics only leaves numerous gaps in the analysis.

Table 15 Results of the integrated choice latent variable model

Variable	Equation	Estimate	SD	t-test
Age 20-34	S.E. LV1: Fare Incentives	0.165	0.066	2.498
Full-time worker		-0.194	0.064	-3.045
No transit use (pandemic)		-0.181	0.063	-2.855
Second wave of the survey		0.133	0.063	2.122
Age 20-34	S.E. LV2: Other Incentives	0.364	0.066	5.506
Full-time worker		-0.134	0.062	-2.133
No transit use (pandemic)		-0.415	0.063	-6.642
Second wave of the survey		0.111	0.062	1.801
Has kids		0.306	0.069	4.416
ASC Change Route	Utility Change Route	2.396	0.221	10.844
Medium income		0.414	0.179	2.315
Undergraduate degree +		0.250	0.189	1.325
Full-time worker		-0.050	0.187	-0.272
No transit use (pandemic)		-0.262	0.184	-1.422
LV 1: Fare Incentives		0.255	0.118	2.158
LV 2: Other Incentives		0.663	0.117	5.678
Threshold 1		0	-	-
Threshold 2		1.504	0.102	-
Threshold 3		3.675	0.149	-
Threshold 4		5.504	0.194	-
ASC Change Time	Utility Change Travel Time	3.102	0.236	13.131
Medium income		0.436	0.180	2.423
Undergraduate degree +		0.472	0.190	2.486
Full-time worker		-0.652	0.189	-3.447
No transit use (pandemic)		0.895	0.187	4.780
LV 1: Fare Incentives		0.722	0.123	5.862
LV 2: Other Incentives		0.472	0.115	4.109
Threshold 1		0	-	-
Threshold 2		1.530	0.120	-

Variable	Equation	Estimate	SD	t-test
Threshold 3		3.638	0.162	-
Threshold 4		6.069	0.213	-
Correlation Change Route and Change Travel Time		2.325	0.111	20.89
Number of observations: 1201				
Number of parameters: 70				
Log-likelihood of the whole model: -15422.72				
AIC: 30985.44				
BIC: 31341.8				

Notes: Given the nature of the Ordered Logit model and thresholds, t-tests against zero are not relevant; The first thresholds of the utility functions were fixed at 0 to avoid correlation with constants.

5.7 Discussion

This study confirmed that people who favour incentives tend to consider changing their travel behaviour in response to crowding. It also provided evidence on the types of incentives that have a higher chance of engaging public transit riders and the demographics of individuals who should be targeted with those incentives. This section will focus on how this knowledge can be used for a more efficient implementation of incentive schemes to manage crowding on public transit.

While I established that positive preferences for incentives and considerations to change travel behaviour in response to crowding go hand in hand, it is also clear that not all incentives have an equal effect, and their impact can differ depending on the type of action that is being supported. Preferences for different incentives also vary, which underlines the necessity to deploy a diverse range of incentives to engage the full population. I summarize the findings of the incentives that received the highest support from the respondents in Figure 18. The figure demonstrates that incentives that decrease the cost of the commute have the highest level of support across the board and as the modelling suggests, these incentives should be deployed to facilitate the change in travel start time. While it is intuitive that transit riders value the decrease in the service cost most, it can also be the result of actual familiarity with this type of incentive. Out of the eight scenarios proposed in my study, it is very likely that in practice the majority of respondents were only familiar with fare discounts, as it is the type of financial tool currently in use on Metro Vancouver transit and other cities that riders might be familiar with. The lesson that can be learned is that any new incentive that the transit agency might consider implementing should be well-advertised, communicated, and promoted, with an explicit focus on the value that users might personally receive. At the same time, connections can be made with other programs, as it is likely that many users subscribe/participate in other non-transit incentive/loyalty initiatives and value their benefits.

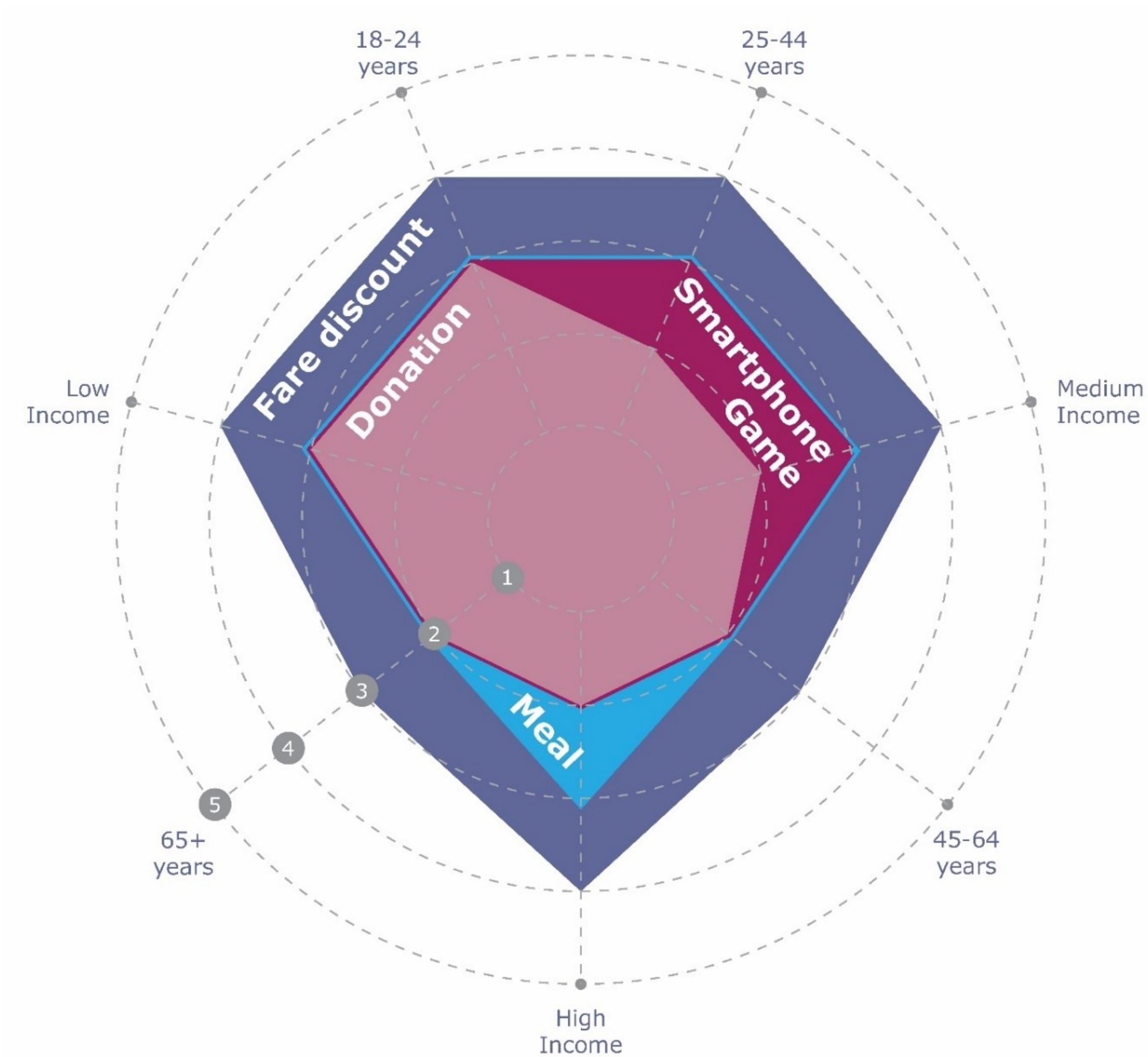

Figure 18 Disaggregate summary of the highest-rated incentives in the sample as captured by the 5-point Likert scale

Another takeaway from this study is that incentives that offer benefits other than a discounted fare tend to be more impactful on the choice to change a public transit route in response to crowding. The descriptive and modelling parts of the analysis point out millennials with middle incomes respond to incentives with gamification elements, like smartphone games where players can win points that can be exchanged for rewards. Millennials tend to be more tech-savvy (Ng, Schweitzer, and Lyons 2010) and better engage in activities that reward participation, not accomplishments (Meister and Willyerd 2010). It is also possible that millennials grew up with loyalty/incentive programs more than their older cohorts and thus tend to engage with them more. Incentives offered in the form of easy smartphone games or challenges (i.e. focusing on engagement rather than the desire to win) can be potentially more successful at changing the travel behaviour of this population segment. Gamification has been found successful at increasing levels of physical activity (Cheong, Filippou, and Cheong 2014) and learning outcomes (Barata et al. 2013). Moreover, the potential for public transit incentive schemes with gamification elements to be successful is suggested by the uptake of such programs in Singapore (C. Pluntke and Prabhakar 2013) and San Francisco (Greene-Roesel et al. 2018). However, as previously, it is recommended that agencies deploy an educational campaign to familiarize the potential users with the opportunity before the program start.

It also seems that younger generations of different incomes are not opposed to the idea of changing their travel behaviour if offered a coupon for a free coffee or a discount for a meal. Such incentives can be established in collaboration with local businesses willing to attract more customers, something that they particularly struggled with due to the COVID-19 pandemic (Bartik et al. 2020). Framed as not only a crowding management measure, but an economic development policy, such collaboration can draw inspiration from the frameworks established during the public-private collaborations for transportation infrastructure planning and development (Pettersson and Hrelja 2020).

Finally, as previously noted, I did not see the appearance of donations to a charity among the most favoured incentives overall. Interestingly, I found that higher-than-average support is present among younger and less affluent individuals. Additional investigation of societal trends reveals that it is likely not a fluke, as more young Canadians donated to charities during the pandemic than senior ones (Simpson 2021), while it is a well-established knowledge in the nonprofit sector that low-income households donate a larger share of their income than their more affluent peers in the US (Greve 2009). This is a compelling finding that should be tested in a pilot program to improve understanding of the feasibility of managing crowding on public transit using such an offering. If proven to hold the ground, it could be an incredible public policy advantage, contributing to an increase in public good through less crowded transit and more support towards those in need.

None of these recommendations can be instantly deployed at large, as accounting for the continuous change in preferences and other exogenous factors needs to be made. However, the findings indicate the potential that various incentive schemes hold to manage crowding on public transit that waits to be harnessed by eager policymakers and transit riders.

5.8 Conclusions

This study investigated the differences in preferences for various incentive schemes on public transit and assessed the relationship between the riders' eagerness to modify their travel patterns in response to crowding and the likelihood of responding to incentives that influence them to do the same. I found that people who favour incentives tend to be more likely to change their travel behaviour in response to crowding and that incentives that reduce the cost of travel on public transit have more potential to shift riders' travel time, while other incentives have a more pronounced effect on the decision to travel via a less crowded public transit route. Similarly, I identified the incentive schemes that received the highest support and the demographics of potential users who favour those. The findings provide evidence and recommendations for the transit agencies interested in implementing incentive schemes to manage demand on public transit, as well as increase the body of knowledge on the effect of the pandemic on rider preferences and travel behaviour.

Nevertheless, this study was subject to several limitations that should be acknowledged. First, the analysis was performed using a stated choice survey, which does not necessarily mean that the opinions respondents expressed would reflect their actual behaviour. This also means that the preference for some incentives, as well as how they were clustered, could have been affected by the wording used in their description. Similarly, some people might be highly favourable to incentives but have very limited options to change their travel time or route in practice. As such, future research should explore the opportunities to analyze the revealed choices of public transit riders when it comes to incentives. Secondly, both waves of the survey data were collected during the COVID-19 pandemic, and this time of heightened attention to public health and fewer systematic professional and personal travel needs could have affected the results obtained.

Researchers are encouraged to seek opportunities to investigate incentives in real-world settings through partnerships and pilots with operators to gain further insights across geographic, cultural, and linguistic settings. More evidence needs to be accumulated when it comes to the use of incentives on public transit. For example, in the context of motor vehicle congestion management, there is evidence of the lack of prolonged effect of incentives when they are taken away (Ben-Elia and Ettema 2011), while past studies have also indicated that combination of behavioural interventions with monetary incentives may have a larger impact on transportation choices (Center for Advanced Hindsight, 2020). We also need a better understanding of how varying tolerance of crowding levels affects riders' interest in incentive schemes. Future field experiments and case studies should supplement the findings of this chapter and provide the needed guidance on effective public transit demand management approaches to operators which also benefit overall customer comfort.

Chapter 6[17]: The effect of digital crowding level information on the revealed route choice of transit riders

6.1 Chapter overview

This study relies on a unique revealed choice dataset to investigate the impact of crowding information provision on the route choices of smartphone navigation application users. Extensive processing steps are documented, and data validation is performed to ensure that the dataset is representative of the travel behaviour in the Metro Vancouver region, as well as of the crowding conditions on its transit system. A mixed logit model is used for the analysis to account for the panel effect of the dataset. The estimates indicate that information about crowding has a meaningful effect on the travel decisions transit navigation application users make, with the increase in crowding lowering the chances of a route being selected. The identified effects of crowding are also comparable to the estimates that the other sources of revealed preferences on transit (like smart card records) provide. For example, it is found that the time multiplier is 1.16 for conditions with some crowding and 1.18 for an average crowded trip. This study should be of interest to both the research and the professional community, as it provides more accurate findings than those coming from stated preference surveys and simulations, which are subject to limitations like uncontrolled biases and potential errors. At the same time, its results can inform transit agencies about the effect of crowding information provision and can potentially facilitate the possibility of expanding that effort (e.g. ensuring higher accuracy and broader availability of the data).

[17] This chapter is based on the article: Kapatsila, B., Bahamonde Birke, F., van Lierop, D., Grisé, E. (Under review). The effect of digital crowding level information on the revealed route choice of transit riders.

6.2 Introduction

Public transit crowding is a negative externality of a transit agency's success in connecting riders with the places where they want or have to go. It reaches the level of a challenge when available transit capacity cannot satisfy the demand, resulting in schedule deviations for the operator, and loss in comfort and time for passengers (in case of denied boarding), potentially leading to riders turning away from the service (Haywood, Koning, and Monchambert 2017; de Oña and de Oña 2015; Cho and Park 2021). There are multiple origins of transit overcrowding, some of them likely overlapping and resulting in strong cumulative effects. First of all, there is a natural gap between the change in supply and demand coming from the continuous urban population growth (L. Sun et al. 2020) that outpaces the expansion of transit service, particularly in North America (La Vita 2023; Freemark 2023; Wanek-Libman 2023). At the same time, some people also consider transit in response to the increase in the cost of driving, particularly due to high gas and oil prices (Bliss 2022; Chu 2022; Belloc, Giménez-Nadal, and Molina 2023). All of this is happening against the backdrop of the overall growth of distances between where people live and where they work (Kneebone and Holmes 2015), especially for low-income individuals (Blumenberg and Siddiq 2023), rendering active modes like walking and biking infeasible. Transit agencies oftentimes do not have the resources and time to respond quickly to those larger societal trends and accommodate an increase in demand, pushing some riders away. For example, customer satisfaction surveys used by the Bay Area Rapid Transit (BART) system reveal that transit overcrowding, among other factors such as transfers, and travel time compared to driving, became a nuisance large enough to contribute to the decline in ridership in the 2010s (Wasserman and Taylor 2023). Effective transit crowding strategies are needed to ensure customers' loyalty to transit.

More recently, transit ridership has been severely impacted by COVID-19 pandemic restrictions, however, crowding has been outpacing ridership growth in the recovery that followed. For example, by the end of 2022 transit use was only at 82% of the pre-pandemic level in Metro Vancouver, Canada, while 8% of buses were already overcrowded - just 1% less than there were in 2019 (TransLink 2023c). At the same time, people became more cautious about crowding on transit during the public health emergency, and while the level of concern declined since the government restrictions have been removed and the medical response has become more effective, sensitivity to crowding has not resorted to the pre-pandemic levels (Cho and Park 2021; Flügel and Hulleberg 2022). Overall, it is obvious that crowding remains an acute problem for transit agencies and has to be addressed to accommodate the growth of the cities, retain existing riders, and bring back those who stopped using buses and trains during the pandemic and switched to private vehicles (Bucsky 2020; Kapatsila et al. 2022).

Technological advancements allow transit agencies to motivate behavioural change by informing riders about crowding on their systems. This strategy can be found at work in London, UK (Malouff 2017) and Sydney, Australia (Hendry 2019) where information screens at platforms offer opportunities for immediate behavioural change. At the same time, many more cities around the world partner with information technology companies like Transit[18] and Google that provide onboard crowding information together with travel directions. Nevertheless, empirical evidence on the effectiveness of such information provisions is scarce. This chapter aims to bridge this gap in existing knowledge by capitalizing on access to a unique dataset with information about the revealed travel behaviour of transit riders who used the route navigation smartphone application Transit to choose a transit route for their trip in Metro Vancouver, Canada, and who were presented with the historical level of crowding for all of the alternatives that were suggested to them. Analyzing this dataset provides empirical evidence about the revealed choices of riders who have information about crowding levels on different transit routes. It also quantifies the crowding effect in monetary terms based on the actual decisions people made, which is a significant contribution to the literature on transit overcrowding saturated with knowledge coming from stated preference surveys. It is expected to be of interest to academics in the field of transit demand management research, as well as practitioners interested in the ways to encourage transit riders to make socially beneficial travel choices (e.g. travelling on a less crowded route).

[18] Transit is a smartphone application designed to provide users with real-time information and assistance in navigating transit services.

6.3 Literature overview

This study employs a unique dataset of revealed choices of transit riders to estimate the effect of crowding information provision. In doing so it relies on the existing knowledge about the use of crowding information by information technology companies, previous studies on the effect of information provision about crowding levels on the travel behaviour of transit users, and the existing work on crowding valuation. I review relevant studies below.

6.3.1 Transit route navigation services and crowding information

The use of navigation services, either desktop or smartphone-based, has been on the rise due to the increased availability of real-time travel information, with the revenue for the sector expected to reach $11 billion in 2023 for Google only (Wylie 2023). Though that revenue includes not only transit users, but also services for people using Google for driving navigation, taxi services, and anyone else trying to get directions from one place to another, it is illustrative of the growing impact such technological solutions have on the way people travel. There is an overall consensus that online real-time information about transit services has a positive effect on transit riders' experience (Bian, Li, and Lee 2023). Past studies have found that access to transit service information via smartphone-based services increases ridership by lowering the negative impact of wait time as people can make more accurate travel plans using transit (Brakewood, Macfarlane, and Watkins 2015). Likewise, it is natural to expect that information about crowding information can also improve riders' experience. As early as 2020, Transit app, a smartphone application for transit trip planning and navigation, provided information about the level of crowding in as many as 35 cities worldwide, with information coming from real-time onboard passenger counters (where available), crowding predictions based on historical ridership trends (reported accurately in 88% of cases), and information from in-vehicle riders, the latter resulting in just a 10-minute delay from the real-time crowding information (Mass Transit 2020). Despite the growing availability of such information, no academic studies have evaluated the effectiveness of this provision on route choices so far.

6.3.2 The impact of crowding information on riders' choices

Existing knowledge about the effects of the provision of crowding information on riders' choices is very limited. Most of it comes from studies that used stated preference surveys and simulations and generally point in the direction of having a positive effect on transit crowding management (Preston, Pritchard, and Waterson 2017). In Seoul, South Korea, information on the availability of a larger number of empty seats increased the likelihood of boarding a bus for survey respondents (Kim, Lee, and Oh 2009). Multiple stated preference studies reported a similar trend in the context of trains in the UK (Preston, Pritchard, and Waterson 2017). Findings presented by Drabicki et al. (2023) suggest a possible increase in survey participants' satisfaction and reduction of crowding as a result of information on vehicle occupancy. Along the same lines, a simulation based on the agent-based public transit model BusMezzo applied to the context of Stockholm's subway in Sweden suggests that passengers presented with information on crowding levels should board train cars more evenly to avoid overcrowding (Peftitsi, Jenelius, and Cats 2022). Nevertheless, some researchers suggest that stated preference studies do not capture real travel behaviour due to the multiplicity of factors that cannot be replicated in a survey setting (e.g. fluctuation of crowding levels) (Wardman and Whelan 2011). Similarly, simulations are only applicable within the limits of their assumptions.

Assessments of crowding information provision in a revealed choice setting are even more scarce. A short pilot study in Stockholm evaluated the impact of crowding information announcements at a metro station and found that the number of passengers in the first two cars (which were usually the most occupied) went down by 4% (Y. Zhang, Jenelius, and Kottenhoff 2017). On the other hand, Chen et al. (2023) inferred travel time, crowding levels, and route choices from the smart card data at the Chengdu metro in China. They found waiting time due to delayed boarding to be valued 50.5% more positively than sitting time in a crowded metro car and standing time to be viewed 25.3% more negatively than being in a seat.[19] More evidence informed by revealed choices is needed to identify the real effect of crowding information provision and this study responds to that challenge. To

[19] It should be noted that this study did not directly assess the effect of crowding information provision, but rather assumed the riders to be informed about train occupancy via the means available to them (e.g. observations, experience, or trip planning applications). I include it in this review to showcase the existing scarcity of empirical evidence on the choices riders make in response to crowding, and the length at which the researchers go to find alternatives to stated preference surveys.

the best of the authors' knowledge, it is the first study to evaluate the effect of crowding information inclusion into routing suggestions of smartphone applications and online services where route choices were revealed.

6.3.3 Valuation of crowding on public transit

Multiple studies quantified the effect of crowding on public transit using stated preference surveys. Douglas and Karpouzis (2006) used photos of station areas and crowded trains when asking respondents to choose between hypothetical trips that had different wait times, travel times, and in-vehicle crowding in Australia. Depending on the scenario (e.g. whether a respondent had a seat, or were to stand for more than 20 minutes) and the level of crowding, the perceived travel time multiplier was estimated at 1.17 - 2.52, meaning that a minute-long trip under normal conditions can be perceived as a 1.17-2.52 minutes in a crowded vehicle. Methodologically similar studies by Vovsha et al. (2014) in the US, Haywood and Koning (2015) in France, and Tirachini et al. (2017) in Chile arrived at comparable results. Kroes et al. (2014) moved away from just stated preference surveys and added qualitative research, as well as passenger, counts in France to arrive at the maximum multiplier of 1.5 for seated passengers on a bus and of 1.7 for standees. At the same time, Batarce et al. (2015) supplemented stated preference data collected in Santiago, Chile with revealed route choices from the origin-destination survey and found the marginal disutility of a crowded transit vehicle to be twice as large as the marginal disutility of travel time in a vehicle with low level of crowding. These values went significantly up during the COVID-19 pandemic, with a study from Chile suggesting multipliers of 3-5 for high crowding and low masking conditions (Basnak, Giesen, and Muñoz 2022). It should be acknowledged that some researchers question the reliability of crowding impact evaluation based on stated preference surveys (Yap and Cats 2021). Nevertheless when Sadeghi et al. (2023) compared the results from virtual reality and stated preference experiments, they acknowledged the relative consistency of findings, with the difference being only in the loss of the temporal effect (i.e. the increase in perceived trip length of a crowded trip) in the stated preference framework.

More recent studies took advantage of the technological advancements in transit and employed information gathered from the route choices collected via smart cards and trip attributes from automatic vehicle location records to estimate crowding multipliers. Hörcher et al. (2017) used this approach in Hong Kong to estimate the standing multiplier of 1.3, with every passenger per square metre adding an additional 0.12 on average. Yap and Cats (2021) also relied on smart card data as a source of revealed travel preferences in the Netherlands and found the crowding multiplier for time to be 1.16 on average, and 1.31 for frequent travellers. These studies point out the discrepancy between the stated and observed preferences (i.e. how a person thinks they feel and act, as opposed to the decisions they make in reality), suggesting that the results based on hypothetical scenarios potentially overestimate the effects of crowding.

Overall it is clear that despite the numerous studies, there is a lack of certainity in the accuracy of crowding valuation coming from stated preference surveys. Moreover, there is no empirical knowledge of the effects of the provision of crowding information on the revealed choices transit riders made. My evaluation of crowding information provision addresses the shortcomings of most previous studies by analyzing a unique revealed preferences dataset and contributes to the literature by increasing the understanding of the impact of digital crowding information provision and crowding valuation. As choices are evaluated in a quasi-experimental framework, the shortcomings of the traditional stated preference surveys do not affect the results, and the bias associated with the assumption of perfect information is reduced.

6.4 Data processing and model formulation

This study has two primary objectives. The first one is to evaluate the effect of the provision of information about in-vehicle crowding levels in a third-party smartphone application on the revealed travel behaviour of transit users in a mature urban environment served by a robust transit system. Likewise, I aim to understand if crowding information provision has the potential to be a transit demand management approach that can redistribute temporal spikes in demand for transit services. The study area, Metro Vancouver, Canada, is an extremely suitable setting for such an evaluation. It is home to more than 2.6 million people (Statistics Canada 2022a), has a dense urban core, and a developed transit system overseen by a single agency, TransLink, that provides transit services using buses, light rail transit (LRT), and small ferries. Before the COVID-19 pandemic, TransLink had been experiencing the largest increase in ridership in North America, resulting in some of its routes seeing significant passenger congestion more than 30% of the time (TransLink 2019). As a measure to inform passengers about crowding levels, TransLink, in collaboration with Transit app, has been providing information on the occupancy of buses and light rail trains along the route options in Metro Vancouver since August 2021 (Chan 2021). Figure 19 illustrates the interface of Transit's app. In Metro Vancouver, the Transit app uses archived records on ridership for every route, providing riders with estimates of expected crowding levels. The current study relies on Transit app data to analyze the effect of that information on the route choices of the app users.

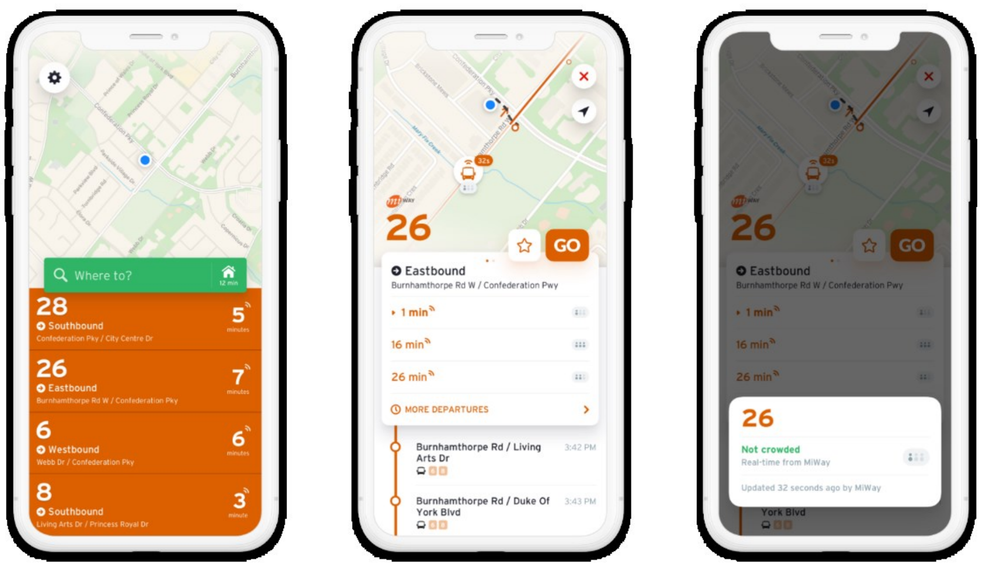

Figure 19 Example of Transit app crowding information provision (Transit 2023)

6.4.1 Transit app data processing

I obtained a unique dataset covering five days of anonymous historical records between April 19th and 23rd 2022 for Transit app users who not only explored the available travel options but also selected one of them using the "Go" function of the application. This selection was considered to constitute a choice of one of the routes, amounting to approximately 50,000 trips in total. The data cover both weekdays and weekends, as well as different meteorological conditions, though due to geography, April weather conditions are fairly mild in Metro Vancouver, with an average temperature of 8°C (46.4 °F) (Government of Canada 2023).

The schematic representation of the data obtained is presented in Figure 20. For any user *i* the dataset provided information about all of the route options that were displayed to them when they used the application for trip planning purposes. Each route option had associated information about the crowding level that was displayed (no crowding (0-50% occupancy), some crowding (50-89% occupancy), and crowded (90% + occupancy)) as well as details on each leg of the trip, including the mode (walking, transit, bike, or bike share), time and location for the start and end of each of the travel legs, and additional attributes for transit options (like service name, route name, stop name). It should be noted that the definitions of levels of crowding used by Transit differ from the ones that TransLink uses, which vary by service type. For example, according to TransLink, for 51-66% occupancy, a rapid service vehicle needs to have all seats occupied, and a third of riders standing, while for a regular bus service, that level of occupancy is reached when some seats are still available and only a few people stand (TransLink 2018). Moreover, the Transit app presents and records the level of crowding as a single value for the whole trip by taking the maximum level of crowding for the whole route option. This means that even if there were three legs involving different transit services for the route option, two of which had no crowding and one was crowded, the user saw the whole option as crowded.

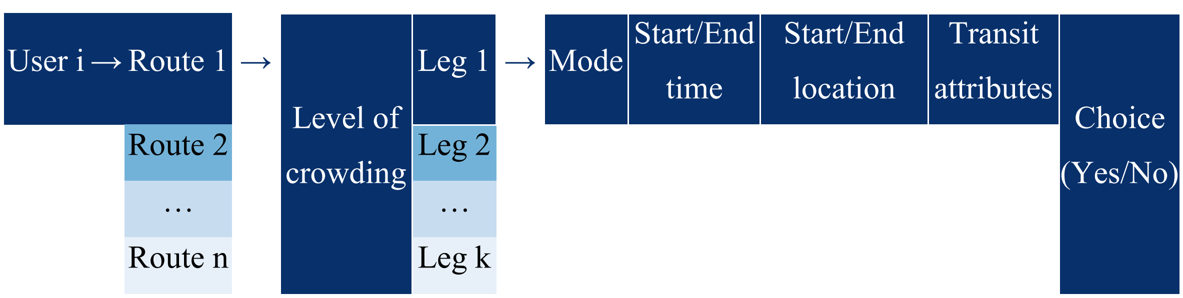

Figure 20 Schematic representation of the Transit app data

The last piece of information available from Transit is the route suggestion that was selected by a user *i*. These came as a separate dataset, though both samples had the same unique user ID and trip request time that allowed for the selected routing suggestions in the sample of full trips to be indicated. Only route suggestions for the user IDs that used the "Go" function for a unique session were retained for the analysis.

It should be acknowledged that not every user of the Transit application makes an in-app selection of a transit route (which in the framework of this study is treated as a choice), but rather consults it for trip scheduling purposes. Likely, people who select the route option to see additional details are infrequent travellers who rely on such insights, as a study on the use of smartphone applications for trip planning suggests (van Lierop and Bahamonde-Birke 2023). In the sample available to us there were about 12,000 active Transit app users per day, however, only 5,000 of them selected one of the suggested routing options daily. Moreover, no information about the demographics of app users is available, however, a study in New York City reported no association between the income, ethnicity, and age of Transit app users and the neighbourhoods where they started trips, suggesting that personal characteristics did not have a significant influence on the use of the application (Ghahramani and Brakewood 2016). The order of presentation of routing options is also not recorded by the app. Nevertheless, despite these limitations, the dataset offers a unique opportunity to investigate the effect of crowding information on travel behaviour through the revealed choices in a quasi-experimental framework, as opposed to the stated preference and simulation approaches available in the literature.

The data available for the analysis required extensive processing and the performed steps are illustrated in Figure 21. First of all, I limited the dataset to only users who made a selection of a routing suggestion. In cases where there were multiple records of a choice for the same user session, only the latest choice was retained. If the suggestions were requested for a date that differed from the date of the inquiry (i.e. for the future), those sessions were also removed from the dataset. Furthermore, if one of the suggested routing options involving a transit leg did not have crowding information recorded (due to technology issues or the absence of historical information), that session and all associated routing suggestions for a given user were excluded from the analysis. Data from different legs were aggregated to the level of a suggested route, with travel time capturing all of the legs of the trip (walking to the stop, travel time, transfers, and walking to the final destination). Trips with zero or negative time values were considered as erroneous and the suggestions that had such estimates were also eliminated from the analysis. Another time variable inferred from the dataset was the wait time, estimated as the difference between when the request for routing suggestions had been made and the recommended start of the trip. I also estimated the number of transfers between routes a rider would have to make to reach their destination, as well as the number of services they had to use, differentiating between walking, biking, bus, frequent bus (10 minutes or better frequency throughout the day (TransLink 2018)), and LRT.

The last step of data preparation involved the elimination of outliers for the key trip parameters. I primarily relied on Tukey's interquartile range (IQR) approach (Tukey 1977) to detect and remove outliers using the lower and upper fences for the trip time (to remove both extremely short and lengthy trips), and the upper fence to remove route suggestions with extended wait times. Suggestions with more than four transfers (the upper fence as per IQR approach) were removed as well, which also eliminated any of the trips that originated or ended outside of Metro Vancouver, as they all involved more than four transfers to complete the trip. I should also acknowledge that while some users had only one route suggestion, one user had more than forty, subject to the number of available routes at the location of request and time of day. I again relied on the IQR method to remove the user sessions where the suggestions had more than eight options. Lastly, for modelling purposes, the data were structured in a wide format, so that trip attributes for every alternative were all aggregated into a single row for the same session for the unique user. However, if a user used the Transit app multiple times, those records were retained as a new row in the data.

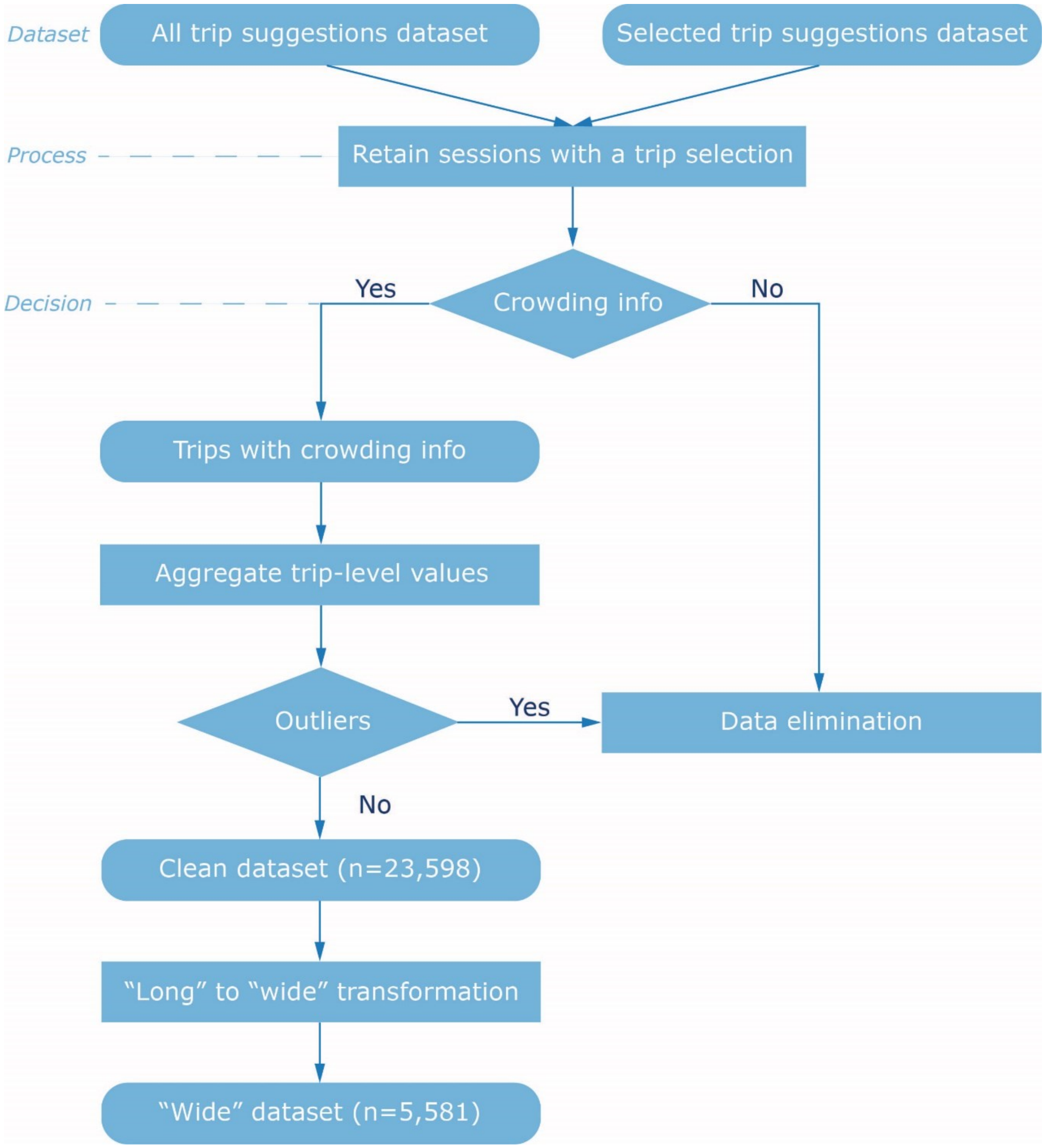

Figure 21 Data processing steps

Given the rich level of detail about the trip available in the dataset, it was also possible to estimate the trip cost for every suggestion. Nevertheless, several assumptions had to be made with regard to the cost. Two scenarios of fare costs were assumed for the users. In the first scenario all users were assumed to pay for transit using a full cash fare of $3.15 for a single zone trip (TransLink, n.d.-c) given that the "GO" function users of

Transit app are likely to be irregular riders who might not hold a contactless payment card to pay a reduced fare. The other scenario assumed the discounted fare of $2.55 for a single zone trip available to contactless payment card holders based on the fact that about 95% of TransLink's users rely on those (Kieltyka 2016), which makes it possible for the significant portion of Transit app users to pay a reduced fare. In both scenarios transit trip costs were then adjusted based on the number of zones crossed and the time of day travel to reflect TransLink's fare strategy. Similarly, for bike share suggestions, the costs were calculated as an average of a bicycle and e-bicycle rental on a per-ride basis (as opposed to a discounted daily or monthly pass) for the vendor that operates in Vancouver Metro - Mobi by Shaw Go (Vancouver Bike Share, n.d.). These two fare cost scenarios were then modeled separately to account for the potential differences in consumer surplus.

This processing resulted in the final sample comprised of 2,931 unique users, who selected 5,581 routing options out of 23,598 suggested. The average wait time in the cleaned sample was 18.85 minutes per trip, though some suggestions were to start more than an hour (up to 82 minutes) after the route search started, as presented in Figure 22. This large maximum value highlights the limitation of the dataset, as I had no way of verifying whether a Transit app user was exploring their options for a trip in the future, or if they were about to leave towards a transit stop after they selected a suggestion, or if they were already on the go. Without that knowledge, I can only hypothesize whether that time was just a proxy for headway and therefore route type, or personality type (e.g. people who plan beforehand or check the app when the need occurs on the spot). Several approaches were tested to capture the dubious nature of the wait time variable at the modelling stage, including the introduction of latent classes and wait time capping, with none providing satisfactory results, so it was not retained in the final specification. I discuss those attempts in greater detail in the methodology section.

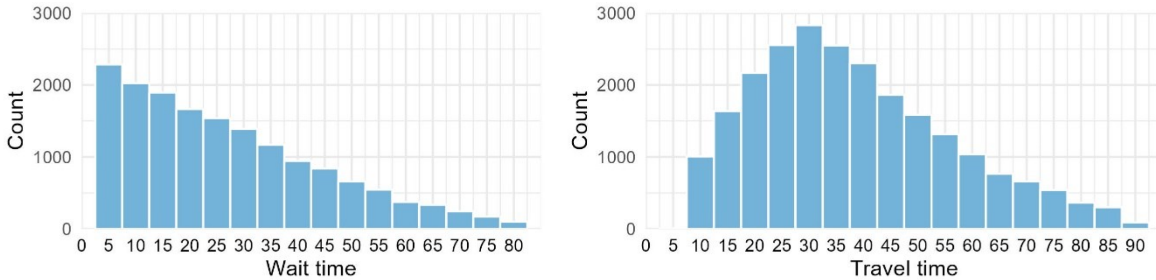

Figure 22 Wait time and travel time distribution of all trip suggestions in the final sample

I also provide the distribution of trip times in Figure 22, where the mean value for the trip was 38.48 minutes with a standard deviation of 18.1 minutes. This is less than the average transit commute time of 42.6 minutes as estimated by the most recent Census (Statistics Canada 2022b), although not surprising since Transit app users opened it for navigating not only work trips. Summary statistics for the wait and travel times, as well as the other variables extracted from the dataset, are presented in Table 16. It suggests that on average, Transit app users were exposed to a combination of walking and another transport mode while having about 3 route options to choose from.

Table 16 Summary statistics of trip characteristics in the final sample

Variable	Mean (SD)	Min, Max	% of trips
Wait time (min)	18.85 (19.24)	0.02, 81.17	100
Travel time (min)	38.48 (18.10)	7.45, 94.85	100
Trip cost ($)	2.34 (1.66)	0, 10.73	100
Number of transfers	0.47 (0.7)	0, 4	100
Number of services	1.85 (0.68)	1, 4	100
Number of suggested alternatives	2.94 (1.62)	1, 8	100
Trips with LRT leg	-	-	12.87
Trips with frequent bus leg	-	-	11.90
AM peak trips			18.33
Trips “Not crowded”	-	-	58.87
Trips “Some crowding”	-	-	29.64
Trips “Crowded”	-	-	11.49

Spatially the trips covered all of Metro Vancouver, though more than half of them originated and ended in the City of Vancouver and the City of Surrey, the two most populous municipalities in the region (Metro Vancouver 2021). I visualize only origins in Figure 23 since the spatial allocation of destinations by municipality was virtually the same.

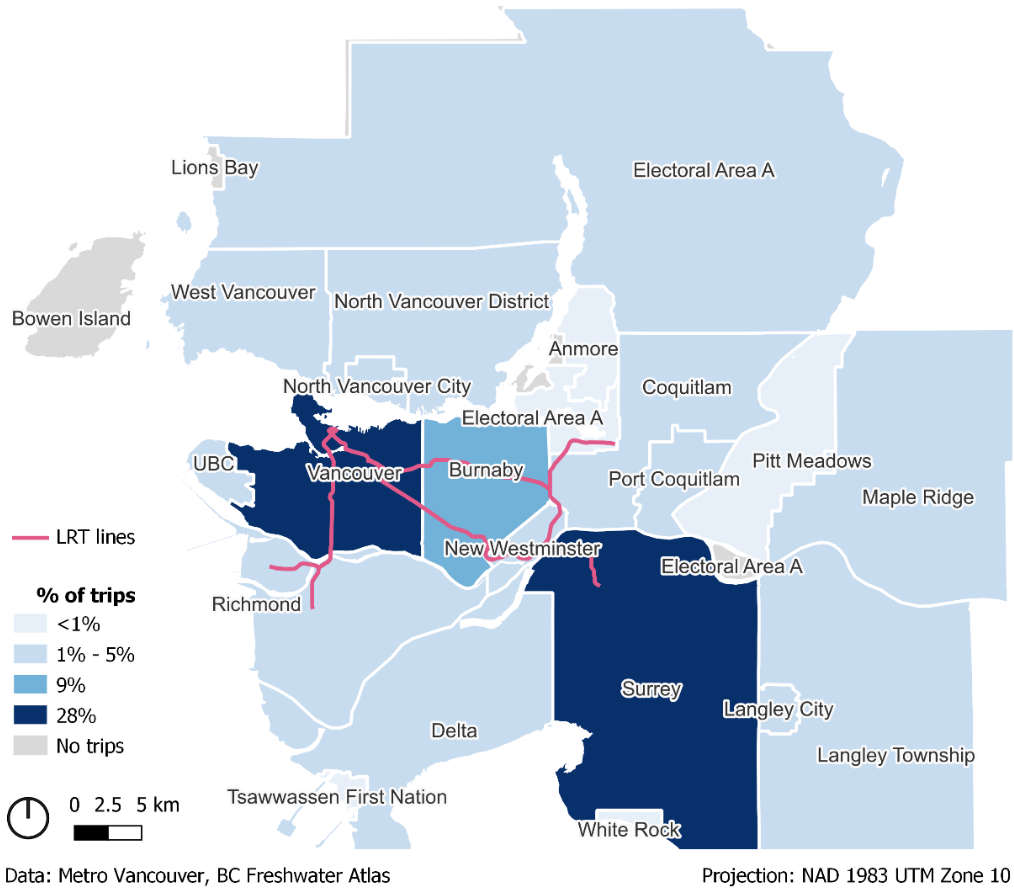

Figure 23 Trip origins of the study sample (n=5,581)

6.4.2 Transit app data validation

Table 16 also provides insights into the distribution of crowding in the study sample. Most of the trip suggestions were not crowded (58.87%), while only 11.49% were presented as crowded. I look closer at the crowding levels of the routing suggestions that were selected in Table 17. There, it is easy to see that the municipalities with the highest share of all trips also had a more considerable share of crowded trips, 22.7%, and 17.4% for the City of Vancouver and the City of Surrey respectively. Though the share of selected crowded trips was the highest in White Rock, only 23 trips originated there (0.4%), while 23.6% of selected trips (3.7% of the total) that started at the University of British Columbia (UBC) were crowded.

Table 17 Spatial distribution and crowding levels of chosen trips among Metro Vancouver municipalities

Municipality	Trip starts					Trip ends				
	Count	% of total	% Not crowded	% Some crowding	% Crowded	Count	% of total	% Not crowded	% Some crowding	% Crowded
Vancouver	1563	28.0	27.6	49.7	22.7	1566	28.1	27.8	49.7	22.5
Richmond	251	4.5	40.2	46.2	13.5	266	4.8	39.5	45.1	15.4
Delta	201	3.6	45.8	43.8	10.4	206	3.7	46.1	43.2	10.7
Surrey	1525	27.3	32.8	49.8	17.4	1507	27.0	32.6	49.8	17.5
White Rock	23	0.4	47.8	21.7	30.4	30	0.5	53.3	26.7	20.0
Langley Twp.	163	2.9	57.1	35.6	7.4	174	3.1	54.0	37.9	8.0
Langley City	96	1.7	54.2	41.7	4.2	89	1.6	59.6	37.1	3.4
Maple Ridge	95	1.7	88.4	10.5	1.1	91	1.6	90.1	8.8	1.1
Pitt Meadows	23	0.4	95.7	4.3	0.0	24	0.4	91.7	8.3	0.0
Port Coquitlam	109	2.0	85.3	11.0	3.7	117	2.1	85.5	12.0	2.6
Coquitlam	256	4.6	78.1	18.0	3.9	246	4.4	78.5	17.1	4.5
New Westminster	170	3.0	38.2	48.2	13.5	175	3.1	39.4	44.0	16.6
Burnaby	489	8.8	42.5	43.1	14.3	487	8.7	43.5	43.5	12.9
Port Moody	32	0.6	78.1	9.4	12.5	31	0.6	67.7	12.9	19.4
Anmore	3	0.1	100.0	0.0	0.0	4	0.1	100.0	0.0	0.0
North Vancouver	89	1.6	68.5	24.7	6.7	94	1.7	64.9	23.4	11.7
University of British	208	3.7	32.7	43.8	23.6	190	3.4	30.0	47.9	22.1

Municipality	Trip starts					Trip ends				
	Count	% of total	% Not crowded	% Some crowding	% Crowded	Count	% of total	% Not crowded	% Some crowding	% Crowded
Columbia (UBC)										
District of North Vancouver	217	3.9	65.9	27.6	6.5	208	3.7	67.3	28.4	4.3
District of West Vancouver	64	1.1	42.2	46.9	10.9	71	1.3	40.8	46.5	12.7
Electoral Area A	4	0.1	50.0	50.0	0.0	5	0.1	60.0	40.0	0.0

In order to ensure that Transit app data is representative of the regional trends and validate it, I looked at the spatial distribution of app users in the final sample as well as compared crowding records of the suggestions in the sample with those reported by TransLink. The trips and their respective crowding levels were aggregated to the Dissemination Area (DA) level (Statistics Canada's geographic unit that has a population of 400-700 people (Statistics Canada 2021)) to see how crowded trips were distributed within municipalities. These trends are visualized in Figure 24, with a particular focus on the municipalities where most of the trips started and ended. I hypothesized that denser parts of the region might explain high shares of crowded routes adjacent to those areas, however when I tested the correlation between the share of crowded trips that originated in DAs with their population density using Spearman's Rank correlation test, I arrived at a very low ρ (Cohen 1988) (ρ=0.04, p = 0.05), suggesting that other factors than population density likely contribute to overcrowding.

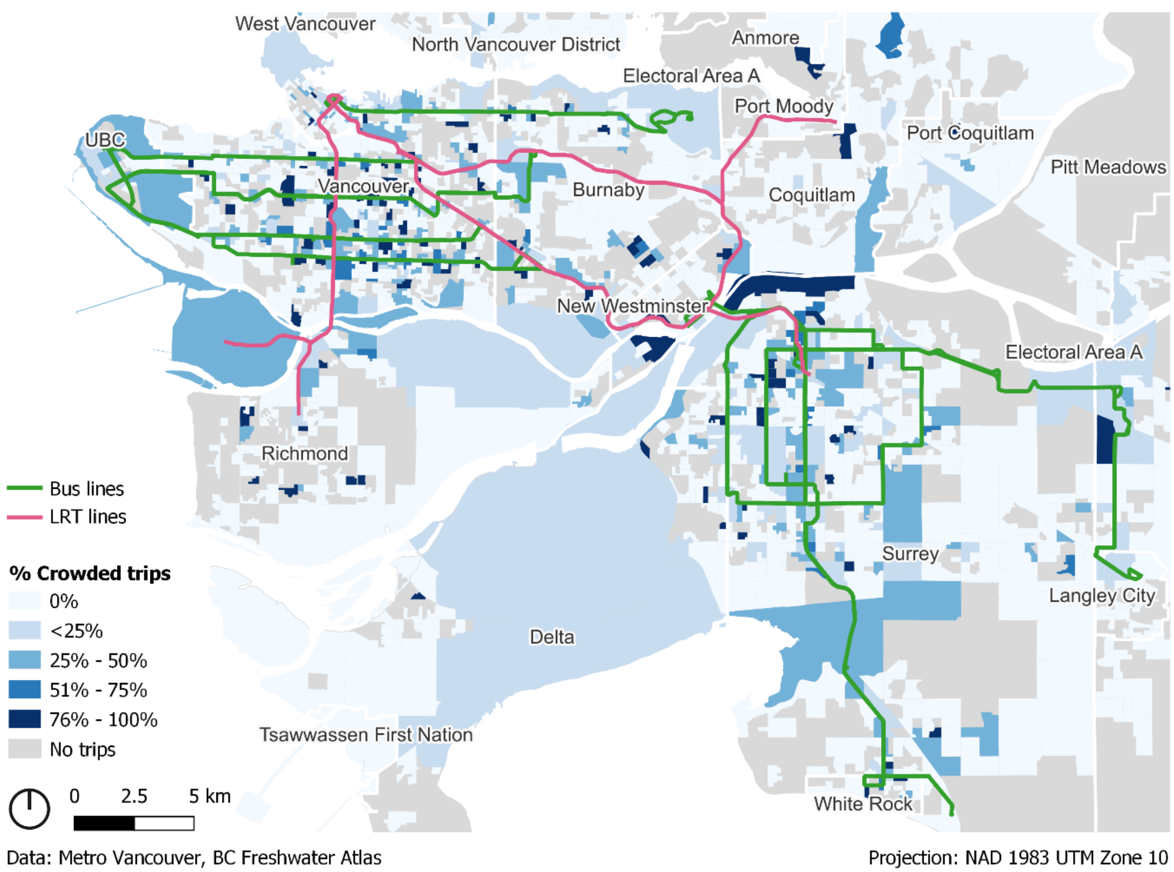

Figure 24 Share of crowded trip starts among the selected options at the dissemination area level (n=5,581)

On the other hand, I also visualize crowding levels of chosen trips by their destination DAs in Figure 25. It indicates the major employment areas of the region (like the University of British Columbia) to be destination points for Transit app users in my sample, as supported by a Spearman's Rank correlation test ($\rho = 0.51$, $p = 0$), and, to a smaller degree, to correlate with the routes that have high levels of crowding, as captured by the Spearman's Rank correlation test ($\rho = 0.35$, $p = 0$) for the number of crowded trips and the number of people who travelled for work there according to 2016 Canadian Census. These indicators validate the representativeness of my data in terms of the overall travel trends in the region.

Lastly, Figure 24 and Figure 25 visualize the top ten most used crowded bus routes ranked by the number of times they were selected by Transit app users in my sample. Six of them correspond to the top overcrowded routes as reported by TransLink for the pre-pandemic period – Routes 25, 49, 99 B-Line, 319, (RapidBus) R4, and (RapidBus) R5 (TransLink 2020a). In the study sample, these routes had the share of crowded trips that ranged from 17.3% to 43.5% of the instances they were selected, similar to what can be observed in TransLink's reports. For example, 99 B-Line was overcrowded for 31% of its service in 2019 (TransLink 2020a), while my records show that the same route was crowded for 27% of the selected trips. The other four routes, namely 321, 323, 335, and 501 were crowded from 21.6% to 40.6% of the time. The shares of crowded trips with LRT legs were comparable to those presented for most selected bus routes. While the Millennium Line had only 8.8% of selected trips crowded, the Canada Line, and the Expo Line had 26.2% and 20.4% of crowded trips respectively.

Overall, the data shows that subject to standard processing techniques, it provides a fairly representative snapshot of the use of transit in Metro Vancouver, as well as the distribution of crowding within its transit system. The rest of the section is dedicated to the identification of the optimal model specification for the evaluation of the effect of crowding information on the route choices of Transit app users while accounting for the available information and data limitations.

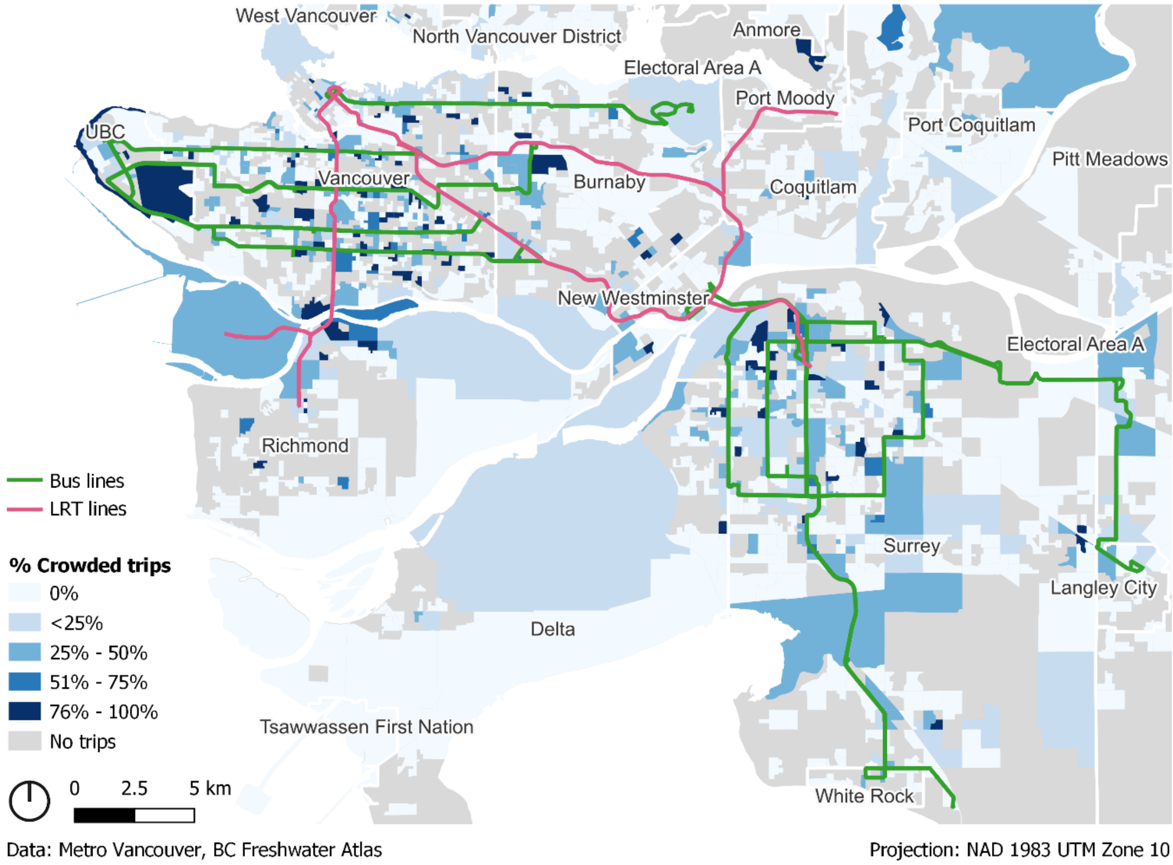

Figure 25 Share of crowded trip ends among the selected options at the dissemination area level (n=5,581)

6.4.3 Model formulation

This study estimates a discrete choice model to evaluate the impact of crowding information on the route choices of Transit app users. Conceptually it is based on the random utility maximization (RUM) theory (McFadden 1974) and assumes that each user chooses a route that maximizes their utility. I define utility for every route option based on route-specific attributes (e.g. travel time, number of transfers, etc.) and a random error component that is distributed across the population. The distribution of the random component is assumed to be Gumbel, which leads to the logit specification of the choice model that can be written as follows:

$$P_{ir} = \frac{e^{\lambda V_{ir}}}{\sum_k e^{\lambda V_{ik}}} \tag{19}$$

where P_{ir} denotes the probability of user *i* choosing the route *r*, V_{ir} is the utility of choosing that route, and λ is the scale factor measuring the variance of the error term that is normalized to one for the sample of unique individuals. The denominator of Equation (19) represents the sum of utilities for all other k routes available to user *i*. The utility function is commonly assumed to be linear, which in my case takes the following form:

$$V_{ir} = \beta_{TT}TT_{ir} + \beta_{TTam}[TT_{ir} \times AM] + \beta_C C_{ir} + \beta_{TR}TR_{ir} + \beta_{SC}SC_{ir} + \beta_{LRT}LRT_{ir} + \beta_{FB}FB_{ir} + \beta_{CrM}CrM_{ir} + \beta_{CrH}CrH_{ir} + \varepsilon_{ir} \tag{20}$$

where for the user *i* being presented with route *r,* TT_{ir} is the estimated travel time, AM is a dummy capturing if the trip *r* occurred during AM peak time (6:00AM-9:00AM in Metro Vancouver), C_{ir} is the total monetary cost of the trip, TR_{ir} captures the number of transfers, SC_{ir} stands for the number of services user *i* would have to use, LRT_{ir} is equal to 1 if one of the route legs included an LRT line, and RB_{ir} is equal to 1 if any part of the trip was suggested to take place on a frequent bus line. The effect of crowding is captured with two dummy variables, where CrM_{ir} accounts if a route had some crowding on it, and CrH_{ir} is equal to 1 if the route is crowded. Lastly, *β*s capture the preference parameters for the respective variables, and ε_{ir} is the error term. With this linear assumption, the logit probability can be rewritten as:

$$P_{ir} = \frac{e^{\beta'_i x_{ir}}}{\sum_k e^{\beta'_i x_{ik}}} \tag{21}$$

where x_{ik} is the vector of observed variables for the alternative route *k.*

As previously mentioned, some of the users are represented in our sample more than once, which required the extension of the logit model to account for that panel effect by multiplying the probabilities of all observed alternatives for a given individual. This means that (21) takes the following form:

$$P_{irt} = \prod_{t=1}^{T} \left[\frac{e^{\beta'_i x_{ir_t t}}}{\sum_k e^{\beta'_i x_{ikt}}}\right] \tag{22}$$

where r_t is the observed alternative for a given time period *t.*

Along the same lines, we introduced the mixed logit (ML) structure to avoid potential correlations between the choices the same user made. All these assumptions lead to the logit probability expressed in the following form:

$$P_{irt} = \int \left(\frac{e^{\beta'_i x_{ir_t t}}}{\sum_k e^{\beta'_i x_{ikt}}} \right) f(\beta) d\beta \tag{23}$$

where $f(\beta)$ is the mixing distribution which gives weights to the weighted average of logit probabilities in (21) assessed at various values of β in (22) (Train 2009). I allowed for the travel time, cost, and crowding parameters to be estimated by accounting for this random heterogeneity, while the other variables displayed reliable performance without mixing. The ML framework also allows for parameters to be not only random but also follow the assumed distributions (Hensher and Greene 2003). In line with the previous applications (e.g. Tirachini et al. (2017) and Yap and Cats (2021)), time and crowding were assumed to have a normal distribution, while I used uniform distribution for the cost parameter since it was expected to be negative for everyone (Train 2009) and to arrive at the range that would not include a zero. As a result, the final log-likelihood function took the following form:

$$LL = \sum_i \ln\left(\int P_i(k_i|\beta) g(\beta|\theta) d\beta\right) \tag{24}$$

where $g(\beta|\theta)$ is the density of IID βs that capture taste preferences, and θ is a vector of parameters describing that distribution, like mean and variance for the normal distribution, and mean and spread for the uniform distribution. Since the integral in (24) does not have a closed-form solution, it is approximated via simulation (Train 2009).

Aside from the ML model, I considered other frameworks to model my data. In line with Yap and Cats (2021), I assumed that there might be different classes of transit users in the study sample. I particularly focused on the variables that were calculated with the uncertainties discussed above, i.e. wait time and cost. In both cases I experimented with a latent class (LC) specification that assumed taste parameters to have a random discrete distribution, however, I was unsuccessful at identifying variables that could predict class allocation and meaningfully explain the classes. Similarly, for the LC model based on the cost I used the full price of the trip and the 26% lower value (the average cost for the holder of a concession (discounted) ticket) to predict one of the two respective classes, however did not obtain meaningful results. On the other hand, for the wait time LC model, I used the average wait time between all of the options suggested to a user to predict if they were making a decision on the go, or planning a trip in advance. That attempt did not result in meaningful results either.

I also used the maximum headway for the standard bus service of 30 minutes (TransLink 2018) as a cap for the wait time, however, that did not improve the estimate for the parameter. On the other hand, the simple use of wait time in the ML model produced an estimate with an expected negative sign, however extremely low consumer surplus value of about \$0.20, leading to a decision to estimate the final model without it. Nevertheless, the estimates for other variables remained virtually unaffected by taking the wait time parameter out. Lastly, while I tested various combinations of variables to identify potential interaction effects, none were statistically significant except for morning peak travel time.

The calculation of the final likelihood was performed in the Apollo package (Hess and Palma 2019) using R statistical software (R Core Team 2013). I relied on the Bunch-Gay-Welsch maximum simulated likelihood estimation (Bunch, Gay, and Welsch 1993) by using 1000 Sobol draws (Sobol' 1967) to approximate the distribution for the integration. The final model estimated 14 parameters and had a log-likelihood of -4690.23. The estimated values were used to calculate the marginal rate of substitution using the travel time and travel cost estimates. Due to the uniform distribution of the cost, I generated 10,000 uniform draws based on the lower and upper bounds from the model estimates to find the mean value of the cost.

6.5 Results and discussion

A discrete choice modelling framework was applied for the analysis to evaluate whether information on crowding levels onboard influenced the choice of the route for the Transit app users. I estimated an ML model where the cost parameter was assumed to be uniformly distributed. The other variables that were tested to have the presence of normally distributed random heterogeneity were travel time and crowding parameters, though in the case of the morning peak travel time the standard deviation was not significant. I provide the estimation results of the full fare model in Table 18 and the discounted fare model in Table 19. Given the negligeable differences between the models' results, I will focus on the discussion of the results of the full fare model only. We can see that an increase in travel time leads to a negative utility, and it is even more detrimental if the trip is during the AM peak. The need to use multiple services and transfer between the lines is also viewed unfavourably by Transit app users. On the other hand, the presence of an LRT segment is viewed favourably, which is in line with the previous studies that reported the “rail effect”, i.e. positive influence of rail transit on the route choice (Yap and Cats 2021; Bunschoten, Molin, and van Nes 2013), while the negative effect of a frequent bus likely captures the general crowdedness of those routes. Lastly, occupancy increase to “Some Crowding” or "Crowded” levels has a negative effect on the utility, which aligns with the assumptions of utility-maximization and previous studies.

Table 18 Mixed logit estimation results (Full fare)

Variable	Estimate	Std.err.	t-test
Mean travel time (minutes)	-0.158	0.006	-24.32
Std. travel time (minutes)	-0.063	0.008	-8.15
Mean AM peak travel time (minutes)	-0.042	0.013	-3.20
Std. AM peak travel time (minutes)	0.024	0.044	0.53
Cost upper bound ($)	-0.524	0.056	-9.29
Cost spread ($)	-3.075	0.301	-10.22
Number of transport services	-1.295	0.129	-10.07
Number of transfers	-1.255	0.057	-21.92
Route included light a rail transit line	0.594	0.176	3.37
Route included a frequent bus	-0.192	0.081	-2.37
Mean some crowding	-0.991	0.082	-12.03
Std. some crowding	-1.344	0.142	-9.49
Mean crowded	-1.118	0.115	-9.70
Std. crowded	-1.187	0.229	-5.19

Number of observations: 5,581

Number of parameters: 14

Log-likelihood of the whole model: -4690.23

AIC: 9408.47

BIC: 9501.25

Table 19 Mixed logit estimation results (Discounted fare)

Variable	Estimate	Std.err.	t-test
Mean travel time (minutes)	-0.155	0.006	-24.19
Std. travel time (minutes)	0.062	0.007	8.61
Mean AM peak travel time (minutes)	-0.046	0.014	-3.26
Std. AM peak travel time (minutes)	-0.042	0.033	-1.27
Cost upper bound ($)	-5.407	0.391	-13.81
Cost spread ($)	5.221	0.408	12.81
Number of transport services	-0.862	0.122	-7.05
Number of transfers	-1.219	0.057	-21.40
Route included light a rail transit line	0.235	0.173	1.35
Route included a frequent bus	-0.241	0.082	-2.94
Mean some crowding	-1.002	0.082	-12.25
Std. some crowding	-1.287	0.140	-9.21
Mean crowded	-1.140	0.116	-9.86
Std. crowded	-1.213	0.229	-5.30

Number of observations: 5,581

Number of parameters: 14

Log-likelihood of the whole model: -4849.07

AIC: 9726.13

BIC: 9818.91

The findings presented in Table 18 and Table 19 can be also perceived as trade-offs concerning the cost or travel time. I summarize them in Table 20. The value of travel time for Transit app users was estimated at $ 5.97/hr, and the morning peak trip adds to this value even more, suggesting that an average Transit app user is willing to pay CA$ 1.60 more to avoid an additional hour of travel (or CA$ 0.39 for 15 minutes) between 6AM and 9AM. Similarly, it can be expected that the user is willing to pay CA$ 0.82 to avoid switching from one service to another (e.g. bus to LRT) and CA$ 0.79 to sidestep a transfer. On the other hand, I see the willingness to pay an additional CA$ 0.37 to travel via LRT. Importantly, switching between the modes and valuation of LRT presence are the two variables with significant differences between the full and discounted fare scenarios. They are significantly lower in the discounted fare scenario, following the intuition that a good of a lower cost is valued less.

Table 20 Marginal rates of substitution for Transit app users

	Full fare scenario		Discounted fare scenario	
Variable	**Cost ($)**	**Time (min.)**	**Cost ($)**	**Time (min.)**
Travel time (hour)	5.97	-	6.05	-
Mean AM peak travel time (hour)	1.60	-	1.80	-
Number of transport services	0.82	8.20	0.56	5.58
Number of transfers	0.79	7.95	0.79	7.88
Route included a light rail transit line	0.37	3.76	0.15	1.52
Route included a frequent bus	0.12	1.22	0.16	1.56
Some crowding	0.62	6.27	0.65	6.48
Crowded	0.70	7.08	0.74	7.37

Looking at the second column in Table 20 I can see how different parameters can be quantified in terms of time. For example, every transfer is perceived as an additional 7.95 minutes, while a trip that includes an LRT leg is perceived as 3.76 minutes shorter.

Finally, looking at the model estimates in Table 18 I can see that information about an increase in crowding has a statistically significant negative effect on the choices Transit app users make. In consumer surplus terms, this translates into CA$ 0.62 a user is willing to pay to avoid some crowding on a trip, and CA$ 0.7 to sidestep crowded conditions. To make it comparable to the previous studies, I look at an average trip of 38.48 minutes and calculate the multiplier for conditions with some crowding of 1.16, and a multiplier of 1.18 for a crowded trip. These results are comparable to the multipliers estimated from smart card data by Hörcher et al. (2017) in Hong Kong, and Yap and Cats (2021) in the Netherlands. Likewise, they are lower than the values estimated from stated preference surveys, confirming the concern expressed by Yap and Cats (2021) about the inflated multipliers coming from stated preference data.

Overall, my analysis provides evidence that information on crowding has a meaningful effect (in terms of a user making a rational choice to avoid it). This indicates that the provision of crowding information via smartphones influences the travel behaviour of Transit app users. I use available information to discuss this finding in the broader regional context. TransLink served around 15.11 million journeys in April 2022, which averages to about half of a million per day (TransLink 2023b), while for the 5-day Transit app data sample available for the study, I identified around 12,000 unique daily users. This suggests that only about 2% of riders in the region could have used the Transit app in April 2022 per day. Moreover, accounting for the data availability for all trip suggestions, the number of people who saw the crowding information in the app was even lower. Obviously, transit riders in Metro Vancouver could have received their routing suggestions and information about crowding levels from other sources (e.g. Google), but it remains to be studied if the share of such riders is significant. In the context when both Metro Vancouver residents and decision-makers call for action to tackle the transit overcrowding challenge (Hamilton 2023), my study suggests that extending the quality of crowding information (real-time instead of historical status) and the reach of the service (like dissemination of information through stop screens and radio announcements) can be a fairly low-cost solution that is expected to alleviate some of the crowding externalities by directing people to less crowded routes, and this study provides evidence for policymakers to consider those options.

More broadly, my study advances existing knowledge about the potential for the application of behavioural insights to transportation. A field that emerged at the intersection of social psychology and behavioural economics, it has received significant attention among policymakers for its ability to increase the public good via simple means. Areas where the application of behavioral science has been successful include healthcare (e.g. encouraging more people to donate organs in case of sudden death) and personal finance (like nudging more workers to start saving for retirement) (Metcalfe and Dolan 2012). Behavioural insights should not be confused with incentives, as incentives increase the utility for a person, whereas behavioural insights aim to identify the factors that motivate people's actions and use those findings to develop the policies that encourage people to make decisions that have a better individual or social impact but do not limit or penalize the alternatives. In simple terms, the concept can be illustrated by placing healthier meals (like veggies and fruits) at eye level at a food court, while making unhealthy food options more expensive cannot be considered a behavioural insight-informed policy (Thaler and Sunstein 2021). There is a consensus that behavioural insights can be successful in the transportation context, however, empirical evidence is still rather scarce (Kormos, Sussman, and Rosenberg 2021). The provision of crowding information is one of the approaches from the behavioural science toolkit (e.g. no financial incentives or penalties are instituted), and unlike the other public transit demand management approaches, it is a relatively affordable strategy (for example, compared to the provision of incentives). Yet it remains an intervention that can be deployed fairly quickly (in contrast to the procurement of additional vehicles or building new lines) and potentially can provide relief to the transit system's links that are challenged by capacity constraints.

6.6 Conclusions and future work

The impact of crowding information provision on the revealed route choices of smartphone navigation application users suggests that information about crowding has a meaningful effect on the travel decisions users make, with the increase in crowding lowering the chances of a route being selected. The findings of this study have important implications for both research and practice as the results are based on a unique revealed preferences dataset, and provide support to the evidence on the effect of crowding on the perceived travel time from previous studies that relied primarily on stated preference surveys and simulations, which are subject to limitations like uncontrolled biases and potential errors. At the same time, it informs transit agencies about the effect of crowding information provision and can potentially facilitate the possibility of expanding that effort (e.g. ensuring higher accuracy and broader availability of the data). Lastly, it provides empirical evidence on the application of behavioural insights to public transit demand management, effectively expanding existing knowledge on the interventions that can influence the travel behaviour of transit riders.

Several limitations of this study have to be acknowledged. First of all, the estimation of the cost of the trip for every user was based on the assumption that no traveller paid a reduced fee. I also was not able to meaningfully distinguish between the time a Transit app user had to wait for the transit service, and the instances when they were exploring their travel options for some trip in the future where the time before the arrival of the next vehicle had no effect. Lastly, I had no information about the demographics of the app users in my sample and their preferences, effectively limiting my ability to discern different classes of riders and derive insights about their behaviour. Future work can potentially include considerations for the other modelling frameworks that can better incorporate the uncertainty about the trip cost and wait time in the estimation process, as well as identification of the sources of information about the individuals and their preferences, like the use of in-app surveys or active encouragement of voluntary disclosure of demographic information in the app profile. Likewise, studies using similar revealed preference data from other geographies and other providers would also benefit the research community. More work remains to be done to identify effective approaches for transit demand management. Given the challenges transit agencies face due to ridership loss and budget constraints, as well as discomfort and stress that transit riders experience in crowded vehicles, it is important that researchers equip decision-makers with the tools that allow quick and cost-effective approaches to tackling the factors that have a negative effect on transit riders' experience, like crowding, as well as allow for more efficient use of the existing public resources by redistributing the demand in space and time.

Chapter 7: Conclusion

7.1. Summary of the findings

The ongoing evolution of where, how, and when people choose to travel presents a challenge for transport systems planners, engineers, and decision-makers to cost-effectively meet the demand in real-time. It is a particular challenge for public transit systems that are planned along fixed routes based on infrastructure with limited capacity to respond to rapid spikes in real-time (especially rail-based transit), unlike the other modes (e.g. private vehicles, biking, walking) that have more flexibility to accommodate excess demand via existing street network (e.g. by taking a longer, but less crowded routes). Moreover, not only does transit infrastructure expansion take time for planning, procurement, and provision, but the planning process that relies on existing or past trends is incapable of predicting unplanned disruptions (e.g. the COVID-19 pandemic requirement for physical distance), or might not be a financially feasible response to spikes in demand that are relatively rare (e.g. a monthly hockey game or an annual fair). Nevertheless, none of these temporal spikes in demand can be overlooked, as unaddressed overcrowding on transit can lead to environmental ramifications (e.g. people choosing less sustainable modes as an alternative), as well as social and economic consequences (employees being late for work, or employers struggling to retain workers due to commute challenges). As such, this dissertation aimed to expand the existing knowledge on policy solutions to overcrowding by identifying interventions that engage different behavioural profiles of transit riders and evaluating their effects. In doing so, it identified behavioural science tools that can be effective in the field of public transit, as well as documented the reasons for the observed effects.

The dissertation began by systematically reviewing programmatic responses to transit overcrowding that were evaluated using empirical evidence in Chapter 2 and used the findings to inform the areas with opportunities and gaps for research. More specifically, Chapters 3 and 4 demonstrated how the application of more accurate probabilistic market segmentation allows for more realistic identification of behavioural profiles of transit riders (as opposed to deterministic methods) and opens opportunities for the development of more nuanced interventions capable of engaging a larger customer base. On the other hand, Chapters 5 and 6 were more applied, as they offer insights on how preferences for incentives are expected to influence the choices transit riders make in response to crowding in the case of the former, and the effect of crowding information provision on the route choice in the latter. All these findings add to the toolkit of transport researchers and professionals seeking guidance on the operationalization of behavioural science principles, i.e. knowledge on the actual (not assumed or theorized) behaviour of people, in transportation in general, and in tackling transit overcrowding in particular.

Chapter 2 synthesized the findings of 13 transportation demand management programs that aimed to reduce crowding using incentives or discounts, engagement and gamification principles, alternative work schedules, as well as their combination. The review of the ex-post evaluation of those programs showed that financial tools used in a blanket fashion (like a discounted fare before the morning rush hour) influenced only a small portion of peak riders – no more than 6.1%, and most likely did not result in behavioural change, but rather rewarded people who already travelled outside of peak time. The use of behavioural mechanisms, like commitment to the program, or in combination with incentives, like the ability to participate in raffles or games where credits gained for changed travel behaviour can be multiplied, could result in up to 22% reduction in peak period travel, though the effect size is very dependent on the methodology used for evaluation, and likely requires further investigation. At the same time, the studies that evaluated the introduction of alternative work schedules reported the largest effect size, of up to 50% reduction in passenger demand during the busiest 15-minute period of morning peak. Agencies are encouraged to use this evidence as an argument to develop partnerships with large employers able to introduce staggered or flexible work schedules that increase employees' flexibility to travel outside the peak periods and be engaged by other transit agencies' demand management programs.

Chapter 3 employed a probabilistic market segmentation of transit riders in the Metro Vancouver area using their preferences collected in a stated preference survey. This approach is superior to traditional deterministic techniques that assume each respondent to belong just to one class, which is behaviorally unrealistic. In the probabilistic paradigm, each participant is assigned a probability of belonging to every identified class. Along those lines, Chapter 3 segmented riders into six classes based on their concern for safety due to crowding and flexibility to change travel behaviour. A recommended framework for policy interventions based on those classes was then presented, such as the provision of information on crowding levels to those riders who have high concern towards crowding and high flexibility (as well as motivation) to change travel time or route to avoid crowding. Based on the findings, transit agencies are also recommended to explore partnerships with large employers to institute programs that would increase riders' flexibility and thus engage riders in those classes as well.

In Chapter 4 the classification of riders performed in Chapter 3 was applied to understand the factors that affected the riders' decision to board and the level of comfort of riding a crowded bus before and during the COVID-19 pandemic in Metro Vancouver. In particular, it demonstrated the importance of accurate classification of riders, highlighting class-specific differences in crowding perception. For example, I found that low and medium concern classes would have tolerated an additional 12% of crowding before the pandemic but would not accept an additional 24% of crowding during COVID-19, while the pre-pandemic tolerance for high concern class was just for an additional 9% of crowding, and their unwillingness to tolerate crowding was triggered by 19% increase during the pandemic. While such a detailed understanding of riders' preferences is most useful for the design and evaluation of programs aimed at behavioural change of transit riders, it also points out the benefits of its application in the regional travel behaviour models to arrive at more accurate demand projections and effectively plan for the infrastructure to accommodate it.

Next, the role of preferences was explored in how transit riders respond to transportation demand management programs. Chapter 5 evaluated the effect of preferences toward incentives in the stated preference survey disseminated to riders in Metro Vancouver. It found that a favourable view of incentives could be attributed to people who were more likely to express their willingness to change travel behaviour. It also identified that incentives offering benefits not directly related to transit (discounts for meals, participation in a raffle, or discounts for other modes among the others) were more likely to influence the choice of travelling via a less crowded transit route, while a reduction of fare cost (concurrent or future) had a higher chance of shifting the travel time. The effect of personal flexibility was again detected, with full-time workers displaying a lower propensity to respond to incentives in general. This chapter underscored the role personal preferences play in riders' response to demand management programs, and how their nuanced understanding, which can be potentially achieved via probabilistic segmentation employed in Chapters 3 and 4, provides insights into tailoring the programs towards a desired effect.

The last empirical study of this dissertation took the findings and recommendations from the analyses that relied on the stated preference survey and evaluated the effect of crowding information provision on the route choices of transit riders in the revealed preference framework. A dataset that recorded the users' route choices made using a trip planning application, Transit, in Metro Vancouver made that possible. By analyzing that dataset in Chapter 6, two behavioural mechanisms were evaluated, the effect of commitment (users had to download the application and thus made a conscious decision to be more informed about transit travel options) and the effect of information on crowding. As hypothesized, when informed, the users tend to choose routes with lower levels of crowding, which confirmed the results of simulations and stated preference surveys that focused on the topic in the past. This suggests that transit agencies should consider expanding the coverage of crowding information to the full network (currently not all routes are covered), the accuracy (Metro Vancouver crowding data were based on historical trends), and the reach, so that not only smartphone users can access the information (e.g. via information screens at the stops).

All in all, these studies highlight the potential for transit demand management programs to be more successful at influencing socially optimal travel choices of riders when their design is informed by a nuanced understanding of riders' preferences. They point to the importance of flexibility as an enabler for the change, and the role of preferences in the process of facilitating choices that are alternative to travelling at peak times or via the most crowded routes for transit riders. While the adoption of the approaches evaluated in this dissertation is methodologically complex (in part due to high data collection, skill, and computational power demand) and organizationally challenging (in the case of collaboration with employers for alternative work schedules), the findings equip transit agencies with empirical evidence on how their programmatic efforts can be more effective at addressing temporal spikes in demand if infrastructure expansion is not feasible, or while the process of planning and adding supply takes place.

7.2. Contributions of the dissertation

Given the paper-based format of the thesis, every empirical chapter included in this dissertation highlights the specific contributions to the literature a respective study made. Nevertheless, this section summarizes the dissertation's overarching contributions to academic knowledge and professional practice.

Recent advancements in understanding the factors that influence people's travel choices, the development of new and more realistic approaches to identifying and representing the preferences of riders, and the proliferation of sources for travel behaviour data collection offer transit agencies opportunities to better understand and respond to the needs of their customers, as well as nudge their travel choices towards socially optimal spatial and temporal patterns. The major contribution of this dissertation lies in its interdisciplinary nature that applied cutting-edge approaches across several different academic fields, namely behavioural science, market segmentation, and transport demand management, to identify the programmatic approaches that can effectively influence transit riders' choices. Systematic evaluation of existing policy approaches to public transit demand management based on ex-post studies identified that engagement of riders and facilitation of their flexibility via the introduction of alternative work schedules offer the highest potential for the policy interventions to affect travel behaviour. This intentional engagement can be achieved via accurate identification of riders' preferences, which is accomplished in Chapter 3 via a deliberate effort to collect information about preferences and probabilistic classification that relied on it. Chapter 4 then showed how various classes respond to crowding differently, which allowed me to hypothesize how and which interventions can be more effective at engaging different groups of transit riders. These insights were then used to expand the knowledge of the program-specific impacts of transport demand management. In particular, Chapter 5 provided a comprehensive evaluation of the effect of preferences for various incentives on the choices transit riders considered making while Chapter 6 dealt with the analysis of the revealed preferences on crowding-informed route choices using data from a third-party provider.

Overall, data processing, analysis of behaviour, and program design presented in this dissertation are expected to guide transit agencies on how riders' preferences can be effectively identified and embedded in the development of transportation demand management programs, while evaluation of various approaches systemically enriches the knowledge about the programs that should be prioritized depending on the context and goals. While the empirical findings of this dissertation were generated within the context of Metro Vancouver in Canada, and thus are representative of the preferences of riders in the region, the methods for the identification of those preferences, conceptual frameworks for their introduction into program design, and potential avenues for implementation and evaluation are largely universal.

Another contribution of this dissertation lies in the expansion of the knowledge on the use of behavioural insights to influence the travel behaviour of transit riders using empirical evidence. As seen from overall trends of support for various incentives in Chapter 5, those that offer direct financial benefits, like fare discounts, tend to have larger support than the other offerings. Nevertheless, those other approaches, like the ones with gamification elements, can also have an effect and particularly influence the decision of which route a person may consider taking. On the other hand, Chapter 6 demonstrates that providing riders with more information, like the level of in-vehicle occupancy, affects their route choice. Effectively, with these empirical evaluations, this dissertation moves the discussion of behavioural insights in the public transit domain from the hypotheses about their potential to their program and context-specific effects. Moreover, it enriches the literature on how insights about the preferences of various behavioural profiles can be generated, as well as embedded in the program design and evaluation, paving the way for more robust experiments and practical applications among transit agencies. Figure 26 summarizes the main components of the framework developed in this thesis.

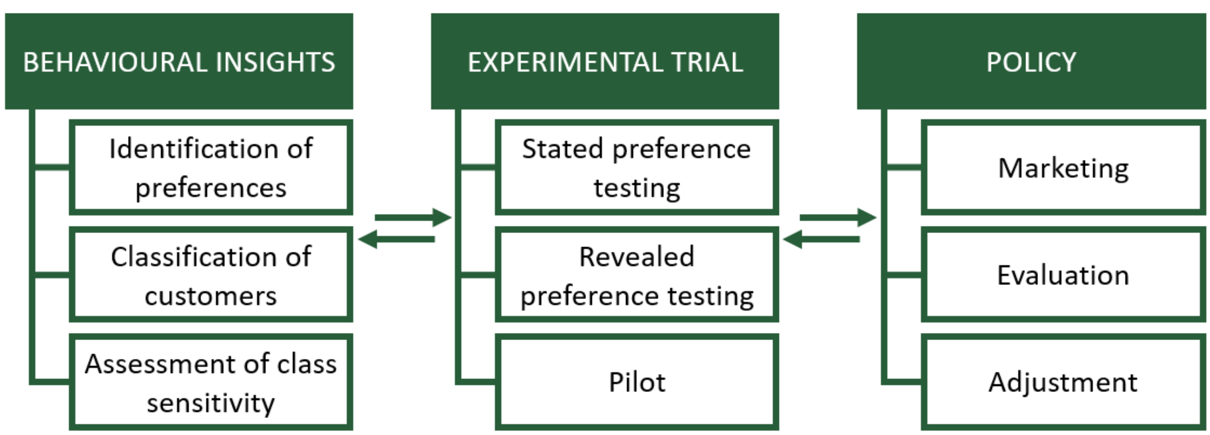

Figure 26 The framework for the development of interventions informed by behavioural insights

Lastly, this thesis generates accurate crowding valuation multipliers using revealed preference data. Prior to it, existing knowledge was mainly based on stated preference surveys, virtual reality simulations, as well as smart card data records, which in the case of the latter approach had an unrealistic assumption of the fully informed choice of the rider. While the crowding multipliers calculated in Chapter 6 are in line with those reported in previous studies that relied on more robust data sources (i.e. smart card data compared to stated preference surveys), their verification offers more confidence for the estimates' use in model calibration for the assessment of transit demand and impact of interventions. Moreover, to the best of my knowledge, this is the first study that quantified crowding multipliers for a Canadian metropolitan region.

As such, while using the advancements in different fields, this study contributes to knowledge not only in transportation but also in the disciplines that informed it. The frameworks developed in this dissertation for knowledge about preferences to inform policy-making can be applied in other areas seeking to advance the public good using the principles of behavioural science. On the other hand, the demonstrated potential and benefits of probabilistic classification should be used as an argument for its application in other areas of policy-making, like the promotion of sustainability practices or active style of life.

7.4. Policy recommendations

Each empirical chapter of this thesis, namely chapters 2 through 6, offers research-informed recommendations that should be considered by transit agencies interested in the topic of demand management. This section provides a summary of the main recommendations:

- The level of success of travel demand strategies depends on the riders' flexibility to change their travel time or itinerary. As such, transit agencies are encouraged to partner with large employers and introduce flextime and staggered work schedules that allow workers greater freedom when travelling. Once that flexibility is expanded, other strategies that appeal to riders' preferences might have a larger effect as well;
- Using probabilistic classification that allows for a rider to be assigned to several profiles with a degree of certitude, rather than deterministically to a single profile allows for the people's preferences to be captured more realistically. These classes can be used for interventions, such as tailored messaging based on the preferences of a targeted, leading to higher chances of influencing individual travel choices. For example, informational campaigns that emphasize the benefits and safety of a less

crowded vehicle during off-peak times, have a higher chance of shifting travel patterns of groups concerned with it to before or after rush-hour periods;

- Incentive schemes are favoured by transit riders in general, with fare-based incentives (like reduced fare or credit for a monthly pass) seeing the highest support among different age and income groups. Moreover, people who favour incentives tend to be more likely to change their travel behaviour in response to crowding and incentives that reduce the cost of travel on public transit have more potential to shift riders' travel time, while other incentives (e.g. smartphone games, raffles) have a more pronounced effect on the decision to travel via a less crowded public transit route. Those other incentives tend to have broader support among millennials and people of low and medium income;
- Crowding information provision affects the route choices of smartphone navigation application users. It is recommended that transit agencies invest in the introduction and expansion of the effort (e.g. ensuring higher accuracy and broader availability of the data) so that it can reach a broader user base. Unlike the other approaches to demand management studied in this dissertation, this is a clear application of behavioural insights to the problem of crowding, and it is likely that the level of concern for safety that went up during the COVID-19 pandemic also increased the number of riders who can change their travel behaviour if informed about crowding levels.

7.5. Recommendations for future research

This dissertation presented meaningful contributions to the topic of the use of behavioural insights in transportation in general and its application to transportation demand management on transit in particular. Specific limitations of each of the studies as well as recommendations for future research are presented at the end of each research chapter (Chapters 2-6). This section presents a broader outlook for future research that this dissertation as a whole opened.

First of all, more work is necessary for the empirical quantification of the benefits that the use of probabilistic classification presents. While the influence of this dissertation can be traced in TransLink's strategic thinking and planning, particularly in the recognition of the rider's multidimensionality (i.e. simultaneous association with different classes) in the 2022-2027 Customer Experience Engagement Plan (TransLink 2022a), the capitalization on the full scope of opportunities that the probabilistic segmentation of transit riders gives to the agency has yet to take place. This dissertation demonstrated that the identification of probabilistic behavioural classes produces better insights into class-specific effects crowding has, developed policies that can engage those different classes, and hypothesized about their impact. Nevertheless, the exact effect and the scale of change such an approach takes remains to be quantified via pilot applications and analysis of revealed choices of transit riders. The main obstacle to this is institutional, as most transit agencies have policies in place that prevent them from providing access for non-agency researchers to personal disaggregate travel behaviour data (as recorded via smart cards) in connection with personally identifiable information, even if personal consent from the riders were to be received. Changes to agencies' data-sharing policies are necessary to remove such an obstacle and to allow for researchers to bring in the expertise and quantify the benefits of class-specific interventions while protecting users' data privacy.

On the other hand, even the empirical findings of the probabilistic classification can be expanded using a broader array of preferences, new geographic contexts, and the evolved context of the post-pandemic society. This dissertation performed behavioural classification using preferences towards two themes, namely concern for safety and flexibility to start trips, using the data collected during the COVID-19 pandemic. The post-pandemic preferences of riders have likely evolved, with other themes, like houselessness and affordability, gaining more attention from transit riders. Identification of the post-pandemic preferences and classification based on attitudes to a broader array of themes should be explored in future research to identify the behavioural triggers that offer opportunities for the engagement of transit riders and can be facilitated to change their travel behaviour towards socially optimal patterns.

Another prominent line for future research in the area of transport demand management lies in the exploration of the opportunities that smartphone solutions bring to transit planning, navigation, and use, and the avenues for the analysis of more revealed preference data they provide. This thesis analyzed travel behaviour and choices of Transit app users in Chapter 6, however, the knowledge of the preferences of transit riders in Metro Vancouver analyzed in Chapter 3, Chapter 4, and Chapter 5 came from a classic stated preference survey that also relied on the historical memory of riders' transit experience pre-pandemic. In practice, this means that the classification method that aimed to increase the accuracy and represent the complexity of behavioural profiles relied on data that is subject to biases and limitations. This limitation could be remedied via experiential sampling when the user reports the perception or attitude toward a certain scenario (e.g. level of crowding) as they experience it in real-time, improving the accuracy of the recorded sentiment (Kahneman et al. 2004). Smartphone applications like Transit regularly use short customer experience surveys to gain insights about the preferences of their users, and this avenue can be employed to collect information about riders' sentiments in a systematic manner suitable for representative classification. Furthermore, the integration of transportation demand management strategies and existing platforms for trip planning can potentially reduce the adjustment time required for riders' familiarization and adoption of a new smartphone tool, and potentially have a more prominent effect (e.g. more people using it in a shorter time), while also offering the necessary infrastructure for the deployment and evaluation of gamification and engagement elements.

Finally, researchers are encouraged to continue pursuing travel behaviour topics, including transportation demand management, relying on modern advancements and robust methodologies at use in fields other than transportation. For example, randomized controlled trial studies are the gold standard for interventions in psychology and marketing, applied to correct for the biases that other approaches to testing interventions have, and thus reporting realistic (and oftentimes more modest) results (Arnott et al. 2014). Yet, only two of the 20 studies reviewed in Chapter 2 relied on this framework. While the increased complexity and thus cost of such research in transportation can not be doubted, even marginal improvements in research accuracy may result in significant financial savings for the transit agency that invests in the improvement of areas with higher returns (e.g. by encouraging more people to use transit and increasing farebox revenue), or postponing infrastructure expansion (e.g. in scenarios when programmatic interventions reduce overcrowding to the levels that no longer cause operational disruptions and overall ridership loss). On the other hand, the ongoing proliferation of smartphone applications that cater to different aspects of transit experience (like trip planning, and electronic tickets), reduces the opportunity cost for at least pseudo-experimental studies on transit and should be capitalized on.

7.6. Concluding remarks

When I started working on this dissertation in the Fall of 2020, there was a coalescence of my interest in the application of behavioural insights to transportation with the academic and professional discussions about their potential opportunities. Those discussions were largely "hand-wavy" in nature, attempting to translate the gains from the domains of personal finance, health, and sustainable consumption into the transportation sector. Fast-forward to 2024 and many more actual examples and demonstrations of the use of behavioural insights in transportation are available, accompanied by a broader understanding of the concept in the professional and academic community, as signalled by the formation of a dedicated behavioural science committee of the Transportation Research Board. Yet, one should acknowledge that most of the projects explored still mainly translate the knowledge from the other fields, like testing specific messaging that can engage travellers, rather than transportation-specific opportunities. The major exception to that trend includes the development of personalized transit routing offerings based on the person's origin and destination in an attempt to nudge them from driving. However, even in that case, the researchers threw spaghetti at the wall and looked at what sticks. While a legitimate technique, it can be hardly viewed as systematic, especially given how preferences can differ depending on the context. As this dissertation has repeatedly argued, before proposing interventions, we need to properly measure and systematically capture customer preferences and use those insights to develop interventions. Having an understanding of distinct behavioural classes of transport users and marketing interventions that can nudge their choices, like targeting concerned and flexible transit riders with information about crowding levels on transit, is an illustration of a more systematic approach to the application of behavioural insights in transportation. As such, the framework applied in this dissertation remains as topical as it was when the research started.

It is also quite obvious that the time when the dissertation started, the Fall of 2020, influenced the focus of the use of behavioural insights to transit demand management. It was clear that the pandemic introduced new requirements for much faster approaches than years of planning and delivering more infrastructure (i.e. supply increase) to manage temporal spikes in demand for transport infrastructure. While the social distancing measures no longer constraint the number of people who can board a transit vehicle, and transit ridership on average struggles to recover from the pandemic's decline in most contexts, the transit routes that were crowded pre-pandemic already experience the limits of their capacity at peak travel times, rendering the necessity for travel demand management approaches discussed in this dissertation topical. Moreover, crowding management is not the only area where systemic knowledge about riders' preferences (i.e. classification) and its use to develop policies can be used to retain existing and attract new users. Tackling the effects of broader societal issues like public space disorder and safety as they manifest themselves on transit systems can be equally achieved by developing an understanding of the expectations and preferences of different classes of transit riders. Knowledge of the main priorities and sizes of classes will allow decision-makers to introduce policies that will likely better respond to the concerns of larger groups and have a more pronounced system-level effect. All in all, whether it is a perennial issue of the demand and supply mismatch, more recent safety challenges, or the everlasting attempts to facilitate broader use of transit, the approaches applied in this dissertation offer opportunities for the efforts to be advanced. While a consistent and continuous understanding of people's preferences is necessary, it should also be systemically categorized into classes to understand targeting which groups will have the higher return on invested resources. The interventions should also capitalize on the advances in modern technologies (like dissemination of information via social media and smartphone applications) to ease and increase the reach of information and help retain existing and bring new transit riders.

Overall, this dissertation offers guidance to both researchers and practitioners on how the recent advances in the knowledge about people's behaviour, communication technology, and approaches to classification can be applied to manage demand for transit more effectively. Nevertheless, the framework is equally applicable to the broader context of transportation challenges, like mode choice, distracted driving, and parking management among others. As such, it is my hope that this dissertation opens up a new chapter in how the knowledge about people's preferences is capitalized on to facilitate socially optimal choices of transport users.

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