DECIPHERING THE HETEROGENEITY IN TRANSIT SERVICE QUALITY

DECIPHERING THE HETEROGENEITY IN TRANSIT SERVICE QUALITY: THE ROLE OF UTILITARIAN, PSYCHOLOGICAL, BEHAVIOURAL, AND BUILT ENVIRONMENT ASPECTS

By

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Abstract

A thorough understanding of transit customers' preferences and travel behaviour is fundamental to offering a high-quality urban transportation system. The dominant approach in transit quality literature is rooted in understanding current transit users' preferences. However, disregarding the heterogeneity in transit customers' desired quality yields suboptimal conclusions regarding their preferences. Therefore, an effective transit system should strive to understand the broad spectrum of transit and non-transit users' preferences to increase transit ridership. Towards that end, this research aims at deciphering the heterogeneity associated with transit customers' service desired quality. The research utilized a primary dataset elicited from an online survey that was part of Hamilton Street Railway (HSR) Public Engagement efforts in Hamilton, Ontario, Canada. The research employed state-of-the-art discrete choice models (e.g., error components logit models, latent class choice models, nested logit models) along with multivariate statistical and spatial analysis. In this respect, this dissertation quantified and unveiled latent heterogeneity in transit customers' preferences and its implications on their willingness to pay for service improvements through various techniques and specifications. Unlike the conventional classifications for transit customers, our research classifies transit customers into three latent segments: Direct Trip Enthusiastic (DTE), Cost-Sensitive (CS), and Real-time Information Supporter (RIS). The dissertation also investigated and further quantified the influence of subjective psychological factors in shaping transit customers' preferences towards service attributes. For instance, environmental consciousness is found to be associated with less sensitivity to walking time while higher appreciation to at-stop real-time information provision. Furthermore, the research highlighted how the built environment and its contextual effects influence customers’ travel behaviour while accounting for variations in socioeconomic characteristics. The spatial analysis concluded that the built environment's influence is not equally efficacious over geography. Overall, this research presents a unique contribution to the knowledge of public transit research for practitioners, policymakers, and academia.

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Declaration of Academic Contribution

This dissertation was prepared in accordance with the guidelines for the sandwich thesis format set by the School of Graduate Studies (SGS) at McMaster University. The sandwich thesis is a compilation of journal articles published or prepared for publication. Chapters 2, and 3 are already published as journal articles, while chapters 4, 5, and 6 are submitted for publication as journal articles. This dissertation presents the research carried out solely by Gamal Eldeeb. Advice and guidance were provided for the whole thesis by the academic supervisor Dr. Moataz Mohamed. Also, Dr. Antonio Páez provided additional advice and guidance on the paper reported in Chapter 6. Information presented from outside sources, which has been used towards analysis or discussion, has been cited where appropriate; all other materials are the sole work of the author. This thesis consists of the following manuscripts in the following chapters:

Chapter 2: Eldeeb, G., & Mohamed, M. (2020). **Quantifying Preference Heterogeneity in Transit Service Desired Quality Using a Latent Class Choice Model**. Transportation Research Part A: Policy and Practice, 139 (September 2020), 119–133. https://doi.org/10.1016/j.tra.2020.07.006

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<u>Chapter 6:</u> Eldeeb, G., Mohamed, M., & Páez, A. (2021) **Built for active travel? Investigating the influence of the built environment on transportation mode choice**. Journal of Transport Geography (Accepted).

CHAPTER 1

Introduction

1.1 Background and motivation

Understanding the transit market is the first and most fundamental step towards offering a high-quality urban transportation system. Efficient public transit service is essential in reshaping our cities into more environmentally sustainable and economically viable communities. Transportation is responsible for approximately 25% of greenhouse gas (GHG) emissions in Canada and globally (Natural Resources Canada, 2020), and much of this is attributed to motorized road transportation. Urban areas are often associated with a higher percentage of GHG emissions due to their demographic weight, reduced speeds, and traffic congestion (Urban Mobility Task Force, 2020).

The ultimate goal of public transit agencies is to provide an efficient well-harmonized transit service that satisfies current transit users and attracts new riders (El-Geneidy et al., 2011; Mahmoud, 2012; Mahmoud and Hine, 2013; Mahmoud and Hine, 2016). Periodic service evaluation and adjustments are vital to improving transit service quality and efficiency required by transit customers (Postorino & Fedele, 2006), especially with the advent of new service modes such as on-demand and ride-sharing. The concept of Service Quality Loop, developed by the European Committee for Standardization (2002), could be adopted to define the relationship between transit service customers and transit service providers, as shown in Figure 1-1. From customers' perspectives, which is the focus of this research, the service quality loop differentiates between transit service desired and perceived quality.

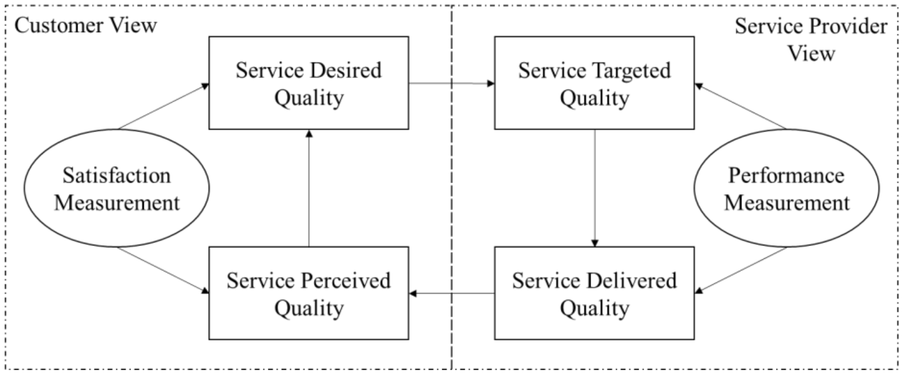

Figure 1-1 Service quality loop (EN 13816)

Understanding service desired quality for transit customers and their travel behaviour are of utmost importance for transit agencies and policymakers. However, disregarding the heterogeneity in transit customers' desired quality yields suboptimal conclusions regarding their preferences, resulting in favouring a specific group over the others (Mazzulla and Eboli, 2006). For instance, current and potential transit customers reveal different preferences towards service quality aspects (Krizek and El-Geneidy, 2007; Mahmoud et al., 2011), and service improvements aimed at satisfying current customers might not be sufficient to attract new riders. The heterogeneity of transit customers' preferences towards service quality aspects could be attributed to the qualitative nature of various service quality aspects, the wide spectrum of transit customers' socioeconomic characteristics, and their subjective psychological tendencies (Eboli and Mazzulla, 2011).

Subjective psychological factors are latent unobserved variables that influence individuals' mode choice behaviour (Anable, 2005; De Witte et al., 2013). Psychological factors manipulate transit customers' preferences and are proved to have a significant influence in shaping transit customers' satisfaction towards transit service and its quality aspects (Carreira et al., 2014; Şimşekoğlu et al., 2015; Fu et al., 2018; J. de Oña, 2021).

Customers' attitude towards transit (Zhao et al., 2013; Susilo and Cats, 2014), social norm and perceived behavioural control (Fu and Juan, 2017), travel habits, and previous experience (Susilo and Cats, 2014; Şimşekoğlu et al., 2015; Fu and Juan, 2017), public transit image (van Lierop and El-Geneidy, 2018) are significant factors in explaining public transit use behaviour and affecting customers' satisfaction with various service quality aspects.

Other sources of heterogeneity in transit customers' preferences and travel behaviour are the variations in the trip and travel mode characteristics and the spatial and built environment attributes. Those factors play a pivotal role in shaping individuals' mode choice behaviour and travel needs (Ferrer and Ruiz, 2018; Cheng et al., 2019; Ton et al., 2019). For instance, the choice of motorized travel modes is greatly associated with long travel distances (Sun et al., 2017), while the choice of active travel modes is associated with short travel distances (Muñoz et al., 2016; Winters et al., 2017). Street density and sidewalk density (i.e., built environment attributes) significantly affects travel behaviour for university students in Hamilton, Ontario (Whalen et al., 2013).

A prior classification of the transit market is commonly used to capture preference heterogeneity among different transit customer groups in transit service quality research. Public transit customers are frequently classified into Current users who use transit on a regular basis and consider transit as their primary mode of travel, and Potential users who hardly use transit and consider other modes as their primary travel modes (dell'Olio et al., 2011; Susilo and Cats, 2014; Deb and Ali Ahmed, 2018). Also, it is quite common to classify transit customers into Captive transit users who do not have access to any travel modes except transit and Choice transit users who have access to other travel modes than transit (Beimborn et al., 2003; Venter, 2016; van Lierop and El-Geneidy, 2017). Recently, other studies adopted more advanced classification approaches such as the spatial-behavioural segmentation approach, which utilizes transit passengers' geolocations and travel behaviour (Kieu et al., 2018), and a segmentation approach based on spatial and contextual factors (Grisé and El-geneidy, 2018).

"The dominant approach in the existing transit service quality literature focuses on investigating current transit users' preferences; however, an efficient and sustainable public transit service should also strive to attract new riders by luring people out of their cars. The existing studies lack investigating the preferences of the transit market as a whole and identifying the unique and shared preferences among different market segments. Moreover, the heterogeneity in transit customers' preferences is rarely studied in an inclusive preference-based approach. Instead, the majority of the literature adopts a prior classification approach based on customers' travel behaviour (e.g., transit and non-transit users) or accessibility to other modes (e.g., captive and choice users). Preference heterogeneity affirms the dire need to investigate transit customers' desired quality in a customer-specific approach as an alternative to the generalized approach adopted by most studies. The customer-specific approach, such as the persona-based approach, is proven to succeed in many disciplines such as software engineering, webpage development, and the automotive industry (the inevitable competitor to public transit).

The notion of preference heterogeneity poses a complex multifaceted problem that included different observed and non-observed aspects. For instance, the literature on transit service quality affirmed the pivotal role of psychological and attitudinal factors in shaping customer satisfaction with the service. However, the role of the psychological factors in shaping customers' preferences towards specific service attributes is yet to be sufficiently investigated. Additionally, the characteristics of other transportation modes and customers' contextual variations are believed to affect customers' preferences and travel behaviour. That said, investigating how the built environment attributes influence mode choice behaviour on a context-specific approach is essential for policymakers to better understand their residents' travel behaviour.

Given the aforementioned aspects, the work presented in this dissertation focuses on quantifying the preference heterogeneity of transit customers towards service desired quality to better tailor service improvement plans for the key market segments. The role of subjective psychological aspects in shaping customers' perceptions towards service attributes is also investigated. Additionally, this dissertation examined the influence of the built environment and its spatial effects on travel behaviour while accounting for variations in socioeconomic characteristics.

1.2 Research objectives

The primary goal of this dissertation is to inform transit service quality improvements through a multi-criteria quantification of users' preferences. In particular, the models developed herein acknowledge and measure the heterogeneity associated with transit customers' preferences and travel behaviour through various quantifiers. Additionally, the influence of improving external quality improvements (e.g., built environment) on travel behaviour, including public transit use, is examined. As such, the following objectives were identified:

1. Quantify preference heterogeneity associated with transit customers' service desired quality with respect to their socioeconomic characteristics and travel behaviour.
2. Unveil the latent heterogeneity in transit customers' preferences towards service desired quality and identify customers' latent classes with homogenous preferences.
3. Investigate the preferences of the dominant transit market segments using a persona-based approach.
4. Advance the persona-based approach, beyond its qualitative nature, by quantifying personas' preferences and willingness to pay values for service improvements.
5. Investigate transit customers' willingness to pay (WTP) heterogeneity and estimate WTP for various service improvements for various user groups.
6. Investigate how subjective psychological aspects of transit customers affect their perceptions towards public transit service attributes.
7. Examine the association between transit customers' socioeconomic characteristics and their subjective psychological aspects.
8. Investigate the influence of built environment and socioeconomic characteristics on mode choice behaviour for the City of Hamilton, Ontario, Canada.
9. Examine to what extent the city geography moderates the impact of built environment attributes on travel behaviour while considering socioeconomic characteristics.

1.3 Survey instruments design

This section summarizes the development process of the "*Hamilton Street Railway (HSR) Public Engagement Survey*" and the types of data gathered through this exercise. The survey is part of the Hamilton Street Railway (HSR) Public Engagement efforts in the City of Hamilton, Ontario, Canada. HSR is the municipal public transit provider for the city of Hamilton and provides a service coverage area of 243 square kilometres through 35 regular bus routes (City of Hamilton, 2020).

The survey is aimed at benchmarking the quality of HSR service based on Hamiltonians' preferences and expectations. The survey is intended for those who currently use the HSR service or may in the future. The McMaster Research Ethics Board (MREB) application associated with this survey was submitted on May 27th, 2018, and ethics clearance was received on July 18th, 2018, MREB protocol: 2018 109. The MREB ethics clearance is presented in Appendix A. The following four sections describe the survey development process.

The survey is structured into four main sections, including socioeconomic characteristics and travel behaviour, HSR perceived and desired quality, stated preferences experiment, and attitudinal and behavioural orientations.

1.3.1 Socioeconomic characteristics and travel behaviour

The importance of socioeconomic and demographic (SED) characteristics cannot be overemphasized in explaining the travel behaviour of individuals. Additionally, market segmentation based on SED characteristics offers useful insights for policy/decision-makers to better understand their customers and more effectively reach out to them. In particular, the survey collected a comprehensive list of SED attributes, as shown in Table 1-1.

Table 1-1 SED characteristics and their relevance for HSR engagement efforts

Attributes	**Rationale to include in the survey**
Gender, age, marital status, household size and structure	• Investigate the travel behaviour and needs of each group and test if there are significant differences. • Introduce tailored-made policies based on each group
Level of education and employment status	• Investigate the impact of the level of education and employment status on travel behaviour. • Fine-tune HSR marketing strategies for each category
Number of vehicles, holding a driving license or not, and planning to apply for a driving license.	• Investigate how car ownership and holding a driving license affect travel behaviour. • Determine the percentage of current and future HSR captive users
Personal annual income	• Investigate the influence of income on travel behaviour. • Investigate the travel behaviours associated with different income levels.
Type of dwelling unit	• Investigate the correlation between dwelling type and mode choice.
Home and work location	• Investigate the relationship between Hamiltonians' geographical distribution and travel behaviour. • Investigate HSR service coverage from Hamiltonians' perspective.
Do you have a phone or mobile internet plan?	• Investigate usage rates of online HSR app at the stop/onboard.

Studying Hamiltonians' travel behaviour as well as available travel modes is important for HSR transit planners and decision-makers. The survey adopts a revealed preference approach to observe their actual travel behaviour in real-life conditions. Particularly, the survey collected a wide range of travel behaviour attributes as shown in Table 1-2.

Table 1-2 Travel behaviour attributes and their usage

Attributes	**Usage**
No. of trips on a weekday/weekend	• Determine an average number of trips generated on a weekday/weekend.
Primary and secondary travel modes on weekdays/weekends	• Specify Hamiltonians' actual preferences for different travel modes on weekdays/weekends. • Estimating Hamiltonians' mode split on weekdays/weekends.
Primary travel mode during each season	• Investigate the effect of season change on Hamiltonians' mode choice.

Attributes	Usage
Time leaving home on a typical weekday/weekend? Time of returning home on a typical weekday/weekend.	• Identifying the AM as well as PM peaks on weekdays and weekends • Specify the span of HSR service needed to accommodate Hamiltonians' needs.
Which HSR routes do you use? And how do you access HSR service?	• Investigate the satisfaction level associated with each route. • Investigate how Hamiltonians access HSR.
Average waiting time for a bus transfer	• Investigate the average transfer waiting time for the HSR system.
Average door-to-door journey time/trip cost	• Investigate the average journey time and trip cost for trips in Hamilton.
Walking time from home/work to the nearest bus stop.	• Investigate how accessible HSR service to Hamiltonians. • Investigate the impact of walking time on mode choice.
Parking cost at work/school.	• Investigate how parking cost affects Hamiltonians' travel behaviour.

1.3.2 Stated preference experiments

Stated preference experiments captured respondents' preferences, expected future choices, and willingness to pay for service improvements as well as capturing the independent influence of service attributes on respondents' travel behaviour.

The stated choice experiment includes three stages: model specification, experimental design, and questionnaire (Bliemer & Rose, 2006). In addition, the stated choice experiment model specification includes defining alternatives, attributes, and the levels associated with each attribute. Put another way, the stated choice experiment could be seen as creating a bundle of alternatives and each user chooses an alternative that best describes their preferences.

To better understand transit customers' preferences and travel behaviour, two sets of experiments were designed: unlabelled and labelled choice experiments. The design of the stated choice experiments is of utmost importance to provide a good explanatory and the prediction power of the developed model. Therefore, the design process is based on an extensive review an initial list of attributes was compiled and then revised with HSR through focus group discussions. Lastly, a pilot survey of 62 respondents, 248 records as each respondent faced four-choice scenarios, was administrated to inform the model specifications and to ensure respondents' comprehension of the survey and the stated preference experiments. Respondents did not raise any serious concerns to comprehend and answer the survey.

The unlabelled stated choice experiment includes three bus transit alternatives. Each alternative combines seven attributes with different levels, and all alternatives represent bus service options. Table 1-3 reports the attribute levels for the unlabelled experiment.

Table 1-3 Unlabelled SP experiment attributes and their associated levels

Service attributes	**Levels**
Trip cost (one-way trip)	$ 3, 4.5, 6
Travel time (min) (one-way trip)	20, 30, 40 minutes
Walking time (min) (to / from bus stop)	0, 5, 10, 15 minutes
Service headway	5, 10, 15,30 minutes
Number of transfers (during one-way trip)	0, 1, 2 transfers
Real-time Trip Information	On bus, At stop, None

The labelled stated choice experiment includes three alternatives representing a different service: HSR, auto-driver, and ride-sharing. Table 1-4 reports the attribute levels for the "labelled" experiment where choice alternatives are specifically identified.

As mentioned in (Hensher et al., 2005), the experimental design definition is the observation of the effect of one attribute given the manipulation of other attributes' levels. Since the use of a full factorial design, which produces all possible combinations between attributes' levels, is impossible, this research adopted the optimal (efficient) design to develop the stated choice experiments. The efficient design maximizes the amount of information gathered from stated choice experiments and increases statistical efficiency. The recent literature emphasizes the superiority of the efficient over orthogonal design as mentioned in (Twaddle, 2011; Idris, 2013; Rose et al., 2018).

Table 1-4 Labelled SP experiment attributes and their associated levels

Service attributes		**Levels**
Fare / operation (one-way trip)	HSR	$ 3, 4.5, 6
	Auto Driver	$ 3.5, 5.5, 7.5
	Ridesharing (Taxi, Uber, Lyft)	$ 10, 15, 20
Parking fees (per day)	HSR	$ 0
	Auto Driver	$ 0, 4, 8
	Ridesharing (Taxi, Uber, Lyft)	$ 0
Travel time (min) (one-way trip)	HSR	20, 30, 40 minutes
	Auto Driver	
	Ridesharing (Taxi, Uber, Lyft)	
Walking time (min) (Out-of-vehicle travel time)	HSR	5, 10, 15 minutes
	Auto Driver	0, 2.5, 5 minutes
	Ridesharing (Taxi, Uber, Lyft)	-----
On-time performance	HSR	2 mins Early, On-time, 5 mins Late
	Auto Driver	------
	Ridesharing (Taxi, Uber, Lyft)	------
Freedom and flexibility	HSR	5, 10, 15,30 minutes
	Auto Driver	At your disposal
	Ridesharing (Taxi, Uber, Lyft)	On-demand
Access to real-time trip information	HSR	At stop, On buses, None
	Auto Driver	"Mobile device, GPS & radio"
	Ridesharing (Taxi, Uber, Lyft)	Mobile app

The Ngene 1.2.0 software was used to generate an efficient design while minimizing the determinant of Asymptotic Variance-Covariance matrix Dp-error and C-error, which is ideal in dealing with the willingness to pay estimations (Rose et al., 2018). The efficient experimental design generated 12 scenarios in three blocks to alleviate the survey burden. Each respondent experienced four-choice situations for each design.

The unlabelled stated choice scenarios asked respondents to choose between three bus transit alternatives, as shown in Figure 1-2, to measure the independent bearing of each attribute on transit utility and to estimate willingness to pay for service improvements.

Trip & Service Attributes	Option - A	Option - B	Option - C
Bus Fare (one-way trip)	$ 3.00	$ 4.50	$ 6.00
Time Spent Travelling on Bus (one-way trip)	30 min	30 min	20 min
A Bus Departs from My Stop (at the start/end and transfer stops)	every 15 min	every 5 min	every 15 min
Walking Time to/from Bus Stop (includes walking time between transfer stops)	10 min	5 min	5 min
Number of Transfers Between Buses (during one-way trip)	1 Transfer	0 Transfer	2 Transfers
Real-time Trip Information (e.g. about delays)	None	At Stop	On Board
To Complete My Regular One-Way Trip, I Would Choose	○	○	○

Figure 1-2 Example of the unlabelled stated choice scenarios

The labelled stated choice scenarios asked respondents to make a choice between HSR bus service, auto-driver, and ride-sharing alternatives, as shown in Figure 1-3, to capture respondents' preferences, willingness to pay for service improvements relative to other modes, and the independent influence of each attribute relative to the other modes.

Trip & Service Attributes	HSR	Auto Driver	Ridesharing (Taxi, Uber, Lyft)
Trip Cost - Fare/operation (one-way trip)	$ 3.00	$ 7.50	$ 20.00
Parking Cost	–	$ 0	–
Time Spent Travelling on Bus/Car (one-way trip)	20 min	40 min	30 min
Walking Time (to/from bus stop or parking)	2.5 min	0 min	–
Reliability (On-time Performance)	5 mins Late	–	–
Freedom & Flexibility	Bus Departs every 15 mins	At your disposal	On demand
Access to Real-time Trip Information	At Stop	Mobile device GPS & Radio	Mobile App
To Complete My Regular One-Way Trip, I Would Choose			

Figure 1-3 Example of the labelled stated choice scenarios

1.3.3 Service quality aspects

Transit service evaluation is essential for efficient transit service. However, the evaluation process's most challenging part is defining the evaluation criteria as there is no consensus on an evaluation index for all transit agencies. Thoughtful selection of the evaluation criteria is essential to ensure a holistic evaluation process as suggested by (Dhingra, 2011). The evaluation criteria have to be comprehensive, comparable, accessible, transparent, and cost-effective, and these criteria should reflect social, economic and environmental aspects.

In order to fulfill the multidimensional nature of transit service quality, we investigated the operation and evaluation standards of several transit authorities (e.g., MBTA, 2017; LAC-MTA, 2015, European Committee for Standardization, 2002), and investigated a broad list of studies (e.g., among others, Mistretta et al., 2009; Litman, 2016, Eboli and Mazzulla, 2011; Morton et al., 2016; Shen et al., 2016; de Oña et al., 2016).

Therefore, the quality aspects are structured in five main domains, which include comfort and cleanness of the service, service operation and reliability, accessibility and transfer, stops and amenities, and provision of information. The survey measures the levels of satisfaction (perceived quality) associated with various quality aspects, as shown in Table 1-5. Current transit users were asked to assess their satisfaction with each service quality aspect on a 5-point Likert scale.

Table 1-5 HSR perceived quality indicators

Consider each of the following 29 aspects and, based on your experience using HSR, tell us how satisfied you are.
Walking distance from home to the bus stop.
Walking distance from the bus stop to work.
Number of transfers needed to accomplish a daily trip.
Total trip time (door-to-door)
HSR service area (i.e., takes me where I need to go)
Service operating hours.
Frequency of service during morning peak/rush hours.
Frequency of service during evening peak/rush hours.
Off-peak service frequency (middle of the day, evening, and late-night)
Frequency of service on weekends and holidays.
Waiting times at transfer/connection points.
Bus crowdedness (seat availability and available standing room)
Service reliability (i.e., service is on time)
Bus accessibility and interior layout (e.g., ease of movement)
Cost of a single trip.
Connectivity to other transportation modes or hubs (i.e., bike share, GO, etc.)
Availability of service information before your trip.
Availability of service information during your trip.
Customer service response to complaints and suggestions.
Staff professionalism and helpfulness.
Cleanliness of the inside of the bus.
Cleanliness of bus stops.
Comfort on the bus (noise, temperature, taking off / stopping, getting on and off)
Weather protection at bus stops.
Comfort amenities at bus stops/shelters.
Bus stop accessibility for people with mobility devices (e.g., wheelchair, etc.)
Safety and security at bus stops.
Availability of extra service during special events and disruptions.
Communication through social media.

In addition, the survey measures the level of importance (desired quality) associated with various quality aspects, as shown in Table 1-6. Current and potential transit users were asked to assess the importance of each service quality aspect on a 5-point Likert scale.

Table 1-6 HSR desired quality indicators

Assess the importance of the following 30 service improvement investments in motivating you to consider/continue using HSR
Walking distance to the bus stop is reduced.
The number of transfers needed for your daily trip is reduced.
Total trip time is reduced (i.e., more similar to using a car)
Service area coverage is expanded.
Service operating hours are extended.
Service is more frequent on weekends and holidays.
Wait time at transfer/bus connection points is reduced.
Real-time information is available at bus stops (e.g., monitors displaying arrival times.)
Seat availability and/or comfortable standing area on the bus is increased.
Service is more often on-time and as scheduled.
Easier to get on or off or move inside the bus.
Available fare options increased (e.g., single ride, weekly, monthly, etc.)
More ways to pay a fare (e.g., mobile phone)
Connectivity to other transportation modes or hubs increased (i.e., bike share, GO, etc.)
Better service information before your trip.
Better service information during your trip.
More timely response from HSR during service disruptions.
Better customer service response to complaints and/or suggestions.
Staff is more professional and helpful.
The inside of the bus is cleaner.
Bus stops are in better/cleaner condition (benches, glass, etc.)
Buses are more comfortable (noise, temperature, taking off / stopping)
Better protection from the weather at bus stops
Comfort amenities at bus stops/shelters are enhanced.
Better bus stop accessibility for people with mobility devices (e.g., wheelchair, etc.)
The availability of secure bike racks at bus stops is increased.
Preventive crime measures on buses and at bus stops are enhanced (e.g., security cameras)
The option to 'Rate-Your-Trip' in real-time is introduced.
USB chargers/plugs are available on buses.
Wi-Fi is available on buses.

1.3.4 Attitudinal and behavioural characteristics

The research in social psychology indicates that psychological factors play a pivotal role in the mode-choice decision-making process, and their inclusion improves the predictions of transit quality assessment models as mentioned in (McFadden and Talvitie, 1977; Ben-

Akiva et al., 2002; Domarchi et al., 2008; Galdames et al., 2011; Muenrit et al., 2017). Recent studies show that symbolic-affective motives (e.g., pleasure and comfort) are as important as traditional instrument-reasoned motives (e.g., travel time and travel cost) in the mode choice process, reflecting that different people have different motives (Anable, 2005).

This survey adopts the theory of planned behaviour (TPB), which was developed by (Ajzen, 1991), in developing the attitudinal and behavioural statements. TPB is an extension of the theory of reasoned action (TRA), which was developed by (Fishbein and Ajzen, 1975). Both TPB and TRA consider attitudes towards the behaviour and subjective norm as determinants of intentions and behaviours, while TPB also considers the perceived behavioural control to capture how individuals evaluate the ease or difficulty to perform a given behaviour. This research investigated the following studies to develop a holistic and optimized psychometric questionnaire (Anable, 2005; Chowdhury et al., 2016; Schuitema et al., 2013; Van et al., 2014; Fu and Juan, 2017; van Lierop and El-Geneidy, 2018).

In total, the survey introduced 31 statements to measure six latent constructs as shown in Table 1-7. HSR current users and potential users were asked about their attitudes, perceived behavioural control, and social norms regarding the use of the transit service and private vehicle in addition to their environmental orientation, while only potential users were tested against car addiction and habitual use as well as car-symbolic motives. Well-established psychometric scales and studies were used for developing the attitudinal and behavioural statements such as (Ajzen, 2013; Montgomery, 2002; Ersche et al., 2017) for

TPB constructs, American Psychiatric Association (2017) for car addiction and habitual use, Goldberg et al. (2006) for environmental orientation, and Anable (2005) and Schuitema et al. (2013) for symbolic motives. Respondents were asked to assess their agreement on the accuracy of each statement on a 5-point Likert scale.

Table 1-7 Attitudinal and behavioural statements

Please review the following few statements and express your Agreement or Disagreement with each one
I am willing to recommend the HSR service to others
I am willing to use the HSR if the service is significantly improved.
I am not willing to use the HSR under any circumstances.
I choose my car for all my trips (work, leisure, shopping, visiting family, etc.).
Even if transit is reliable, fast and free I would continue using my car for most trips.
If I do not use my car for all my trips, I feel uncomfortable.
I have been driving for a long time, I do not need to think about any other modes.
I believe HSR should promote the use of electric buses to reduce Greenhouse Gases (GHG).
I am willing to use HSR if all buses are electric because I will help the environment.
I am willing to ride on an Autonomous bus in the future.
Please carefully rate the following items in terms of how accurately they describe you.
People around me think I should use transit for my commute.
My close friends think I should use transit on a regular basis.
Everyone around me is driving.
Finding routes and schedules for my trip does not require too much effort.
It is easy to travel around the city using the HSR transit service.
Transferring between routes is easy.
Using transit costs a lot of money.
Using transit saves me time and money.
I feel active when using transit.
I enjoy using transit.
I think using transit is a good decision.
Transit is for those who are less fortunate than me.
I would not want others to know that I use transit.
I see driving as more fashionable.
I express myself through my car.
When I am not driving, I prefer to use ride-sharing (Uber or Lyft).
Transit is old fashion.
Using Uber or Lyft is more convenient than buses.
I don’t mind sharing a ride (taxi, Uber, or Lyft) with other people.

I carpool to work, there is no need to use the bus.

1.3.5 Sample information data

The data was collected through an online survey in September 2018 and April 2019. This survey collected a sample of 5781 respondents, 979 responses in September 2018 and 4802 responses in April 2019. After a careful validation process, 154 invalid and unengaged responses were removed. Table 1-8 depicts the distribution of the sample associated with different socioeconomic and demographic characteristics.

The validated sample represents more females (57.45%) than males (39.50%) and also includes 0.76% who self-identify (e.g., non-binary, neutral, Agender, transgender, etc.) while almost 2.3% preferred not to answer, as shown in Table 1-8. The majority of respondents, around 88%, are between 20 to 69 years old, while respondents over 70 years old represent about 5% and under 19 years old represent nearly 7% of the sample. The percentage of vehicle ownership is relatively high, with around 79% of respondents owning/leasing a vehicle. Regarding annual income, respondents might be grouped into three main classes; high-income class (i.e., over $80,000), middle-income (i.e., $40,000 to 79,999), and low-income class (i.e., less than $40,000), which represent 16.37%, 19.00%, and 16.85% of the sample respectively, while the remainder of the sample opted not to answer the question.

It is worth noting that the sample might appear under-representing the low-income class. However, given that 45% of the survey participants did not reveal their income, no firm conclusion could be drawn from the sample income distribution relative to the population of Hamilton.

The majority of respondents, around 42%, live in single-detached houses, around 20% of respondents live in apartments or condos, and about 11% live in semi-detached or townhouses. It should be noted that around 37% of respondents preferred not to reveal their annual income, and about 26% preferred not to report their dwelling type.

Table 1-8 Distribution of the sample into different socio-economic groups

Category	**Sub-Category**	**Respondents (%)**	**Population (%) Hamilton CMA**
Total	Total	5627 (100%)	747545 (100%)
Gender	Male	2222 (39.50%)	48.90%
	Female	3233 (57.45%)	51.10%
	Self-Identity	43 (0.76%)	—
	Prefer not to answer	129 (2.29%)	—
Frequency of use HSR	Daily	2254 (40.05%)	10.54%
	Weekly	1086 (19.30%)	—
	Monthly	641 (11.40%)	—
	Annually	678 (12.05%)	—
	Never	968 (17.20%)	—
Age	15 to 19 years	398 (7.07%)	5.98%
	20 to 29 years	1267 (22.52%)	13.49%
	30 to 39 years	1101 (19.58%)	12.50%
	40 to 49 years	908 (16.136%)	12.87%
	50 to 59 years	951 (16.90%)	15.27%
	60 to 69 years	707 (12.56%)	11.81%
	70 to 79 years	270 (4.80%)	6.92%
	80 years and over	25 (0.44%)	4.91%
Employment Status	Full-time	2666 (47.38%)	35.21%
	Part-time	568 (10.10%)	31.24%
	Self-employed	240 (4.27%)	10.46%
	Student (with a job)	508 (9.03%)	—
	Student	430 (7.64%)	—
	Homemaker	150 (2.66%)	—
	Retired	780 (13.86%)	—
	Not working	285 (5.06%)	—
Vehicle ownership	0	1198 (21.29%)	—
	1	2273 (40.40%)	—
	2	1647 (29.27%)	—
	3 or more	509 (9.04%)	—
Dwelling type	Single detached house	2354 (41.83%)	—
	Townhouse/Semi-detached	627 (11.14%)	—
	Apartment or Condo	1082 (19.23%)	—
	On-campus accommodation	16 (0.28%)	—
	Other	63 (1.12%)	—
	Missing	1485 (26.40)	—

*Self-reported by respondents based on using HSR as their primary mode of travel or not.

Regarding respondents' employment status, full-time and part-time workers represent 47.38% and 10.10% of the sample, respectively, while 13.86% of the sample is retired. Additionally, students form nearly 16.67% of the sample, and almost more than 50% of the students have a job. Other categories, such as self-employed, homemaker, and not working, are also represented by 4.27%, 2.66%, and 5.06%, respectively.

Around 30% of the respondents are casual HSR customers (i.e., never or annually use HSR service), while 30.70% and 40.05% are frequent (i.e., weekly or monthly) and very frequent customers (i.e., daily). In addition, approximately 40% and 36% of survey participants use HSR and private vehicles as their primary travel mode, as illustrated in Figure 1-4.

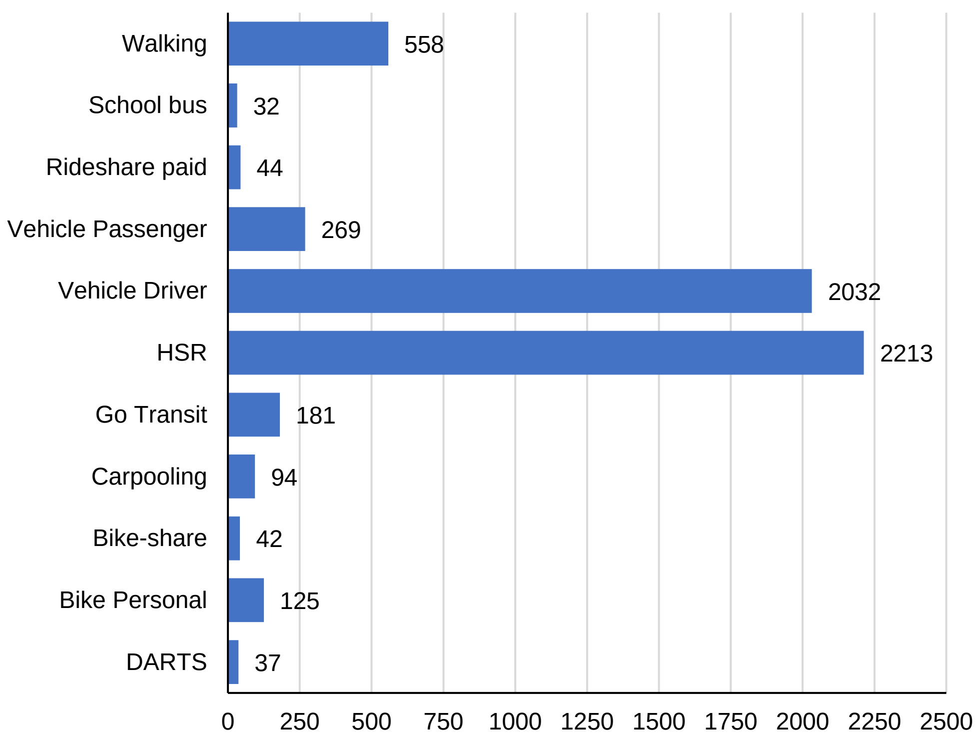

Figure 1-4: Distribution of primary travel mode of survey participants

In addition to the primary dataset obtained through the survey, several secondary datasets have been utilized throughout the study. Also, it is worth noting that the sample size might vary between chapters based on the chapter's primary objectives and due to the nature of the survey (i.e., four independent sections). These are detailed with respect to each chapter.

1.4 Dissertation organization

This section summarizes the content of each of the six chapters in the dissertation as follows:

- Chapter 1: provides the background and motivation of the work presented in this dissertation, research objectives, Survey instruments design, and an overview of the dissertation organization.
- Chapter 2: quantifies preference heterogeneity in transit service desired quality to better-informing service quality improvements. This chapter first presents an investigation of preference heterogeneity in transit service desired quality with respect to transit customers' socioeconomic characteristics and travel behaviour using Error Components (EC) logit model with systematic taste variations. The chapter also unveils the latent heterogeneity in transit customers' preferences and identifies their latent homogenous classes using a Latent Class choice Model (LCM). The results of the Error Components model confirmed transit customers' preference heterogeneity due to the variation in their socioeconomic characteristics and travel behaviour. While the Latent Class choice Model grouped transit customers into three latent classes with homogeneous preferences towards service

quality, namely: Direct Trip Enthusiastic (DTE), Cost-Sensitive (CS), and Real-time Information Supporter (RIS).

- Chapter 3: investigates the preferences of the key transit market segments using a persona-based approach. In this chapter, seven personas were proposed based on four primary characteristics: travel behaviour, employment status, geographical distribution, and perceived behavioural control regarding public transit use. The chapter presents an investigation of preference heterogeneity among the personas' transit service desired quality using an Error Components interaction model. Additionally, the chapter presents a framework for advancing the persona-based approach beyond its qualitative nature through quantifying the personas' preferences and willingness to pay values for service improvements. The results present the shared and unique preferences for service attributes for all personas to help transit agencies tailor their marketing/improvement plans based on the targeted segments. The results also show that, in general, willingness to pay values for service improvements are higher for non-transit users' personas than for transit users' personas.
- Chapter 4: questions the notion of applying willingness to pay (WTP) values for service improvements for the entire population without considering the significant degree of preference heterogeneity. This chapter unveils the heterogeneity in transit customers' preferences based on a prior classification approach and examines its implications on willingness to pay values for service improvements for various user groups. In this chapter, we employed Multinomial Logit (MNL) interaction models

to examine preference heterogeneity across customers' socioeconomic characteristics, travel behaviour, and transit attitude. The Random Parameter Logit (RPL) model unveils the spread of preference heterogeneity around service attributes. The results revealed significant heterogeneity in customers' preferences and WTP towards service improvements due to variations in customers' socioeconomic characteristics, travel behaviour and attitudes.

- Chapter 5: investigates the role of subjective psychological factors in shaping potential transit customers' perception towards transit service attributes using an Error Components (EC) logit model and Confirmatory Factor Analysis (CFA). This chapter investigates the role of five subjective psychological aspects in shaping transit service desired quality: Car Reliance, Transit Aversion, Perceived Behavioural Control, Social Norm, and Environmental Consciousness. The chapter also examines the association between customers' socioeconomic characteristics and subjective psychological tendencies using a multivariate analysis of variance (MANOVA). The results confirmed the significant influence of the considered subjective psychological factors in shaping transit customers' perceptions towards transit service attributes. Moreover, the results proved a significant correlation between transit customers' socioeconomic characteristics and subjective psychological factors.
- Chapter 6: examines the role of the built environment attributes and their contextual effects on travel behaviour. In this chapter, we utilized a Nested Logit (NL) model along with a quadratic polynomial trend surface to spatially examine the influence

of the built environment attributes on travel behaviour while accounting for socioeconomic characteristics. The chapter provides an understanding of how city geography mediates the impact of built environment attributes on mode choice behaviour. The results show that built environment attributes significantly influence mode choice behaviour; however, their influence is not uniformly efficacious across the city. The chapter also presents a simulation exercise to test the consequences of improving the built environment on mode choice behaviour. The simulation results revealed a substantial increase in the probability of using active travel modes while decreasing the probability of using transit and other modes.

- Chapter 7: presents a summary of this dissertation, the conclusions, and suggestions for future work.

It is worth mentioning that chapters 2, 3 and 6 represent standalone manuscripts that have already been published/accepted as peer-reviewed journal articles. Chapters 4 and 5 also represent standalone manuscripts that have already been submitted for publication in peer-reviewed journals. These chapters cooperatively describe a cohesive research body; however, some overlap might exist for the completeness of each standalone manuscript (chapter). The following figure describes the structure of the dissertation and compiles the objectives associated with each chapter.

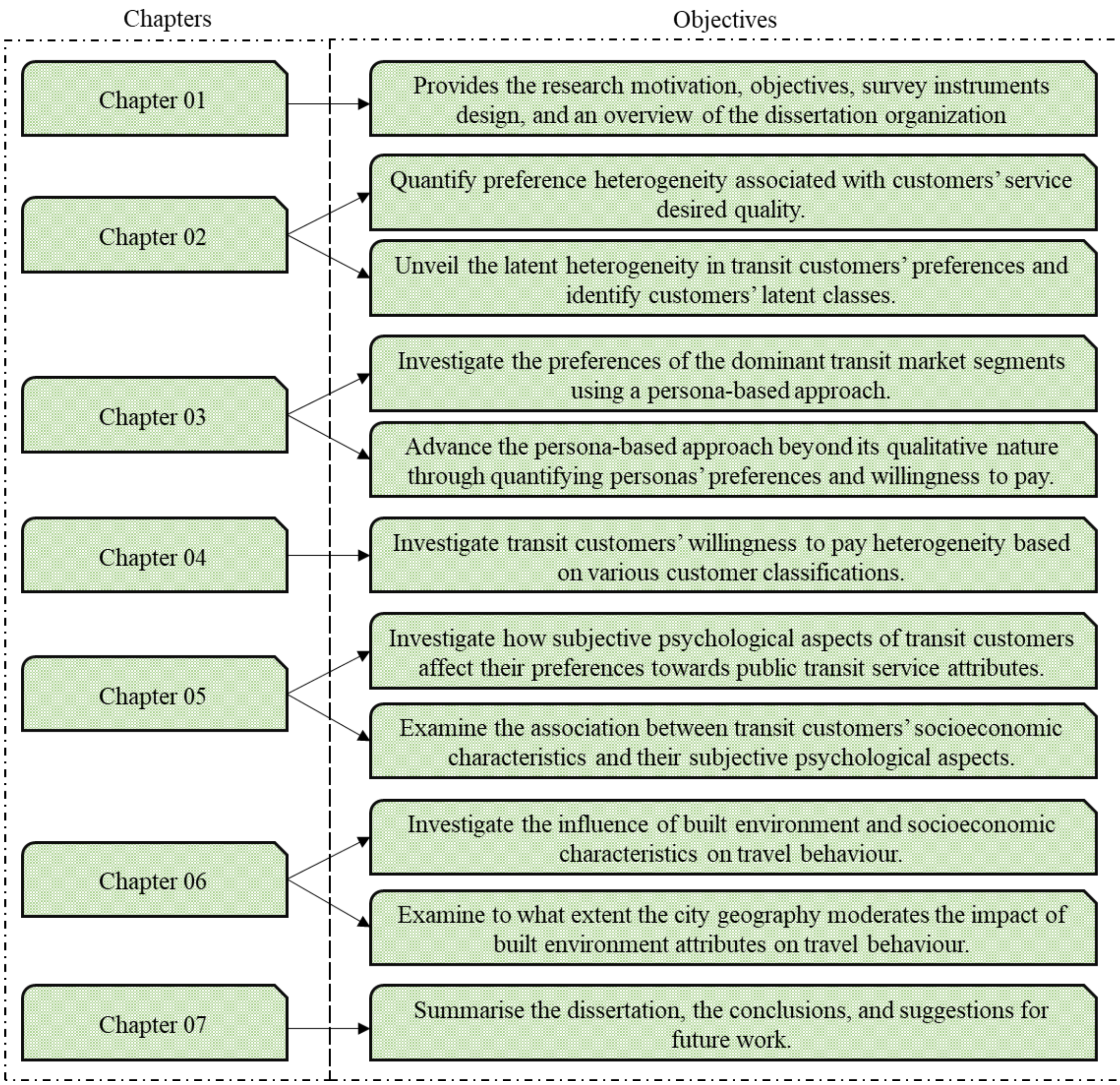

Figure 1-5 The structure of the dissertation

1.5 Appendix A

McMaster University
Inspiring Innovation and Discovery

McMaster University Research Ethics Board (MREB)

c/o Research Office for Administrative Development and Support, MREB Secretariat, GH-305/H, e-mail: ethicsoffice@mcmaster.ca

CERTIFICATE OF ETHICS CLEARANCE TO INVOLVE HUMAN PARTICIPANTS IN RESEARCH

Application Status: ☑ **New** ☐ **Addendum** | **Project Number:** 2018 109

TITLE OF RESEARCH PROJECT:

A Systemic Assessment and Optimization of Hamilton Street Railway (HSR) Network

Faculty Investigator(s)/ Supervisor(s)	Dept./Address	Phone	E-Mail
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Co-Investigator(s):
M. Ferguson

Student Investigator(s)	Dept./Address	Phone	E-Mail
G. Eldeeb	Engineering	24845	eldeebg@mcmaster.ca

Co-Investigator(s):

The application in support of the above research project has been reviewed by the MREB to ensure compliance with the Tri-Council Policy Statement and the McMaster University Policies and Guidelines for Research Involving Human Participants. The following ethics certification is provided by the MREB:

☐ The application protocol is cleared as presented without questions or requests for modification.
☑ The application protocol is cleared as revised without questions or requests for modification.
☐ The application protocol is cleared subject to clarification and/or modification as appended or identified below:

COMMENTS AND CONDITIONS: Ongoing clearance is contingent on completing the annual completed/status report. A "Change Request" or amendment must be made and cleared before any alterations are made to the research.

Reporting Frequency:	Annual: Jul-18-2019	Other:

Date: Jul-18-2018 **Chair, Dr. S. Fast** Susan Fast

Figure A-1-1 McMaster Research Ethics Board (MREB) clearance

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CHAPTER 2

Quantifying Preference Heterogeneity in Transit Service Desired Quality Using a Latent Class Choice Model

Preamble

This chapter addresses the first two objectives of the dissertation. First, it presents an investigation of preference heterogeneity in transit service desired quality with respect to transit customers' socioeconomic characteristics and travel behaviour using an Error Components (EC) logit model with systematic taste variations. Second, the chapter also unveils the latent heterogeneity in transit customers' preferences and identifies their latent homogenous classes using a Latent Class choice Model (LCM).

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2.1 Abstract

This study aims at quantifying preference heterogeneity in transit service desired quality to better-informing service quality improvements. The analysis is performed using a validated dataset elicited from 906 respondents through an online survey. An unlabelled Stated Preference (SP) experiment was utilized in a Latent class Choice Model (LCM), and an Error Components (EC) interaction model. The results of the EC interaction model revealed preference heterogeneity due to differences in respondents' socioeconomic and behavioural characteristics. While the results of the LCM untapped vital information that has not been reported previously in the transit service quality literature. Unlike the traditional user type classification, our study classifies respondents into three segments: Direct Trip Enthusiastic (DTE), Cost-Sensitive (CS), and Real-time Information Supporter (RIS). Each segment exhibits different preferences for transit service attributes, and their willingness to pay for service improvements is distinctly different. Further, the LCM indicates that the heterogeneity of users' preferences is not explicit in their usage pattern nor accessibility to different travel modes; instead, it is a bundle of various parameters.

2.2 Introduction

High-quality public transit service is essential to address the deterioration of traffic conditions and air quality in urban areas resulting from the soaring rates of car ownership. Many research studies have been carried out to identify transit quality aspects that affect service attractiveness and, in turn, promote transit ridership. The dominant approach in the literature is rooted in understanding consumers' preferences with an emphasis on current transit users (Krizek and El-Geneidy, 2007; Mazzulla and Eboli, 2006). Although consumer satisfaction cannot be overemphasized, yet attracting new users is equally vital for a sustainable transit system. Consequently, efficient transit systems should strive to satisfy current users and attract potential users at the same time (Mahmoud and Hine, 2013).

That said, both current and potential users exhibit different preferences associated with transit services (Krizek and El-Geneidy, 2007; Mahmoud and Hine, 2016; Mahmoud and Hine, 2013; Mahmoud et al., 2011), and policies aimed at satisfying current users might not necessarily succeed in attracting new users. In this respect, quantifying the gap, or the lack thereof, in the preferences of different users' groups, offers significant advantages. This indeed enables service providers and policymakers to target a broad spectrum of users with directed service quality improvements.

Methodologically, there is a clear distinction in the literature associated with measuring the preferences of transit users. Some studies adopt discrete choice models based on stated preference experiments. These are similar to the works of (dell' Olio et al., 2011; Diab et al., 2017; Venter, 2016; Eldeeb and Mohamed, 2020), which quantify the required quality improvement based on a utility maximization concept. Other studies employ causality models such as Structural Equation Models (SEM). These studies investigate the relationships between the level of satisfaction expressed by users associated with different service attributes, and the overall service satisfaction. This is mainly implemented to identify service attributes of significant influence (importance) by statistically testing the significance of the relationships (de Oña et al., 2013; de Oña et al., 2015; Deb and Ahmed, 2018; Li et al., 2018; Shen et al., 2016; Zhao et al., 2013).

Other researches applied more robust SEM models such as Structural Equation Multiple Cause Multiple Indicator (SEM-MIMIC) Ordinal Probit model to account for heterogeneity in users' perceptions (Allen et al., 2018), as well as an SEM Multi-Group Analysis model (SEM-MGA) to measure the variation between different population subgroups as it relates to the effect of service attributes on the overall service satisfaction (Allen et al., 2019). Moreover, behavioural theories, such as the theory of planned behaviour (Ajzen, 1991) and norm activation theory by Schwartz (1977), are utilized to inform transit mode choice through a behavioural and attitudinal orientation such as the works of (Chowdhury et al., 2016; Fu et al., 2018).

Therefore, as we argue on the dire need to study preference heterogeneity of transit users, we also argue that preferences, socioeconomic characteristics and attitudinal factors complement each other in shaping the perspective of different categories of users towards bus transit quality. Furthermore, we debate that end-users should not be treated as one homogeneous group, rather a classification of users' types is required to better tailor service quality improvements for each segment in the population.

Toward that end, this study aims at quantifying the heterogeneity in users' preferences with respect to their desired transit service quality. The study utilizes state-of-the-art choice modelling techniques to quantify preference heterogeneity. Specifically, the study incorporates and compares the results of two choice modelling techniques: a Latent Class choice Model (LCM), and an Error Components (EC) interaction model. This approach is fundamental to understand the bearing of the modelling techniques on the generated results and also the differences among the considered choice modelling techniques, with an overarching aim to better-inform service quality improvement policies.

The remainder of this paper is arranged as follows: Section 2 reviews the literature on transit users' preference heterogeneity associated with service desired quality. Section 3 describes the modelling approaches as well as the data collection process. Section 4 presents the results of the EC and LCM models, which is followed by a discussion and concluding remarks section.

2.3 Literature review

The concept of service quality loop, introduced by the European Committee for Standardization (2002), defines the relationships between transit service providers and users. From a user perspective, the quality loop differentiates between the desired and perceived quality. While from a transit agency viewpoint, it distinguishes between the targeted and delivered levels of quality. The comparison between the four quality aspects provides valuable insights into service performance, user satisfaction, expectation, and implementation gaps, as depicted in Figure 2-1.

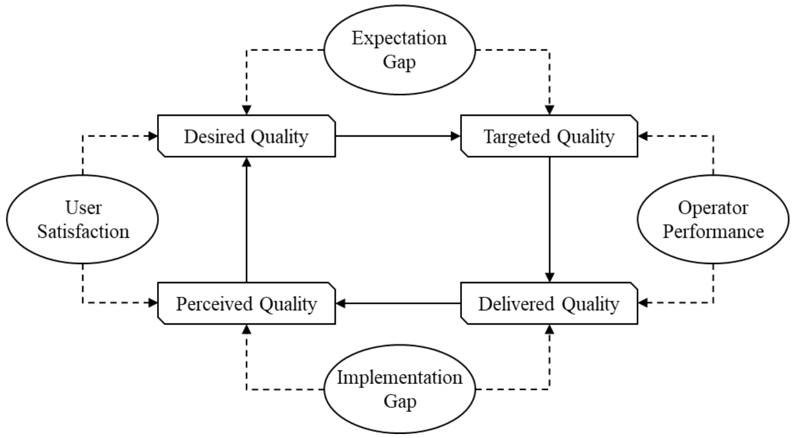

Figure 2-1 The anatomy of the service quality loop

In addition to the quality aspects, previous studies highlighted the importance of subjective factors such as previous experience (Diab et al., 2017; Krizek and El-Geneidy, 2007; Lai and Chen, 2011), habits and attitudes (Fu and Juan, 2017; Fu et al., 2018) in shaping users' desired quality. Therefore, it could be argued that the heterogeneity in transit service quality is attributed to three main aspects: the qualitative nature of some service aspects, different tastes and attitudes, and the variation in the socioeconomic demographic (SED) characteristics as suggested by Eboli and Mazzulla (2011).

Taken together, the varied preferences towards the quality aspects and the variation in SED and attitudinal traits impose a significant level of heterogeneity across transit users. Therefore, one can argue that the desired quality of transit service should be able to address the inherited heterogeneity associated with users' preferences, SED characteristics as well as users' attitudes towards bus transit quality.

Several modelling techniques have been implemented to address this issue. Structural equation models, as an essential tool of causality models, allow the integration of behavioural factors with service quality constructs, this is similar to the works of (Allen et al., 2019; Fu and Juan, 2017; Fu et al., 2018; Lai and Chen, 2011). The results provide clear evidence that users' preferences are not only influenced by the conventional service quality attributes (i.e., travel time, waiting time, facilities) but also by behavioural and attitudinal aspects as well as the level of involvement with the service. For example, Lai and Chen (2011), highlighted the significant positive influence of attitude on the overall service satisfaction and behavioural intention. Moreover, the heterogeneity in users' judgment was clearly stated in Eboli and Mazzulla (2011), where they developed an integrated subjective-objective evaluation of service quality to overcome this issue.

Discrete choice models, based on the random utility maximization (RUM) theory, have been used in transit quality literature to estimate the impact of level-of-service attributes. In addition, such models enable the estimation of the willingness to pay (WTP) for service improvements. For example, a binary logit model was used by Diab et al. (2017) to determine the attributes affecting passengers' willingness to recommend the service. The study concluded that waiting time satisfaction is the most important factor followed by the satisfaction from travel time and on-board experience. To investigate the bearing of each attribute on transit quality for various categories of users, dell' Olio et al. (2011) used multinomial logit models with interactions to estimate the preferences of different user groups. The results showed that cleanliness and comfort have almost the same weight in all users' categories, while journey time, waiting time, and bus occupancy are more valued by casual users compared to frequent users. A mixed logit model was utilized by Venter (2016) to examine users' stated needs and preferences. The results showed that transit-choice passengers have a lower WTP for waiting time savings compared to captive users. Moreover, the study examined and proved preference heterogeneity among captive and choice transit users for in-vehicle travel time and walking time attributes.

In addition, a prior classification of users' types is frequently utilized as an additional layer to capture heterogeneity among different transit users. In this respect, transit users are often classified in the literature into two classes. Current Users, who use transit regularly as their primary travel mode. Potential Users, who do not consider transit as their primary travel mode (e.g., automobile drivers, automobile passengers, etc.) (Deb and Ahmed, 2018; dell' Olio et al., 2011; Mahmoud and Hine, 2013). Some other studies have further classified each type of users into Captive and Choice users (Beimborn et al., 2003; Krizek and El-Geneidy, 2007; van Lierop and El-Geneidy, 2017; Venter, 2016). Where captive users refer to users with access to only one travel mode (e.g. car or transit), while choice users entertain access to multiple travel modes. Furthermore, recent studies have developed spatial segmentation models to assess the heterogeneity among different groups of users (Kieu et al., 2018), as well as to explain the variation of users' satisfaction and SEDs across a spatial dimension (Nikel et al., 2020; Eboli et al., 2018; Grisé and El-Geneidy, 2018).

Table A-2-1 - Appendix A provides a concise list of studies, selected by the authors, on transit service quality and their adopted user classification, context, and sample size.

In this respect, the literature highlights that relative to potential users; current users allocate more attention to operational aspects such as trip fare, travel time, real-time information provision, and punctuality (de Oña et al., 2017; Fu et al., 2018; Machado et al., 2018; Nesheli et al., 2017). While only potential users are reported to consider attributes of service attractiveness and customer interface (Abenoza et al., 2017; Krizek and El-Geneidy, 2007). Further, both current and potential users take into consideration travel time, frequency, safety, reliability, and travel cost (Abenoza et al., 2017; Deb and Ahmed, 2018; Mahmoud and Hine, 2016). Additionally, the willingness to pay values estimated for potential users are very much higher than the values estimated for current users, as reported by (Bellizzi et al., 2020).

Table 2-1 shows the significant service quality aspects for current and potential users, which have been reported at least twice as significant in the literature based on a concise set of relevant studies (see Appendix A).

Table 2-1 Significant service quality aspects in the literature presented in Appendix A

Quality aspects	**Current Users**	**Potential Users**
Service attributes	Travel time (14) Frequency (11) Travel cost (10) Punctuality (10) Information (9) Occupancy (7) Waiting time (4) Stop location (5) Temperature (3) Amenities (2)	Travel time (6) Travel cost (5) waiting time (4) Frequency (4) Stop location (4) Occupancy (2) No. of transfers (2) Amenities (2)
Service constructs[1]	Comfort (13) Safety (12) Reliability (7) Cleanliness (7) Accessibility (6) Staff attitude (6) Courtesy (4) Customer service (3)	Staff attitude (3) Reliability (3) Comfort (3) Service attractiveness (2) Safety (4)

(*) refers to the number of studies reported the aspect as significant.

[1] Latent constructs (factors) are adopted to overcome the qualitative nature of transit service quality; Factor Analysis, Principal Component Analysis (PCA), and Confirmatory Factor Analysis (CFA) are commonly used to extract latent constructs.

Furthermore, the classification of captive and choice transit users showed that choice users are more sensitive to travel cost, travel time, walking times, reliability, and comfort (Krizek and El-Geneidy, 2007; Venter, 2016). While captive transit users are more concerned about waiting time and the number of transfers. Recently, Grisé and El-Geneidy (2018) highlighted eight distinct user types/segments based on a combination of personal traits and satisfaction levels. Each of these segments is argued to exhibit a common geographical distribution.

Given the aforementioned aspects of preference heterogeneity, this study aims at investigating preference heterogeneity of transit users, in a bus service desired quality choice experiment, through an integrated modelling approach. In particular, our study quantifies the impact of service quality aspects on different segments of the population, allowing for tailored policies and service quality improvements. In addition, our study will reveal the heterogeneity associated with preferences, attitudes, and SED traits of different transit users' groups that might have been masked in previous studies due to the restrict prior classification of transit users into binary categories (current and potential users, or choice and captive users).

2.4 Methods and data

2.4.1 Survey instruments design

The study utilizes a primary dataset collected through an online survey in September 2018. The survey is part of the Hamilton Street Railway (HSR) Public Engagement efforts in the City of Hamilton, Ontario, Canada. In a nutshell, HSR provides a service coverage area of approximately 243 square kilometres through 35 regular bus routes. This is in addition to

Disabled and Aged Regional Transportation System (DARTS) and Trans-Cab services (City of Hamilton, 2018). The general purpose of the survey is to benchmark the quality of HSR service based on users' preferences and expectations. The survey is intended for all Hamiltonians, and structured in four sections, detailed as follows:

- SED characteristics and travel behaviour: The survey collected SED information such as sex, age, vehicle ownership. Moreover, the survey collected detailed information about respondents' travel behaviour, such as the primary, secondary, and occasional modes of transportation.
- Stated choice experiments: The survey included unlabelled and labelled choice experiments. The unlabelled stated choice experiment, which is the focus of the present study, asked respondents to choose between three bus transit alternatives.
- Service quality aspects: Current users were asked to assign the degree of satisfaction and importance to a set of service attributes on a 5-point Likert scale, while potential users were requested to assign only a degree of importance to this set.
- Attitudinal and behavioural characteristics: Respondents were asked to assign a degree of agreement on a 5-point Likert scale regarding their transit attitudes.

This study utilizes a sample of 979 respondents and focuses on the unlabelled stated preference component of the survey as well as public transit attitude. The sample was stratified to represent the population of Hamilton while achieving the minimum recommended sample size, as advocated by Johnson and Wichern (2013).

The use of an online (internet-based) survey has various advantages over other types of surveys (e.g. face-to-face interviews, mail, phone interviews), such as 1) Short response and completion times, 2) Flexibility: respondents can answer on their own time, 3) Easy to follow: respondents are directed to the next question through filters, 4) Eliminating the need for decoding and digitizing, and 5) Automatically randomize choice scenarios (Iraguen and Ortúzar, 2004; Lindhjem and Navrud, 2011). In addition, satisficing (shortcutting the response process to a suboptimal choice, which is a common bias in self-administered surveys) proved to be lower in internet-based surveys compared to telephone interviews and mail surveys. Additionally, socially desirable responding bias is lower in online surveys compared to face-to-face interviews and telephone surveys (Lindhjem and Navrud, 2011). As highlighted by Iraguen and Ortúzar (2004), the main disadvantage of online surveys is the sample bias as not all people have access to the internet.

The design of the stated choice experiment follows the procedure suggested by Bliemer and Rose (2006), where the design process considers three stages; model specification, experimental design, and questionnaire. In this respect, the study employed a three-stage sequential process for the selection of the attributes and their associated levels. Based on an extensive review of the literature, as shown in Appendix A, an initial list of attributes was compiled and then revised with HSR through focus group discussions. Formerly, a pilot survey of 62 respondents, 248 records as each respondent faced four-choice scenarios, representing all users' types (i.e. casual 32.26%, frequent 50%, and very frequent 17.74%) was administrated to inform the model specifications and to ensure respondents' comprehension of the survey and the SP experiments. Respondents did not raise any serious concerns to comprehend and answer the survey. The final list of attributes and the associated levels are presented in Table 2-2.

Table 2-2 Unlabelled SP experiment attributes and their associated levels (Eldeeb et al., 2019)

Service attributes	**Attribute levels**
One-way trip cost	\$3, \$4.5, and \$6
One-way trip travel time	20, 30, and 40 minutes
Walking time to and from the bus stop	0, 5, 10, and 15 minutes
Service headway	5, 10, 15, and 30 minutes
Number of transfers[2]	0, 1, and 2 transfers
Real-time information	At-stop, on-board and none

The efficient experimental design method was used to maximize the amount of information gathered from the stated choice experiment and increase its statistical efficiency, as suggested by Kuhfeld et al. (1994). Recent literature emphasizes the outweigh of the efficient design over the orthogonal design in case of information availability regarding attributes' coefficients, or even only prior knowledge of the signs, as reported in (ChoiceMetrics, 2018; Ferguson et al., 2018; Idris, 2013; Twaddle, 2011).

The Ngene 1.2.0 software was used to generate an efficient design while minimizing the determinant of Asymptotic Variance-Covariance matrix D_p-error and C-error. The latter is arguably more robust for willingness to pay estimations (ChoiceMetrics, 2018). Overall, the experimental design process resulted in twelve scenarios grouped into three blocks. Each respondent faced four-choice situations and was requested to choose from three unlabelled bus transit alternatives, as shown in Figure 2-2 It should be noted that the

2 The number of transfers and real-time information attributes are categorical variables, with three levels, which are included in the model as dummy variables. Both two transfers and no real-time information provision were considered the base categories, as these reflect the current HSR operation.

randomization of both choice scenarios and attributes' order were considered to mitigate the sequence/order effect bias see Louviere et al. (2000) and Hensher et al. (2016).

Trip & Service Attributes	Option - A	Option - B	Option - C
Bus Fare (one-way trip)	$ 3.00	$ 4.50	$ 3.00
Time Spent Travelling on Bus (one-way trip)	40 min	30 min	40 min
A Bus Departs from My Stop (at the start/end and transfer stops)	every 5 min	every 10 min	every 10 min
Walking Time to/from Bus Stop (includes walking time between transfer stops)	15 min	5 min	5 min
Number of Transfers Between Buses (during one-way trip)	2 Transfer	0 Transfer	1 Transfer
Real-time Trip Information (e.g. about delays)	None	At stop	On board
To Complete My Regular One-Way Trip, I would Choose	○	○	○

Figure 2-2 Example of a stated preference scenario (Eldeeb et al., 2019)

Respondents' attitudes towards public transit were measured using three attitudinal statements; 1) I feel active when using transit, 2) I enjoy using transit, and 3) I think using transit is a good decision. These attitudinal statements have a Cronbach's alpha of 0.774, which indicates internal consistency. Respondents were asked to assess their agreement on the accuracy of each statement on a 5-point Likert scale.

2.4.2 Survey data

The study utilized a validated dataset elicited from 906 respondents, where 73 unengaged respondents (i.e., provided contradictory answers) were eliminated. Socioeconomic, behavioural, and attitudinal characteristics of the sample compared to the population are introduced in Table 2-3. The sample represents both males and females with relatively equal proportions of 49.34% and 50.66%, respectively. The majority of respondents

(51.55%) are between 30 to 59 years old, while respondents between 15 to 30 and over 60 years old represent 24.72% and 23.73%, respectively.

Respondents were grouped into three annual income classes; high-income (i.e., over $80,000), middle-income (i.e., $40,000 to $79,999), and low-income (i.e., less than $40,000), which represent 42.05%, 27.48%, and 17.33%, respectively. It should be noted that around 13% of respondents preferred not to reveal their annual income, and the sample underrepresents the low-income class while overrepresents the high-income class. This limitation (i.e., sample bias) might be attributed to the internet-based nature of the survey, which proved to be existing even where over 90% of Canadians are frequent internet users (Statistics Canada, 2017). The data shows a high percentage of vehicle ownership among respondents where 38.08% own two or more vehicles, and 51.10% own one vehicle while only 10.82% have no access to a vehicle.

Most of the respondents (41.50%) are casual HSR users (i.e., never or annually use HSR service), while 31.46% and 27.04% are frequent (i.e., weekly or monthly) and very frequent users (i.e., daily). Transit captives (i.e., no other travel modes but transit) and car captives (i.e., no access to HSR transit service) represent 6.07% and 5.85% of respondents, respectively. It should be noted that car captivity is self-reported by users as an agreement to "*I have no access to HSR service*" statement.

Table 2-3 Sample distribution

Category	**Sub-Category**	**Users (%)**	**Population (%)**
Gender	Male	49.34%	48.90%
	Female	50.66%	51.10%
Age	15 to 30 years old	24.72%	35.72%
	30 to 59 years old	51.55%	40.64%

Category	Sub-Category	Users (%)	Population (%)
	Over 60 years old	23.73%	23.64%
Income	Less than $40,000	17.33%	58.00%
	$40,000 to $79,999	27.48%	28.55%
	Over $80,000	42.05%	13.39%
	Prefer not to answer	13.13%	NA
Vehicle ownership	Zero Vehicle	10.82%	13.00%
	One Vehicle	51.10%	87.00%
	Two or more	38.08%	
Frequency of use HSR	Very frequent	27.04%	10.54%
	Frequent	31.46%	89.46%
	Casual	41.50%	
Transit Captivity	Transit captive users	6.07%	NA
	Transit choice users	93.93%	NA
Car Captivity	Car captive users	5.85%	12.51% +
	Car choice users	94.15%	87.49% +

+ spatially measured considering transit service area coverage in contrast with the residential land uses.

2.4.3 Methods

This study utilizes state-of-the-art discrete choice modelling approaches to investigate users' preference heterogeneity in a bus service desired quality choice experiment, and to quantify consumer willingness to pay (WTP). WTP represents the monetary value that a user is willing to pay for an additional unit of improvement of a service attribute (Ben-Akiva and Lerman, 1985; McFadden, 1998).

In general, two different choice modelling techniques are utilized to capture the inherited heterogeneity in different consumer research outside the domain of transit quality literature.

First, an Error Components (EC) interaction model, with systematic taste variations, is used as the base model to investigate the bearing of each service attribute on the overall transit utility, with respect to respondents' socioeconomic characteristics and travel behavioural attributes, while accounting for the panel effect. The considered EC model is a simple Mixed Logit (ML) model with fixed coefficients and an error component (McFadden and Train, 2000). For the EC model, the RUM adopts a rational decision-making approach, which assumes that individual i, picks the choice j, that maximizes their utility U_{ijt}, in the choice situation, t:

$$U_{ijt} = \beta X_{ijt} + \eta_{ijt} Y_{ijt} + \varepsilon_{ijt} \tag{2-1}$$

Where X_{ijt} is the observable component of the utility function, which is a vector of explanatory variables and β is a vector of estimated fixed parameters. While η_{ijt} is a vector of random elements with a distribution (assumed to be normal), with zero mean, assigned by the modeller and Y_{ijt} is a vector of unknown attributes. And ε_{ijt} is the error term, which is assumed to be identically and independently distributed (IID). The explanatory variables might include interaction variables reflecting respondents' characteristics, which adopts the systematic taste variations specification suggested by (Rizzi and Ortúzar, 2003; Ortúzar and Willumsen, 2011). The unconditional choice probability, as mentioned in Hensher and Greene (2003), for individual i, selecting a choice j, based on the EC formulation is expressed as follows:

$$P_{ij} = \int \prod_{t=1}^{T_q} \left[\frac{e^{\beta X_{ijt} + \eta_{ijt} Y_{ijt}}}{\sum_{j=1}^{J} e^{\beta X_{ijt} + \eta_{ijt} Y_{ijt}}} \right] f(\eta)\, d(\eta) \tag{2-2}$$

The EC interaction model is estimated using a range of Modified Latin Hypercube Sampling[3] (MLHS) draws (e.g., 50, 100, 500, 1000) through the Pandas Biogeme package

[3] According to (Hess et al., 2006), the MLHS outperforms other types of Quasi-random number sequences such as Halton draws.

(Bierlaire, 2018). Since the choice experiment being dealt with is unlabelled, all alternative specific constants were excluded (Hensher et al., 2005).

Second, a Latent class Choice Model (LCM) was utilized, which assumes that a discrete number of classes is sufficient to capture respondents' preference heterogeneity where the parameters for each class are estimated using a multinomial logit. Greene and Hensher (2003) and Shen et al. (2016) concluded that the LCM is supported by stronger statistical behaviour compared to the random parameter logit (RPL) model. Moreover, Beck et al. (2013) pointed out that the LCM main advantage is the ability to link taste heterogeneity to socioeconomic and attitudinal attributes. Additionally, the LCM accounts for the panel effect, resulting from the SP experiment, by including the contribution of individual q to the likelihood as the joint probability of the sequence of the choices made (Greene and Hensher, 2003); however, the autocorrelation between each individual's choice scenarios is not considered.

Concerning the LCM estimation process, LCM assumes that individual behaviour depends on observed attributes and latent preference heterogeneity. Hence, individuals are assigned to a predefined number of latent classes with a discrete probability distribution. The LCM simultaneously estimates the probability $P_{iq|s}$, that an individual q, of class s, chooses alternative i, from a particular set J, for S classes, and predicts class membership probability H_{qs}, as individual q, being in class s. Therefore, the unconditional probability P_{iq}, of choosing alternative i, can be expressed as:

$$P_{iq} = \sum_{s=1}^{S} H_{qs} P_{iq|s} = \sum_{s=1}^{S} H_{qs} \left(\prod_{t=1}^{T_q} P_{itq|s}\right) \qquad (2\text{-}3)$$

Where T_q is the number of choice situations of individual q. More information about the LCM, including the estimation process, is provided in (Greene and Hensher, 2003; Shen, 2009).

The integration between the two approaches provides useful insights into understanding the preference heterogeneity of users on different levels. The EC interaction model captures the sample preference heterogeneity based on the interaction of specific socioeconomic and behavioural characteristics. While the LCM presents an overview of the entire sample preference heterogeneities (i.e., divides the sample into different classes with preference homogeneity considering socioeconomic, behavioural, and attitudinal attributes). Such a level of detail enables introducing adequate strategies to satisfy current users and attract new user groups.

Moreover, unveiling respondents' preference heterogeneity helps to alleviate the effect of sample bias towards a specific category (i.e., high-income class) through assembling respondents with preference homogeneity with respect to their characteristics. A related point to consider is that the LCM models were estimated using the econometric software package NLogit 5.

2.5 Modelling results

2.5.1 Error Components Interaction Model

One inclusive EC interaction model was developed to estimate the bearing of each service attribute on the overall transit utility with respect to respondents' socioeconomic characteristics (i.e., Gender, Age, and Vehicle ownership) and travel behavioural attributes (i.e., the frequency of using HSR). A base EC model without any interactions and considering only service attributes was estimated (with -3773.63 log-likelihood at convergence). Then, the EC interaction model was estimated, as shown in Table 2-4.

The EC model with systematic taste variations discloses the heterogeneities in respondents' preferences with respect to their socioeconomic characteristics and travel behaviour. The error component does not prove to be significant; yet it is retained as a precautionary measure to account for the panel effect. Table 2-4 shows only the significant interactions at a 90% confidence level. The EC interaction model shows a significant improvement over the base EC model regarding goodness-of-fit measures (i.e., likelihood ratio test of 207.428 for 21 degrees of freedom).

Table 2-4 Error Components interaction model estimation

Variable	**Coefficient(β)**	**t-Test**	**P-Value**
Journey time	-0.066	-8.790	0.000
Journey time × Male	0.016	1.800	0.072
Journey time × Zero-vehicle	0.024	2.280	0.023
Journey time × One-vehicle	0.021	2.760	0.006
Journey time × Very frequent	0.012	1.720	0.085
Trip fare	-0.731	-9.270	0.000
Trip fare × Age 30 to 60	0.288	4.390	0.000
Trip fare × Age 15 to 30	0.435	5.900	0.000
Trip fare × Male	0.167	2.450	0.014
Trip fare × Frequent	-0.290	-5.440	0.000
Trip fare × One-vehicle	0.135	2.460	0.014
Walking time	-0.058	-5.220	0.000
Walking time × Age 30 to 60	0.036	3.350	0.001
Walking time × Age < 30	0.056	4.480	0.000
Walking time × Male	0.024	2.390	0.017
Service headway	-0.037	-7.160	0.000
Service headway × Male	0.016	2.550	0.011
Service headway × One-vehicle	0.013	2.070	0.038
Number of transfers (2-transfers base-category)			
One transfer	0.131	4.900	0.000
Zero transfer	0.624	10.200	0.000

Variable	Coefficient(β)	t-Test	P-Value
Zero transfer × Male	-0.174	-2.380	0.017
Zero transfer × One-vehicle	-0.147	-2.140	0.032
Zero transfer × Very frequent	-0.419	-6.320	0.000
Real-time information (No info. base-category)			
Real-time information On-board	0.193	6.660	0.000
Real-time information On-board × Very frequent	-0.137	-2.430	0.015
Real-time information At-stop	-0.064	-1.530	0.127
Real-time information At-stop × Age < 30	0.276	4.610	0.000
Real-time information At-stop × Frequent	0.140	2.280	0.023
Real-time information At-stop × Very frequent	0.112	1.760	0.079
Error Component (EC)	0.004	0.739	0.460
Log-Likelihood	**-3669.92**		
Rho-squared	**0.07**		

Number of respondents = 906, number of observations = 3624

With respect to socioeconomic interactions, females prefer direct trips and are more sensitive to journey time, trip fare, walking time, and service headway compared to males. Old respondents (i.e., over 60 years old) are the most sensitive to trip fare and walking time. While young respondents (i.e., from 15 to 30 years old) prefer at-stop real-time information provision more than others. Respondents with one vehicle are the least sensitive to trip fare, service headway, and direct trips, while respondents with two or more vehicles are the most sensitive to the journey time.

Considering travel behaviour interactions, very frequent (i.e., daily) transit users are the least sensitive to journey time, direct trips, and on-board real-time information provision. Frequent (i.e., weekly or monthly) transit users are the most sensitive to trip fare and at-stop real-time information provision.

That being said, although the EC model with systematic taste variations reveals substantial heterogeneity, we wished to test if there was even more by estimating a random parameter logit (RPL) model. But unfortunately, the results of the model were disappointing because the estimated standard deviations of trip fare and zero transfer variables were high and significantly different from zero, suggesting that a significant share of the sample would have a wrong sign (Sillano and Ortúzar, 2005).

2.5.2 Latent Class choice Model

The number of latent classes was defined based on 1) Model interpretability, 2) Adequate class size (i.e., not too large > 50% or very small < 10%), 3) Goodness-of-fit measures (e.g., Rho-square and log-likelihood), and 4) Statistical parsimony measures as Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) (Ferguson et al., 2018; Louviere et al., 2000). As shown in Table 2-5, AIC and BIC show a substantial improvement as the number of classes increases until four latent classes. Then, AIC improvement became substantially low, while BIC started declining. Trials were made to define more than five latent classes, but it did not prove possible to estimate stable calibrated results. Four latent classes are the best regarding goodness-of-fit and parsimony measures, but the class membership model shows that latent classes one and four are not statistically different. Consequently, three latent classes were chosen in favour of model interpretability as it reveals clear and significant differences between classes.

The three latent classes solution with full attribute attendance shows behaviourally implausible estimates (i.e., wrong signs) for the trip fare ($\beta_{\text{trip fare}}$: 0.32270) and walking time ($\beta_{\text{walking time}}$: 0.04278) in the third latent class, as shown in Table 2-6. This implies that a substantial proportion of individuals would have wrong signs for both variables.

Consequently, applying information processing strategies or heuristics approaches such as Attribute Non-Attendance (ANA) is valuable to derive behaviorally plausible results instead of the full attribute attendance approach (FAA). ANA is a heuristic approach where respondents overlook one or more attributes in the decision-making process as a coping strategy to alleviate the complexity of the choice task or as a genuine process of decision making, for more information the reader is referred to (Hensher and Greene, 2010; Hensher et al., 2005; Scarpa et al., 2009). ANA approach was applied for trip fare and walking time in the third latent class while considering the FAA for the first and second latent classes.

Table 2-5 Latent classes selection criteria

No. classes	Rho-squared	Log-Likelihood (LL)	No. parameters (K)	AIC	BIC
2	0.080	-3664.30	23	7374.60	7410.46
3	**0.099**	**-3586.64**	**38**	**7249.27**	**7308.52**
3 ANA	**0.098**	**-3591.73**	**36**	**7255.46**	**7311.59**
4	0.115	-3522.79	53	7151.58	7234.22
5	0.121	-3500.64	68	7137.27	7243.30

Note: Number of respondents = 906, number of observations = 3624

The LCM model with the ANA approach shows behaviourally plausible results, as shown in Table 2-6. Moreover, the goodness-of-fit measures are close, albeit significantly different to the LCM with the FAA. Both approaches demonstrate almost the same general behaviour where the directions (signs) of the attributes are the same. While the magnitudes of attributes and classes' membership probabilities have changed.

The membership probability of the third latent class has increased from 20.80% in FAA-LCM to 37.90% in ANA-LCM yet with an increased number of significant variables (e.g., journey time and one-transfer). Regarding trip fare, ANA-LCM depicts a relatively higher sensitivity to trip fare. This might be attributed to fixing the trip fare parameter to zero in the third class, which results in a more parsimonious willingness to pay estimates. Therefore, the ANA-LCM approach is chosen for the subsequent analyses. Additionally, a comparison between WTP estimates for the two approaches is also presented.

As the EC interaction model is not nesting within the LCM, the likelihood ratio test is not applicable. Consequently, an alternative method, the Relative Likelihood (RL), is used to select the best model associated with minimizing information loss (Burnham and Anderson, 2002). The RL of the model g_i versus the estimated best model g_{min} (min AIC) is calculated as follows:

$$RL = \frac{L(g_i|x)}{L(g_{min}|x)} = e^{\frac{AIC_{min} - AIC_i}{2}} \qquad (2\text{-}4)$$

Since the minimum AIC is associated with the LCM, the Relative Likelihood (RL) for the EC interaction model is $(4.4403e-32)$. Hence, the EC interaction model is less than 0.001 times probable to minimize information loss compared to the ANA-LCM with three latent classes. Therefore, the selected ANA-LCM shows a significant improvement over the EC interaction model.

Table 2-6 depicts the results of LCM models; LCM results include estimates for class membership model and class-specific utility model. The following subsections discuss the results of the class membership model and class utility model of ANA-LCM.

2.5.2.1 Class Membership Model

The specification of the class membership model is based on a group of individual-specific socioeconomic, behavioural, and attitudinal attributes. A class membership model is a probabilistic approach that is implemented in a multinomial logit form and describes respondents' characteristics for each class, considering the third latent class as a reference. The class membership probability might be interpreted as the proportion of the sample represented by this class. Class-specific constants are significant in all classes and seem to be effective in the class assignment process as well as age and gender.

The three latent classes may be interpreted as Direct Trips Enthusiastic (DTE), Cost-Sensitive (CS), and Real-time Information Supporter (RIS) respondents. Figure 2-3 summarizes the socioeconomic, behavioural, and attitudinal characteristics of the three latent classes. DTE class represents 25.5% of sample size, and class members are more likely to be middle-aged female respondents who are casual transit users with a negative transit attitude. While RIS class represents 37.9% of the sample, and class members are more likely to be middle-aged male respondents who are very frequent transit users with a positive transit attitude. Also, the percentage of young respondents (i.e., under 30 years old) is relatively high in the RIS class while the opposite for old respondents (i.e., over 60 years old). Regarding the CS class, it represents 36.6% of the sample, and the distribution of male and female respondents is almost equal within the class as well as the frequency of transit use. Class members are more likely to be middle-aged respondents, with a relatively high ratio of old respondents, who have a positive transit attitude.

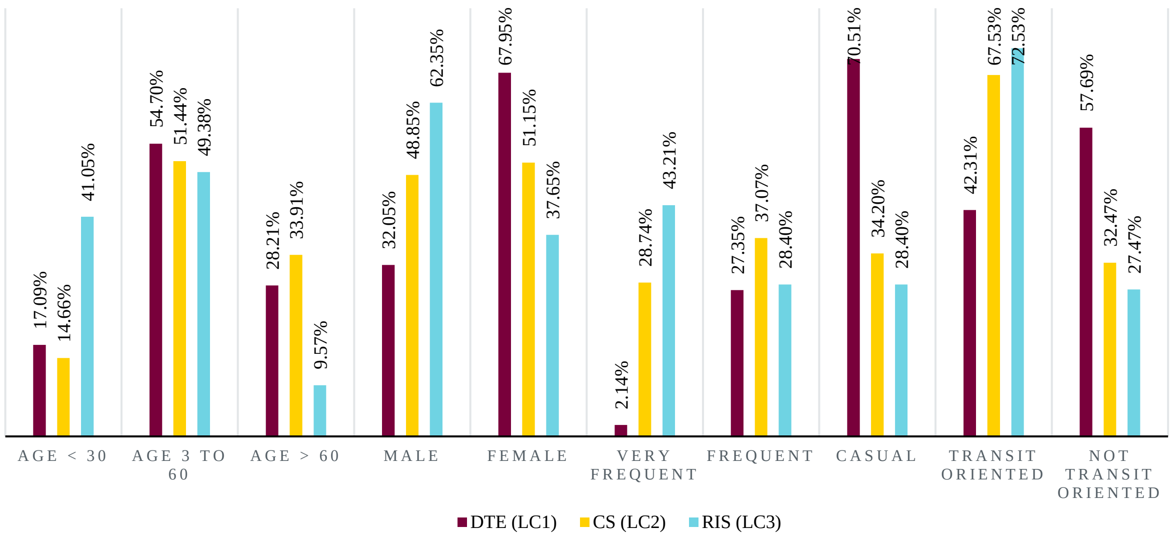

Figure 2-3 The profile of the three latent classes

2.5.2.2 Class-specific Utility Model

Each latent class has a unique combination of preferences for service attributes, as shown in Table 2-6. The significance and bearing of each attribute differ significantly between the latent classes, which indeed capture the preference heterogeneity among respondents.

Here we are explaining the impact of each attribute across the three latent classes to better explain the heterogeneity in users' preferences. *Journey Time* estimates are significant, and the signs are as expected in all classes. Increasing journey time has a negative impact on transit utility in all classes. *Trip Fare* estimates are significant in the first and second classes (DTE and CS) while fixed in the third class (RIS). *Trip Fare* signs are intuitive as there is a negative relationship between trip fare and transit utility. *Walking Time* estimates are significant in the second class (CS) and fixed in the third class (RIS), the sign of the walking time parameter in CS class is behaviourally reasonable as an increase in walking time negatively affects transit utility. *Service Headway* attribute estimates are significant in two classes (DTE and RIS), while insignificant in CS class. The significant estimates signs indicate the tendency of respondents to a higher transit service frequency. *Zero Transfer* estimates are only significant in DTE and CS classes and indicate respondents' preference to direct trips. While *One Transfer* estimates are positive and significant in DTE and RIS classes. *At-stop* and *on-board Real-time Information* estimates are only significant in the third class (RIS).

Explained in a different way, both the characteristics and preferences of the three groups could be described as follows:

- **Direct Trip Enthusiastic (DTE) class**, most of the attributes are significant except walking time and real-time information (at-stop and on-board). DTE class members are more likely to be middle-aged female respondents who are casual transit users with a negative transit attitude. They highly appreciate direct trips over multiple transfers-based trips, and frequent transit service, the highest among all classes. Moreover, class members prefer, ceteris paribus, shorter journey times and lower trip fares but not the most concerned about these aspects.
- **Cost-Sensitive (CS) class**, four out of eight attributes are significant; these attributes are journey time, trip fare, walking time, and zero transfer. CS class members are more likely to be middle-aged respondents, with a relatively high ratio of old respondents, who have a positive transit attitude. They are highly sensitive to trip fare, walking time, and journey time, the highest between classes. In addition, class members favour direct trips over one or more transfers-based trips.

- **Real-time Information Supporter (RIS) class**, four attributes are significant, at a 99% confidence level, including journey time, frequency, at-stop real-time information, and on-board real-time information. While zero transfer is almost significant at a 90% confidence level. Trip fare and walking time were considered as non-attended attributes. RIS class members are more likely to be middle-aged male respondents who are very frequent transit users with a positive transit attitude. RIS is the only class that appreciates real-time information provision. And specifically, class members prefer at-stop real-time information over the on-board option. In addition, they prefer, ceteris paribus, higher service frequency, and shorter journey times yet the least sensitive between classes.

Table 2-6 Estimates of LCM choice models

Attribute	LCM with FAA			LCM with ANA		
	LC1 (FAA)	LC2 (FAA)	LC3 (FAA)+	DTE LC1 (FAA)	CS LC2 (FAA)	RIS LC3 (ANA)
Journey time	-0.0344**	-0.0546***	-0.0143	-0.0542**	-0.0732***	-0.0275***
Trip fare	-0.2822*	-0.9095***	0.3227***	-0.6353*	-1.2919***	Fixed
Walking time	-0.0212	-0.0292***	0.0488***	-0.0058	-0.0489***	Fixed
Service headway	-0.0332***	-0.0282***	-0.0310**	-0.0489***	-0.0143	-0.0337***
Number of transfers (2-transfers base-category)						
Zero transfer	1.2189***	0.1553*	-0.1512	1.8438***	0.2987**	-0.0429
One transfer	0.4359***	0.1166**	0.1062	0.5919***	0.0654	0.0998*
Real-time information (No info. base-category)						
Real-time info. At-stop	-0.0524	0.0343	0.6096***	0.1553	0.0251	0.3133***
Real-time info. On-board	0.2522***	0.0314	0.5190***	0.0498	0.0416	0.2823***
Avg. class probabilities	27.80%	51.40%	20.80%	25.50%	36.60%	37.90%
Log-likelihood	-3586.64			-3591.73		
Rho-squared	0.099			0.098		
Class membership model	**LC1 (FAA)**	**LC2 (FAA)**	**LC3 (FAA)**	**LC1 (FAA)**	**LC2 (FAA)**	**LC3 (ANA)**
Constant	2.4505**	2.6342***	Base	0.8660*	1.0253**	Base
Age < 30	-2.0479**	-2.6838***		-1.0589**	-2.1509***	
Age 30 to 60	-0.6806	-1.1663*		-0.4476	-1.1799***	
Male	-1.5427***	-0.8262**		-0.8838***	-0.4972*	
Very frequent transit users	-1.7088**	0.3735		-1.9810**	0.4669	
Frequent transit users	-0.0272	0.8795*		-0.1294	0.8024**	
Positive transit attitude	-0.9028***	-0.5178**		-0.4390**	-0.1632	

Note: ***, **, and * indicate significance at 1%, 5%, and 10% levels
+ LC3 (FAA) shows behaviourally implausible estimates (i.e., wrong signs) for the trip fare and walking time attributes.

Table 2-7 WTP estimates for LCM models

	FAA-LCM			ANA-LCM		
	LC1 (FAA)	**LC2 (FAA)**	**LC3 (FAA)**	**DTE LC1 (FAA)**	**CS LC2 (FAA)**	**RIS LC3 (ANA)**
Reduction in Journey time (CDN$ per minute)	$0.012	$0.060	—	$0.085	$0.057	—
Reduction in Walking time (CDN$ per minute)	NS	$0.032	—	NS	$0.038	—
Reduction in Service headway (CDN$ per minute)	$0.118	$0.031	—	$0.077	NS	—
Reducing no. of transfers from 2 to 0 (CDN$ per trip)	$4.319	$0.170	—	$2.901	$0.231	—
Reducing no. of transfers from 2 to 1 (CDN$ per trip)	$1.544	$0.128	—	$0.932	NS	—
Provision of Real-time info. At-stop (CDN$ per trip)	NS	NS	—	NS	NS	—
Provision of Real-time info. On-board (CDN$ per trip)	$0.893	NS	—	NS	NS	—

NS: Not Significant & —: Not Applicable.

2.5.3 Willingness to pay

The WTP measure is an essential policy tool to guide public transit service improvements as it enables policymakers to adopt service improvements that are informed by users' preferences elicited from the SP experiment. Despite the flexibility of SP experiments in testing new scenarios, proposed improvements, and a wide range of attributes/levels (Hensher, 1994; Ortúzar and Willumsen, 2011), the SP experiments have a hypothetical bias. This bias is grounded on the differences between the actual behaviour and the stated choices (Ortúzar et al., 2000; Loomis, 2014). Loomis (2014) highlighted that such a hypothetical bias might result in higher WTP estimates compared to real-life, which should be considered by policymakers.

WTP estimates are based on the trip fare attribute coefficient and calculated in CAD$ for the significant attributes only. Respondents' WTP for various service improvements were calculated for both LCM models, as shown in Table 2-7. Overall, WTP estimates for LCM models are generally calculated through averaging WTP estimates across classes using the posterior probabilities as weights (Hensher et al., 2016). In this respect, it is worth noting that, WTP estimates of the ANA-LCM are more conservative than the FAA-LCM except for walking time and zero transfer attributes in LC2.

For instance, the ANA-LCM shows that the CS group would pay only $0.567 to save 10 minutes of journey time, while the DTE class would pay $0.852. While the WTP to save 5 minutes of walking time is $0.189 for the CS class. Additionally, the ANA-LCM shows that the DTE class is willing to pay $0.385 to reduce the headway by 5 minutes.

2.6 Discussion and Concluding Remarks

This study aimed at quantifying the heterogeneity in users' preferences with respect to their desired transit service quality to better-informing service quality improvement policies. The study utilized a validated dataset elicited from 906 respondents through an online survey in September 2018. The sample represents both current and potential users by 58.5% and 41.50%, respectively. The study employed an Error Components interaction model, and a Latent Class Choice model to unveil preference heterogeneity among respondents.

The results of the two modelling approaches show a high level of coherence and provide useful insights into respondents' preference heterogeneity on different levels. For instance, the results of the EC interaction model proved the existence of preference heterogeneity due to differences in respondents' socioeconomic characteristics and travel behaviour attributes. The model revealed that, in general, females are more sensitive to service attributes than males. Additionally, the EC results highlighted the dire need to reduce journey time and the number of transfers as well as the importance of real-time information provision to attract new transit users. The results are aligned with the findings of (dell' Olio et al., 2011; Mahmoud and Hine, 2013), which indicates that casual transit users are more sensitive to journey time, comfort, and waiting time than frequent and very frequent users.

The latent class choice model untapped very important information that has not been reported in the literature. Unlike the traditional classifications of users, our study classifies respondents into three segments: Direct Trip Enthusiastic (DTE), Cost-Sensitive (CS), and Real-time Information Supporters (RIS). Each segment exhibits different preferences for transit service attributes.

In a nutshell, with respect to our sample, DTE latent class members are more likely to be middle-aged female respondents who are casual transit users with a negative transit attitude. They highly appreciate, ceteris paribus, direct trips, shorter journey times, and frequent transit service. These findings are consistent with the work of (Mahmoud and Hine, 2016; Mazzulla and Eboli, 2006) regarding the importance of the number of transfers and service frequency to potential users, and also (Abenoza et al., 2017) that defined travel time and service frequency as central for potential users. CS latent class members are more likely to be middle-aged respondents, with a relatively high ratio of old respondents, who have a positive transit attitude. They are highly sensitive to trip fare, walking time, and journey time. While RIS latent class members are more likely to be middle-aged male respondents who are very frequent transit users with a positive transit attitude.

It is worth noting that RIS is the only class that places significant importance on real-time information provision. RIS members prefer at-stop real-time information over on-board real-time information. This is unlike the results from the EC interaction model, which placed higher importance for on-board real-time information provision over at-stop real-time information provision. This is a clear demonstration that the LCM was successful in unveiling preference heterogeneity that might be masked in other models. In addition, RIS prefer, all else being equal, higher service frequency and shorter journey times which are supported by the works of (Abenoza et al., 2017; de Oña et al., 2016; Nesheli et al., 2017), that emphasized the importance of frequency, speed, and information provision to current users.

From a travel behaviour perspective, casual transit users are more likely to be in the DTE class, and frequent transit users are more likely to be in the CS class members, while very frequent transit users are more likely to be in the RIS class. The fact that each latent class exhibits all types of users (very frequent, frequent, casual), albeit different shares, questions the sufficiency of utilizing only transit use in capturing preference heterogeneity.

Therefore, the conventional binary classifications of transit market based on transit use such as current and potential transit users adopted by (Deb and Ahmed, 2018; dell' Olio et al., 2011; Mahmoud and Hine, 2013), or captive and choice transit users proposed by (Beimborn et al., 2003; Krizek and El-Geneidy, 2007; Venter, 2016) do not prove to be sufficient to capture the wide spectrum of preference heterogeneity in the transit market. This was evident by the results of the LCM, which indicate that the heterogeneity of users' preferences is not explicit in their usage pattern, nor accessibility to other modes, it is rather a bundle of various parameters. Future research efforts should focus on the inclusion of additional dimensions such as psychometric aspects to better reveal transit preference heterogeneity.

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2.8 Appendix A

Table A-2-1 A concise list of relevant studies in the transit quality literature

Study	Context	User type	Sample size
1. (Mazzulla and Eboli, 2006)	Cesena, Italy	Current and potential	382
2. (Krizek and El-Geneidy, 2007)	Twin cities, US	Choice and captive (Current)	4408 (2001)*
		Choice and captive (Potential)	500 (1999)*
3. (Tyrinopoulos and Antoniou, 2008)	Athens & Thessaloniki, Greece	Current	1474
4. (dell' Olio et al., 2011)	Santander, Spain	Current and potential	305
5. (Lai and Chen, 2011)	Kaohsiung, Taiwan	Current	763
6. (Eboli and Mazzulla, 2011)	Cosenza & Renda, Italy	Current	123
7. (de Oña et al., 2012)	Granada, Spain	Current	858
8. (de Oña et al., 2013)	Granada, Spain	Current	1200
9. (Mahmoud and Hine, 2013)	Belfast, England	Current and potential	512
10. (Zhao et al., 2013)	Tongling, China	Current	467
11. (Grujičić et al., 2014)	Belgrade, Germany	Current	449
12. (Nwachukwu, 2014)	Abuja, Nigeria	Current	300
13. (Susilo and Cats, 2014)	Eight cities, Europe	Current and potential	554
14. (Morton et al., 2016)	Scotland	Current	3797
15. (Mahmoud and Hine, 2016)	Belfast, England	Current and potential	512
16. (Venter, 2016)	Johannesburg, S. Africa	Captive and choice	1208
17. (de Oña et al., 2016)	Granada, Spain	Current	3664
18. (Fu and Juan, 2017)	Shaoxing, China	Current	1616
19. (Tao et al., 2017)	Brisbane, Australia	Current	469
20. (Grisé and El-Geneidy, 2018)	GTA, Canada	Current	4750
21. (Diab et al., 2017)	Montreal, Canada	Current	440
22. (Abenoza et al., 2017)	Sweden	Current and potential	453564
23. (Chakrabarti, 2017)	LA, US	Potential (car owners)	7166
24. (de Oña et al., 2017)	Granada, Spain	Current	1278 (2008)*
			1625 (2011)*
			1730 (2014)*
25. (Nesheli et al., 2017)	Auckland, New Zealand	Current	122
26. (Nesheli et al., 2017)	Lyon, France	Current users	118
27. (Allen et al., 2018)	Santiago, Chile	Current users	25094
28. (Deb and Ahmed, 2018)	Agartala, India	Current and potential	400
29. (Li et al., 2018)	Shanghai, China	Current	337
30. (Fu et al., 2018)	Suzhou, China	Current	429
31. (Machado et al., 2018)	Seville, Spain	Current	3198
32. (Sam et al., 2018)	Kumasi, Ghana	Current	103

*Survey year **rail-based transit service

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CHAPTER 3

Understanding the Transit Market: A Persona-based Approach for Preferences Quantification

Preamble

This chapter focuses on the third and fourth objectives of the dissertation. The chapter investigates the preferences of the key transit market segments using a persona-based approach. Additionally, the chapter presents a framework for advancing the persona-based approach beyond its qualitative nature through quantifying the personas' preferences and willingness to pay values for service improvements.

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3.1 Abstract

The study aims at utilizing a persona-based approach in understanding and further quantifying the preferences of the key transit market groups and estimating their willingness to pay (WTP) for service improvements. The study adopted an Error Components (EC) interaction choice model to investigate personas' preferences in a bus service desired quality choice experiment. Seven personas were developed based on four primary characteristics: travel behaviour, employment status, geographical distribution, and Perceived Behavioural Control (PBC). The study utilized a dataset of 5238 participants elicited from the Hamilton Street Railway Public Engagement Survey, Ontario, Canada. The results show that all personas, albeit significantly different in magnitude, are negatively affected by longer journey times, higher trip fares, longer service headways, while positively affected by reducing the number of transfers per trip and real-time information provision. The WTP estimates show that, in general, potential users are more likely to have higher WTP values compared to current users except for at-stop real-time information provision. Also, there is no consensus within current users nor potential users on the WTP estimates for service improvements. Finally, shared and unique preferences for service attributes among personas were identified to help transit agencies tailor their marketing/improvement plans based on the targeted segments.

3.2 Introduction and Background

Luring people out of their cars into public transit is vital for making cities liveable, sustainable, and equitable. Less car-dependent travel behaviour is essential in mitigating congestion and pollution problems in our cities. Transit agencies and decision-makers are striving to understand customers' needs, and hence increasing ridership. As such, there is a continued emphasis in the literature on investigating the desired quality from transit services, such as the work of [1–3]. However, understanding transit service desired quality for a wide spectrum of nontransit users is equally vital to increase transit market share and reduce car dependency.

In this regard, the transit market is often classified, among other classifications, into current and potential transit users [4–7], and/or captive and choice users [8–11]. Choice users have access to multiple modes of travel, while captive users have access to only one mode of travel. A spatial segmentation approach is also adopted to understand the preferences of different groups of transit users from a geographical perspective [12–14]. Additionally, other studies adopted a cluster analysis approach to extract homogenous customer groups with respect to preferences towards transit service quality [12,15,16]. All these prior classification approaches are often utilized to provide additional layers of information to better understand the preferences of different customer groups within the transit market.

Other studies incorporated socioeconomic attributes and travel behaviour characteristics to understand the preferences of different user groups within the transit market, such as the work of [17], who utilized Multinomial Logit (MNL) Interaction Models, [18], who adopted an Ordered Probit Model (OPM), and [3], who employed Multiple Indicators Multiple Cause (MIMIC) Structure Equation Modelling (SEM) approaches. Their central goal, however, is rooted in understanding the heterogeneity in the preferences of transit customers.

In addition, discrete choice models, such as Mixed Logit (ML) Models and Latent Class Choice Models (LCM), are utilized in the literature to understand the broad span of preferences that exist in the transit market. Ventor [10] utilized an ML model to examine the stated preferences of captive and choice transit customers; the study proved the existence of preference heterogeneity within each user group. Also, the ML model was utilized in [19] to investigate observed and unobserved preference heterogeneity within transit users. ML and Latent Class (LC) choice models were utilized in [20] to investigate preference heterogeneity within current and potential transit users' groups, while Eldeeb and Mohamed [21] adopted ML and LC choice models to unveil preference heterogeneity within the whole transit market and classify the transit market into groups with homogenous preferences.

This mosaic of methodological techniques and user classification approaches share the same objective to better understanding the preferences towards transit service quality in a way that represents the entire population.

Nevertheless, recently, transit agencies opt to understand the transit market preferences based on a user-profile approach contrary to investigating the transit market based on independent socioeconomic attributes and/or travel behaviour characteristics. A user–profile approach allows transit agencies to target specific customer groups (i.e., key customer segments) and to consider specific real-life, easy-to-target customers. More specifically, transit agencies such as, among others, Metrolinx [22], TransLink [23], and EMT Madrid [24] are considering a persona-based approach to better understand their customers, as well as their travel behaviours and preferences. According to [25], a customer persona (detailed in Section 2) represents a group of targeted customers that share the same goals, needs, and behaviour.

For example, Metrolinx [22] developed six regional personas to better understand the travel behaviour and preferences of residents of the Greater Toronto and Hamilton Area (GTHA). Those personas are: 1) Time and Balance Seekers, 2) Traditional Suburban Travellers, 3) Frustrated Solution Seekers, 4) Connected Optimizing Urbanites, 5) Satisfied Mature Urbanites, and 6) Aspiring Young Travellers. A detailed description of each persona is available in the Metrolinx 2041 Regional Transportation Plan, Appendix 2D [22].

However, recognizing the scarcity of implementing the persona method in the transit quality literature, the authors argue on the pressing need of public transit agencies to better understand the preferences of the key market segments and advance the use of the persona-based approach beyond its current qualitative nature.

In this respect, the aim of this paper is twofold: 1) Understanding the preferences of the dominant transit market segments considering a persona-based (user-profile) approach, and 2) Advancing the use of the persona-based approach through quantifying personas' preferences and estimating their willingness to pay for service improvements. Accordingly, transit agencies should reconcile their marketing/improvement plans with a better understanding of their key customers' needs and based on quantified measures.

Towards that end, the study adopted an Error Component (EC) interaction choice model along with a persona-based approach in order to investigate shared preferences versus unique preferences associated with different transit market groups and quantify their willingness to pay (WTP) for service improvements. The study utilized a primary dataset of 5238 respondents elicited from an online survey that was part of Hamilton Street Railway (HSR) Public Engagement efforts in the city of Hamilton, Ontario, Canada.

The remainder of this paper is arranged as follows: Section 2 provides a review of previous persona-based studies; Section 3 describes the modelling approach as well as the data collection process; Section 4 presents the results of the Error Components (EC) interaction model, which is followed by a discussion and concluding remarks in Sections 5 and 6, respectively.

3.3 Persona-Based Approach

A persona, first introduced by Cooper [26], is a user-centric design approach. The persona is defined as a fictitious character that portrays a targeted group of customers [26]. A customer persona represents a group of individuals who share common goals, needs, and behaviour [25]. From a practical approach, the customer persona method is used by designers, planners, and developers to identify, and later target, key customer segments. The persona method, as stated in [27], facilitates answering two major questions: first, who are we planning for? and second, who are we not planning for?

The method has been successfully implemented in understanding the actual goals of the targeted customers, prevention of self-referential design, and structuring research data in a more vivid form compared to raw data [27]. A step-by-step methodology of developing personas as a user-centred design method is provided by Nielson [28].

The persona-based approach has been adopted in many disciplines such as, among others, software development and webpage design to allow software/web developers to better understand prospective customers as well as their needs and requirements [29,30]. It was also implemented in automotive manufacturing to ensure that the design team has a common understanding of the customers' needs [31], and to examine different scenarios of vehicle design conception [32]. Further, in health sciences, the persona method was used to develop tailored health education messages to address patients’ preferences [33] and to inform the design of a user-centred information resource regarding natural-products and conventional-drugs interaction [34]. In education, the persona approach is utilized as a pedagogical tool [35,36].

In the transportation research literature, Lindgren et al. [37] used personas to identify the requirements of a dynamic graphical interface for Advanced Driver Assistance Systems (ADAS). Schäfer et al. [38] adopted the persona method in describing escape routes’ users in subway stations to better picture their expectations and requirements. De Clerk et al. [39] employed a persona-based approach to assessing the balance between ownership and external costs associated with electric and conventional vehicle technologies. Kong et al. [40] employed personas to aid the design of human–robot interactions to build acceptance among various user types regarding the use of autonomous buses in mass transit.

However, to the best of the authors' knowledge, the use of the persona method in the transit quality literature remains rare.

Despite the aforementioned advantages, there are some limitations associated with the persona-based approach. The main limitation is the validity of the developed personas. It is argued that personas are hard to validate as they are developed based on the qualitative understanding of the important aspects of the final product/service [41]. Additionally, as argued in [42], the process of persona development might lead to base personas on stereotypes instead of genuine user types. However, the validity of the developed personas could be enhanced by using real data to inform the process of developing personas [43]. Another point to consider is that the prevalence rate (i.e., the proportion in the population) of a persona decreases with the addition of more attributes to describe each persona [44]. Nevertheless, the prevalence issue might be resolved through tuning down the number of attributes used in the persona development.

In this respect, the paper aims at utilizing the persona-based approach as a transit market taxonomy tool and advancing this approach by introducing quantified preferences and willingness-to-pay estimates for each persona. It is worth noting that the focus of this paper is not the development process of the personas; it is, rather, understanding and quantifying the preferences of the salient transit personas.

3.4 Methodology

3.4.1 Methods

This study utilized an Error Components (EC) interaction model to investigate personas' preferences in a bus service desired quality choice experiment, and to estimate the influence of each attribute on the overall transit utility with respect to each persona.

The EC interaction model was used to independently investigate the preferences of the seven personas (explained in the next section), while accounting for the "*panel effect*" that emerged from the Stated Preference (SP) experiment. As one form of the Mixed Logit (ML) modelling family, the EC model was developed based on the works of [45,46] and considered the Random Utility Maximization (RUM) theory [47,48]. For the EC model, the RUM adopts a rational decision-making approach, which assumes that individual i picks the choice j that maximizes their utility U_{ijt}, in the choice situation, t:

$$U_{ijt} = \beta X_{ijt} + \eta_{ijt} Y_{ijt} + \varepsilon_{ijt}, \tag{3-1}$$

where X_{ijt} is the observable component of the utility function, which is a vector of explanatory variables, and β is a vector of estimated fixed parameters, while η_{ijt} is a vector of random elements with a distribution (assumed as normally distributed with zero mean), assigned by the modeller, and Y_{ijt} is a vector of unknown attributes. ε_{ijt} is the error term, which is assumed to be identically and independently distributed (IID).

The explanatory variables might include choice attributes as well as interaction variables reflecting the characteristics of each persona, which adopts the systematic taste variations specification suggested by [49,50]. The unconditional choice probability, as mentioned in [51], for individual i, selecting a choice j, based on the EC formulation, is expressed as follows:

$$P_{ij} = \int \prod_{t=1}^{T_q} \left[\frac{e^{\beta X_{ijt} + \eta_{ijt} Y_{ijt}}}{\sum_{j=1}^{J} e^{\beta X_{ijt} + \eta_{ijt} Y_{ijt}}} \right] f(\eta)\, d(\eta) \tag{3-2}$$

The EC interaction model is estimated using a range of Modified Latin Hypercube Sampling (MLHS) draws (e.g., 50, 100, 500, 1000) through the Pandas Biogeme package [52]. According to Hess et al. [53], the MLHS outperforms other types of Quasi-random number sequences such as Halton draws. Since the choice experiment being dealt with is unlabelled, all alternative specific constants were excluded, and no respondents' specific attributes were introduced [54].

3.4.2 Data and Survey Instrument

The paper utilized a primary dataset from an online survey that was part of Hamilton Street Railway (HSR) Public Engagement efforts in the city of Hamilton, Ontario, Canada. HSR is the municipal public transit provider for the city of Hamilton and provides a service coverage area of 243 square kilometres through 35 regular bus routes [55]. The general purpose of the survey is to benchmark the service quality provided by HSR based on Hamiltonians' preferences and expectations. As mentioned in [56], the survey is designed for all Hamiltonians (i.e., both current and potential transit users) and structured in four independent sections: 1) Socioeconomic demographic characteristics and travel behaviour, 2) Stated Preference (SP) experiments, 3) Service quality aspects, and 4) Attitudinal and behavioural characteristics.

This paper utilized the unlabelled SP experiment, socioeconomic attributes, and travel behaviour characteristics components of the survey. The total number of respondents who answered the online survey by April 2019 was 5781 Hamiltonians. A total of 543 invalid, unengaged, and incomplete responses were removed based on a thorough validation process. Hence, a validated dataset of 5238 participants was utilized in the study.

The design of the SP experiment employed, as advised by Bliemer and Rose [57], a three-stage sequential process (i.e., model specification, experimental design, and questionnaire) for the selection of the attributes and their associated levels. The final list of attributes and the associated levels are presented in Table 3-1.

Table 3-1 Unlabelled SP experiment attributes and their associated levels [56].

Service attributes	**Attribute levels**
One-way trip cost	\$3, \$4.50, and \$6
One-way trip travel time	20, 30, and 40 minutes
Walking time to and from the bus stop	0, 5, 10, and 15 minutes
Service headway	5, 10, 15, and 30 minutes
Number of transfers	0, 1, and 2 transfers
Real-time information	At-stop, onboard and none

The experimental design of the SP experiment adopted the efficient design approach, to improve the statistical efficiency and maximize the amount of information extracted from the SP experiment [58]. For the interested reader, a detailed description of the design process of the unlabelled SP experiment is introduced in [21,56]. Overall, the experimental design produced twelve scenarios grouped into three blocks. Each respondent faced four scenarios, and their choices were made from three unlabelled bus transit alternatives, as shown in Figure 3-1.

Trip & Service Attributes	Option - A	Option - B	Option - C
Bus Fare (one-way trip)	\$ 3.00	\$ 4.50	\$ 3.00
Time Spent Travelling on Bus (one-way trip)	40 min	30 min	40 min
A Bus Departs from My Stop (at the start/end and transfer stops)	every 5 min	every 10 min	every 10 min
Walking Time to/from Bus Stop (includes walking time between transfer stops)	15 min	5 min	5 min
Number of Transfers Between Buses (during one-way trip)	2 Transfer	0 Transfer	1 Transfer
Real-time Trip Information (e.g. about delays)	None	At stop	On board
To Complete My Regular One-Way Trip, I would Choose			

Figure 3-1 Example of a stated preference scenario in the survey [56].

In addition to the stated preferences, Perceived Behavioural Control (PBC) towards public transit was also utilized, which represents how easy/difficult respondents perceive transit use [59]. PBC was measured using three attitudinal statements: 1) Finding routes and schedules for my trip does not require too much effort, 2) It is easy to travel around the city using the HSR transit service, and 3) Transferring between routes is easy. Respondents were asked to assess their agreement on the accuracy of each statement on a 5-point Likert scale. These attitudinal statements have a Cronbach's alpha of 0.770, which indicates internal consistency.

3.4.3 Adopted Personas

Based on semi-structured workshops with HSR personnel, the preliminary seven personas were identified. These personas are deemed to best describe the key groups of the targeted transit market within the city of Hamilton. The personas were developed, independently from the HSR public engagement survey, based on four main characteristics: travel behaviour, employment status, geographical distribution, and Perceived Behavioural Control (PBC).

The seven personas represent around 55.50% of our dataset; and the subsample includes 2907 respondents. Each persona portrays a typical group of Hamiltonians who are current or potential transit users as follows:

1. Persona 01 represents full-time employees who consider public transit as their primary mode of travel and are more likely to have a positive transit PBC and live in urban areas. This persona represents 912 respondents from the sample.

2. Persona 02 portrays students who rely on public transit as their primary mode of travel and are more likely to have a positive transit PBC and live in urban areas. This persona represents 526 respondents from the sample.
3. Persona 03 portrays full-time employees who live in urban areas, consider private vehicles as their primary mode of travel, and have more potential to have a neutral PBC. This persona represents 701 respondents from the sample.
4. Persona 04 depicts retirees who consider private vehicles as their primary mode of travel and are more likely to have a neutral transit PBC and live in urban areas. This persona represents 407 respondents from the sample
5. Persona 05 represents students who consider private vehicles (driver or passenger) as their primary mode of travel and are more likely to have a neutral PBC and live in urban areas. This persona represents 142 respondents from the sample.
6. Persona 06 portrays full-time personnel who consider private vehicles as passengers their primary mode of travel and are more likely to have a neutral PBC and live in urban areas. This persona represents 83 respondents from the sample.
7. Persona 07 portrays full-time employees who live in the suburbs, identify private vehicles as their primary mode of travel, and are more likely to have a negative transit PBC. This persona represents 136 respondents from the sample.

Table 3-2 depicts the distribution of the personas' subsample, 2907 respondents, associated with different socioeconomic and demographic characteristics. The utilized sample represents more females (57.93%) than males (39.32%) and also includes 2.75% gender self-identity (e.g., prefer not to answer, non-binary, neutral, agender, transgender, etc.). Middle-aged respondents are the most represented in the sample (50.33%), while old respondents are the least represented (16.58%). Vehicle ownership ratio is relatively high, where about 83.21% of respondents have a vehicle in their household. Most respondents have a driver's licence (78.57%) and live in urban areas (83.56%).

Table 3-2 Sample distribution.

Category	**Subcategory**	**Users (%)**	**Population (%)**
Total	Total	2907	747,645 (100%)
Gender	Male	39.32%	48.90%
	Female	57.93%	51.10%
	Self-identity	2.75%	
Age	Less than 30 years old	33.09%	35.72%
	30 to 59 years old	50.33%	40.64%
	Over 60 years old	16.58%	23.64%
Vehicle ownership	Zero Vehicle	16.79%	13.00%
	One Vehicle	41.04%	87.00%
	Two or more	42.17%	
Driver's licence	Holding	78.57%	—
	Not holding	21.43%	—
Geographic distribution	Suburban areas	16.44%	36.69%
	Urban areas	83.56%	63.31%

Figure 3-2 summarizes the distribution of different socioeconomic and demographic characteristics for each persona. The highest percentages of males are in Persona 03 and Persona 04, while females are the highest in Personas 02, 05, and 06 categories. Among full-time personnel personas (i.e., Personas 01, 03, 06, and 07), the highest proportion of young respondents is in Persona 01, while the highest proportion of middle-aged respondents is in Persona 07. This corroborates that transit use is more prevalent among young full-time personnel compared to other age categories. The highest ratios of two or more vehicles in the household are in

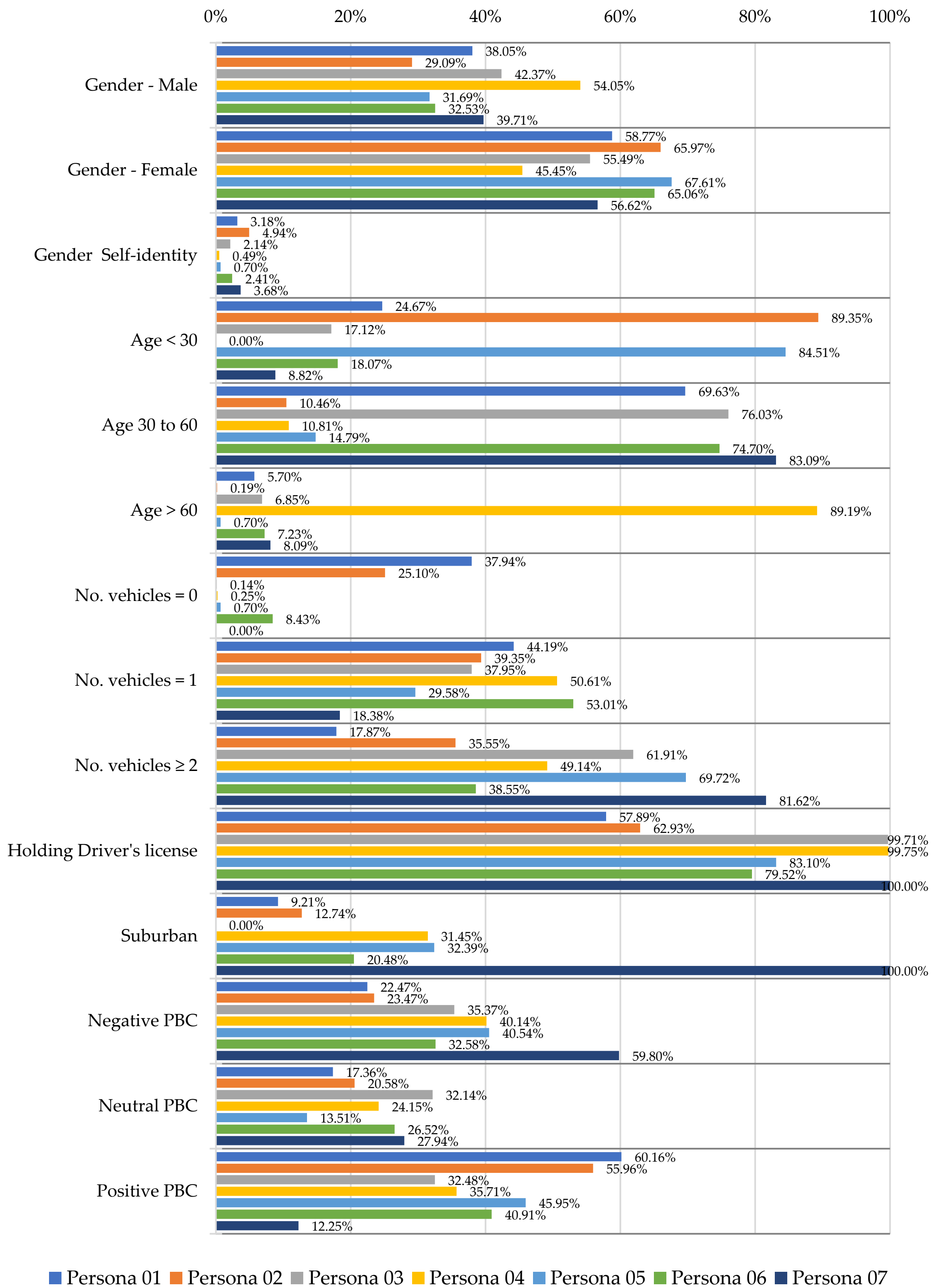


Figure 3-2 The profile of the seven adopted personas.

Persona 07 and Persona 05, while the highest ratio of one vehicle in the household is in Persona 06. Aside from Persona 07, the highest percentage of respondents who live in the suburbs are in Persona 04 (31.45%) and Persona 05 (32.39%). Regarding transit PBC, the highest percentage of respondents with a positive transit PBC is in Persona 01 (60.16%), while the highest with a negative transit PBC is in Persona 07 (59.80%).

3.5 Results

3.5.1 Persona-Based Preferences

One inclusive EC interaction model was developed to estimate the influence of each attribute on the overall transit utility with respect to each persona and to explain personas' preferences and their statistically significant differences concerning service attributes. This, in turn, helps to identify the shared preferences versus the unique preferences associated with different transit market groups.

In our model, Persona 01 is considered the base category, and the results of the EC interaction model are shown in Table 3-3. The results include all personas' interactions with different service attributes in reference to Persona 01. The unique effects (coefficients) of service attributes with regard to each persona are presented in Table 3-4. The error component does not prove to be statistically significant; however, it is retained as a precautionary measure to account for the panel effect.

In the case of journey time, for all personas, transit utility is negatively affected by longer journey times. Persona 03 ($\beta_{03-\text{Journey time}}$: $-0.0412 - 0.0153 = -0.0565$) is the most sensitive to journey time, while Persona 04 ($\beta_{04-\text{Journey time}}$: -0.025) is the most tolerant. Persona 06 ($\beta_{06-\text{Journey time}}$: -0.055) and Persona 07 ($\beta_{07-\text{Journey time}}$: -0.052) are less sensitive to journey time than Persona 03 but more sensitive than all other personas. Persona 05 ($\beta_{05-\text{Journey time}}$: −0.046), Persona 01 ($\beta_{01-\text{Journey time}}$: −0.041), and Persona 02 ($\beta_{02-\text{Journey time}}$: −0.039) are only more sensitive to journey time than Persona 04.

With respect to trip fare, the transit utility of all personas is negatively influenced by increasing trip fare. The most sensitive to trip fare is Persona 01 ($\beta_{01-\text{Trip fare}}$: −0.541), while the least sensitive is Persona 07 ($\beta_{07-\text{Trip fare}}$: −0.306). Persona 02 ($\beta_{02-\text{Trip fare}}$: −0.466) and Persona 03 ($\beta_{03-\text{Trip fare}}$: −0.442) are more sensitive to trip fare than all other personas except Persona 01. Persona 06 ($\beta_{06-\text{Trip fare}}$: −0.400), Persona 05 ($\beta_{05-\text{Trip fare}}$: −0.367), and Persona 04 ($\beta_{04-\text{Trip fare}}$: −0.357) are more sensitive to trip fare than Persona 07 and less sensitive than all other personas.

Walking time to/from bus stop does not prove to significantly impact transit service utility for Personas 01, 05, 06, and 07, which implies that these personas are lenient regarding walking time to/from bus stops. Nonetheless, the most sensitive persona to walking time is Persona 03 ($\beta_{03-\text{Walking time}}$: −0.041), while Persona 02 and Persona 04 ($\beta_{02,\ \&\ 04-\text{Walking time}}$: −0.029) are the second-highest most sensitive to walking time to/from the bus stop.

In regard to service headway (time between consecutive buses), the transit utility of all seven personas is negatively affected by less frequent transit services (higher headway). Persona 02 ($\beta_{02-\text{Service headway}}$: −0.042) is the most sensitive to service headway, while Persona 04 ($\beta_{04-\text{Service headway}}$: −0.011) is the least sensitive to service headway. Persona 01 ($\beta_{01-\text{Service headway}}$: −0.039) and Persona 03 ($\beta_{03-\text{Service headway}}$: −0.034) are more sensitive to service headway than all other personas except Persona 02. Persona 06 ($\beta_{06-\text{Service headway}}$:

−0.030), Persona 07 ($\beta_{07-\text{Service headway}}$: −0.028), and Persona 05 ($\beta_{05-\text{Service headway}}$: −0.021) are only more sensitive to service headway than Persona 04.

With reference to the number of transfers, all the seven personas are positively affected by reducing the number of transfers from two to one transfer per trip. Persona 07 ($\beta_{07-\text{One transfer}}$: 1.230) is the most influenced by reducing the number of transfers from two to one per trip, while Persona 05 ($\beta_{05-\text{One transfer}}$: 0.562) is the least influenced. Persona 03 ($\beta_{03-\text{One transfer}}$: 0.894) is the second most influenced by the number of transfers, followed by Persona 01 ($\beta_{01-\text{One transfer}}$: 0.884) and Persona 02 ($\beta_{02-\text{One transfer}}$: 0.879). Persona 04 ($\beta_{04-\text{One transfer}}$: 0.769) and Persona 06 ($\beta_{06-\text{One transfer}}$: 0.641) are only more sensitive to the number of transfers than Persona 05.

Likewise, all seven personas are positively affected by reducing the number of transfers from two to zero per trip. Persona 07 ($\beta_{07-\text{Zero transfer}}$: 1.940) is the most influenced by reducing the number of transfers from two to zero per trip, while Persona 04 ($\beta_{04-\text{Zero transfer}}$: 1.060) is the least influenced. Persona 03 ($\beta_{03-\text{Zero transfer}}$: 1.540) is the second most influenced by reducing the number of transfers from two to zero per trip, then Persona 06 ($\beta_{06-\text{Zero transfer}}$: 1.260). Persona 02 ($\beta_{02-\text{Zero transfer}}$: 1.190), Persona 01 ($\beta_{01-\text{Zero transfer}}$: 1.160), and Persona 05 ($\beta_{05-\text{Zero transfer}}$: 1.100) are only more influenced by reducing the number of transfers from two to zero than Persona 04. It is worth noting that all personas prefer zero transfer trips over one transfer trip.

With regard to the provision of real-time information, transit utility for all personas is positively influenced by the provision of onboard real-time information. Persona 05 ($\beta_{05-\text{Onboard real-time}}$: 0.504) is the most affected by onboard real-time information provision, while

Persona 04 ($\beta_{04-\text{Onboard real-time}}$: 0.259) is the least affected. Persona 02 ($\beta_{02-\text{Onboard real-time}}$: 0.503) and Persona 07 ($\beta_{07-\text{Onboard real-time}}$: 0.467) are the second and third highest influenced by onboard real-time information provision, respectively. Persona 01 ($\beta_{01-\text{Onboard real-time}}$: 0.388), Persona 06 ($\beta_{02-\text{Onboard real-time}}$: 0.329), and Persona 03 ($\beta_{02-\text{Onboard real-time}}$: 0.321) are only more influenced by onboard real-time information provision- than Persona 04.

As well, all seven personas are positively affected by the provision of at-stop real-time information. Persona 05 ($\beta_{05-\text{ At-stop real-time}}$: 0.486) is the most affected by at-stop real-time information provision, while Persona 04 ($\beta_{04-\text{ At-stop real-time}}$: 0.078) is the least affected. Persona 07 ($\beta_{02-\text{Onboard real-time}}$: 0.388) and Persona 06 ($\beta_{06-\text{Onboard real-time}}$: 0.382) are the second and third highest influenced by at-stop real-time information provision. Persona 02 ($\beta_{02-\text{ At-stop real-time}}$: 0.369), Persona 01 ($\beta_{01-\text{ At-stop real-time}}$: 0.343), and Persona 03 ($\beta_{03-\text{ At-stop real-time}}$: 0.219) are only more affected by at-stop real-time information provision than Persona 04. It is worth noting that all personas prefer onboard real-time information provision over at-stop real-time information provision except for Persona 06.

Explained differently:

- Persona 01 (Full-time employee, Transit user, Positive PBC, Live in urban areas) is negatively affected by higher trip fare (the highest among all personas), longer journey time, and longer service headway, while positively affected by real-time information provision and reducing number of transfers. Nevertheless, Persona 01 is indifferent to walking time to/from bus stops.
- Persona 02 (Student, Transit user, Positive PBC, Live in urban areas) is negatively affected by longer service headway (the highest among all personas), higher trip

fare, longer journey time, and longer walking time, while positively affected by real-time information provision (the highest among all personas regarding onboard real-time info.) and reducing number of transfers.

- Persona 03 (Full-time employee, Car driver, Neutral PBC, Live in urban areas) is negatively affected by longer journey time (the highest among all personas), higher trip fare, longer walking time (the highest among all personas), and longer service headway, while positively affected by real-time information provision and reducing number of transfers.
- Persona 04 (Retiree, Car driver, Neutral PBC, Live in urban areas) is negatively affected by longer journey time (the least among all personas), higher trip fare, longer walking time, and longer service headway (the lowest among all personas), while positively affected by real-time information provision (the lowest among all personas) and reducing number of transfers.
- Persona 05 (Student, Car Driver/Passenger, Neutral PBC, Live in urban areas) is negatively affected by longer journey time, higher trip fare, and longer service headway, while positively affected by real-time information provision (the highest among all personas regarding at-stop real-time info.) and reducing number of transfers (the lowest among all personas). However, Persona 05 is indifferent regarding walking time to/from bus stops.
- Persona 06 (Full-time employee, Car passenger, Neutral PBC, Live in urban areas) is negatively affected by longer journey time, higher trip fare, and longer service headway, while positively affected by real-time information provision and

reducing number of transfers. However, walking time to/from bus stops does not prove to be of influence on this persona.

- Persona 07 (Full-time employee, Car driver, Negative PBC, Live in the suburbs) is negatively affected by longer journey time, higher trip fare (the lowest among all personas), and longer service headway, while positively affected by real-time information provision and reducing number of transfers (the highest among all personas). However, walking time to/from bus stops does not prove to be significant for Persona 07.

Table 3-3 Error component model estimates for personas' interactions.

Variable	Persona 01 (Ref.)	Persona 02 Interaction	Persona 03 Interaction	Persona 04 Interaction	Persona 05 Interaction	Persona 06 Interaction	Persona 07 Interaction
Journey time	−0.041***	*0.003*	−0.015**	0.017**	−0.005	−0.014	−0.011
Trip fare	−0.541***	*0.076*	0.099*	0.184***	0.175*	0.142	0.235**
Walking time	−0.007	−0.022**	−0.035***	−0.022**	−0.017	0.004	0.002
Service headway	−0.039***	−0.003	0.005	0.027***	0.017**	0.008	0.011
Number of transfers (2 transfers base category)							
One transfer	0.884***	−0.005	0.010	−0.115	−0.322**	−0.243	0.344**
Zero transfer	1.160***	0.032	0.384***	−0.092	−0.061	0.100	0.782***
Real-time information (No info. base category)							
Real-time info. onboard	0.388***	0.116	−0.067	−0.128	0.116	−0.058	0.080
Real-time info. at-stop	0.343***	0.026	−0.124	−0.265***	0.143	0.040	0.046
Error component				0.016			
Log-likelihood				−11,580.86			
Log-likelihood ratio test				2750.716			
Rho-square				0.106			

Note: ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively, and Table A-3-1 Appendix A presents the detailed results for the model estimates.

Table 3-4 The unique effects (coefficients) of service attributes with respect to each persona.

Variables	Persona 01	Persona 02	Persona 03	Persona 04	Persona 05	Persona 06	Persona 07
Journey time	−0.041	−0.039	−0.057	−0.025	−0.046	−0.055	−0.052
Trip fare	−0.541	−0.466	−0.442	−0.357	−0.367	−0.400	−0.306
Walking time	−0.007	−0.029	−0.041	−0.029	−0.024	−0.003	−0.005
Service headway	−0.039	−0.042	−0.034	−0.011	−0.021	−0.030	−0.028
One transfer	0.884	0.879	0.894	0.769	0.562	0.641	1.230
Zero transfer	1.160	1.190	1.540	1.060	1.100	1.260	1.940
Real time info. onboard	0.388	0.503	0.321	0.259	0.504	0.329	0.467
Real time info. at stop	0.343	0.369	0.219	0.078	0.486	0.382	0.388

Table 3-5 WTP estimates based on the EC model.

	Pers. 01	Pers. 02	Pers. 03	Pers. 04	Pers. 05	Pers. 06	Pers. 07
Reduction in Journey time ($ per minute)	$0.076	$0.084	$0.129	$0.070	$0.125	$0.138	$0.170
Reduction in Walking time ($ per minute)	$0.000	$0.062	$0.093	$0.081	$0.000	$0.000	$0.000
Reduction in Service headway ($ per minute)	$0.072	$0.090	$0.077	$0.031	$0.057	$0.075	$0.092
Trip with One transfer ($ per trip)	$1.634	$1.886	$2.023	$2.154	$1.531	$1.603	$4.020
Trip with Zero transfer ($ per trip)	$2.144	$2.554	$3.484	$2.969	$2.997	$3.150	$6.340
Prov. of Real-time info. onboard ($ per trip)	$0.717	$1.079	$0.726	$0.725	$1.373	$0.823	$1.526
Prov. of Real-time info. at-stop ($ per trip)	$0.634	$0.792	$0.495	$0.218	$1.324	$0.955	$1.268

The visualization of the preferences of all personas for various service attributes is shown in Figure 3-3. It contrasts the bearing of each service attribute on the overall transit utility for all personas.

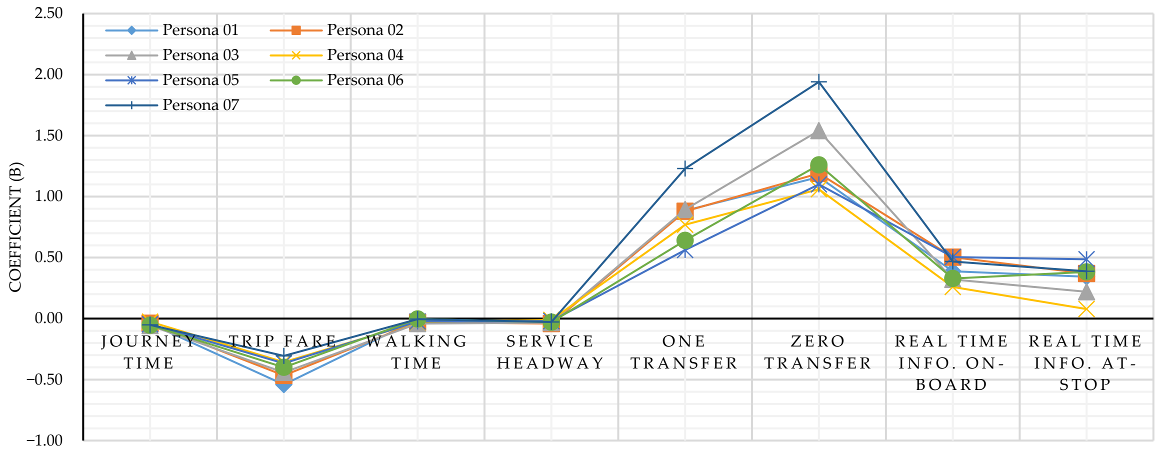


Figure 3-3 Bearings of service attributes on the overall transit utility across personas.

3.5.2 Willingness to Pay

The willingness to pay (WTP) for service improvements is essential for policy-makers as it enables them to adopt service improvements that are consistent with users' preferences elicited from the SP experiment. Despite the flexibility of SP experiments in testing new scenarios, proposed improvements, and a wide range of attributes/levels [60], the SP experiments have a hypothetical bias, which is grounded on the differences between the actual behaviour and the stated choices [50,61]. Loomis [61] highlighted that such a hypothetical bias might, in some cases, result in higher WTP estimates compared to real life, which should be considered by policy-makers.

The WTP estimates were derived based on the ratio of population means, in Canadian dollars (CAD), and based on the trip fare parameter. Persona-specific WTP estimates for various service improvements are presented in Table 3-5.

For journey time, Persona 07 (the highest among all personas) would pay around $1.70 to save 10 minutes in trip time, while Persona 04 (the lowest) would pay only $0.70. The second-highest willingness to pay for a 10 minute reduction in travel time is Persona 06 ($1.38), then Persona 03 ($1.29). Persona 01 and Persona 02 have the second- and third-lowest WTP estimates, $0.76 and $0.84, respectively, for a 10 minute reduction in travel time.

The WTP to save 10 minutes of walking time to/from bus stops is around $0.93 (the highest) for Persona 03, while around $0.62 for Persona 02 (the lowest). Persona 04 is willing to pay $0.81 for a 10 minute reduction in walking time, while Personas 01, 05, 06, and 07 are not willing to pay anything for a walking time reduction, as walking time to/from bus stops is not significantly affecting their choice.

Regarding reducing service headway (time between consecutive buses) by 10 minutes, Personas 02 and 07 are willing to pay around $0.90 (the highest), while Persona 04 would pay only $0.30 (the lowest). Persona 03 and Persona 02, which have the second- and third-highest estimates, respectively, would pay $0.77 and $0.75 to reduce service headway by 10 minutes. Persona 01 is willing to pay $0.72 for reducing service headway by 10 minutes. The second-lowest WTP estimate is associated with Persona 05, which would pay $0.57 for a 10 minute reduction in service headway.

The WTP for reducing the number of transfers from two to one per trip is around $4.00 (the highest) for Persona 07, while $1.53 (the lowest) for Persona 05. Persona 04 and Persona 03 are the second- and third-highest estimates, willing to pay $2.15 and $2.00, respectively, to reduce the number of transfers from two to one per trip. Persona 02 would pay around $1.88 for reducing the number of transfers from two to one. Persona 06 and Persona 01, roughly the second-lowest estimates, are willing to pay around $1.60 for reducing the number of transfers from two to one.

With respect to reducing the number of transfers from two to zero per trip, Persona 07 would pay around $6.30 (the highest), and Persona 01 would pay around $2.14 (the lowest). Persona 03, the second highest, would pay around $3.50 to reduce the number of transfers from two to zero. Personas 04 and 05 are willing to pay around $3.00 for reducing the number of transfers from two to zero, while it is slightly higher for Persona 06 ($3.15). The second-lowest WTP estimate ($2.55) for reducing the number of transfers from two to zero is for Persona 02.

The WTP for onboard real-time information provision is around $1.52 (the highest) for Persona 07 and around $0.72 (the lowest) for Personas 01, 03, and 04. Persona 05, the second highest, would pay nearly $1.37 for onboard real-time information provision, while Persona 06, the second lowest, would pay $0.82. Persona 02 would pay around $1.08 for onboard real-time information provision.

With regard to at-stop real-time information provision, Persona 05 would pay nearly $1.32 (the highest), while Persona 04 would pay only around $0.22 (the lowest). Persona 07 and Persona 06, the second and third highest, would pay $1.27 and $0.95, respectively, for at-stop real-time information provision, while Persona 02 would pay $0.79. Persona 03 and Persona 01, the second and third lowest, are willing to pay $0.49 and $0.63, respectively, for at-stop real-time information provision.

A related point to mention is that the WTP estimates for potential users (Personas 03, 04, 05, 06, and 07) are more likely to be higher than the WTP estimates for current users (Personas 01 and 02). For instance, Persona 07 has the highest WTP for all service improvements except for the at-stop real-time information provision, whereas the highest WTP belongs to Persona 05, which is also a potential user. However, current users (Personas 01 and 02) have higher WTP estimates for at-stop real-time information provision than some potential users (Personas 03 and 04). Figure 3-4 shows the distribution of the WTP estimates for service improvements for all personas.

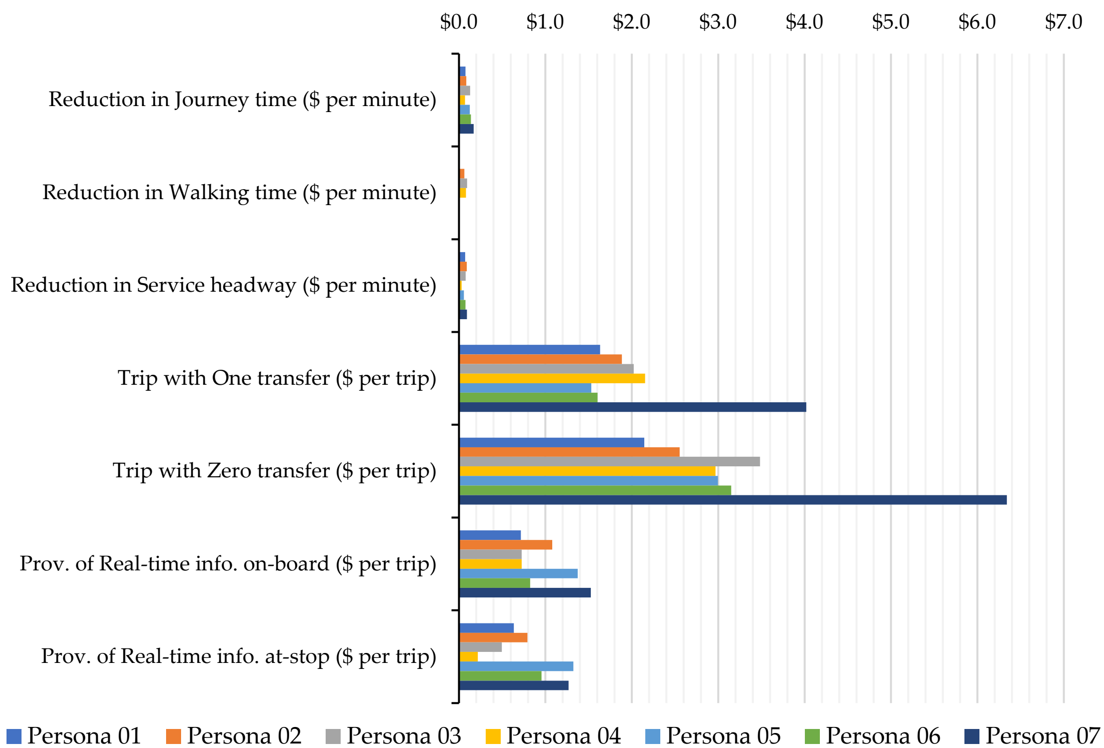


Figure 3-4 Distribution of WTP estimates for each Persona.

3.6 Discussion of Shared and Unique Preferences

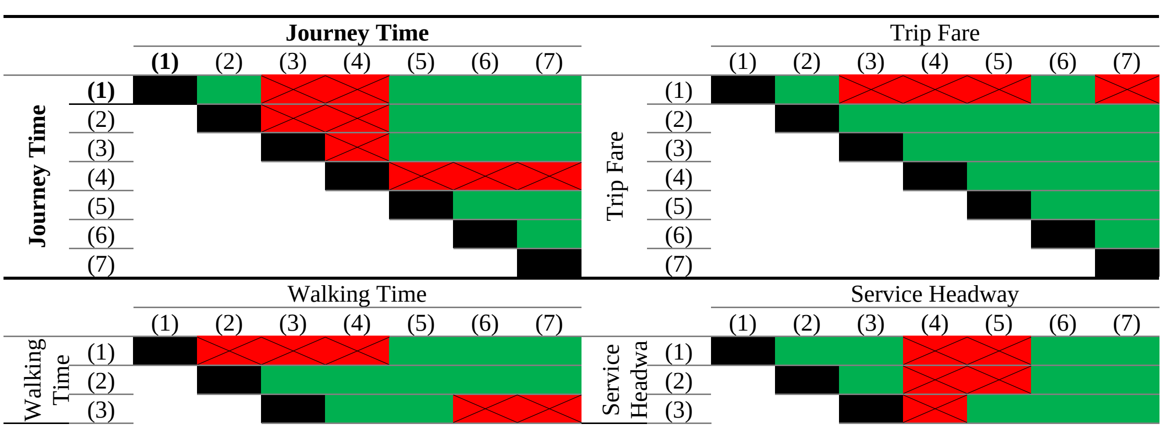
The integration between the persona-based approach and discrete choice models presented an opportunity to further inspect the preferences of a wide spectrum of transit market segments towards service quality. Therefore, we identify the shared versus unique preferences associated with various service attributes and exhibited by each persona. Such identification enables service providers to target numerous market segments with the same service improvements.

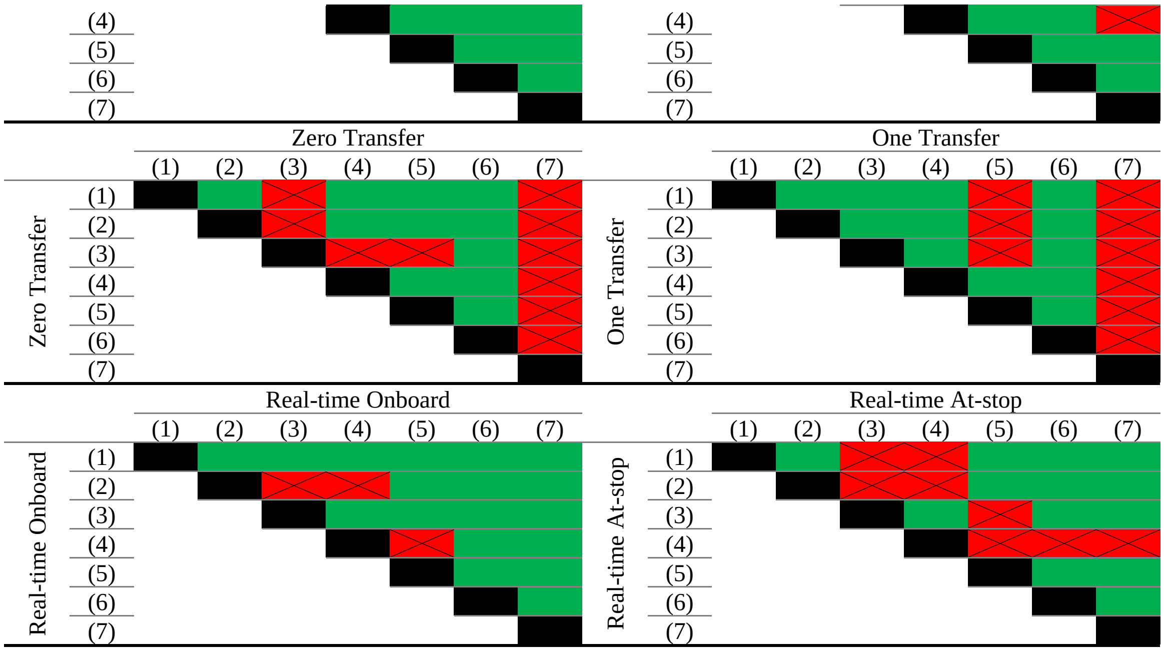
In this respect, shared and unique preferences for service attributes are identified in the light of the statistical significance of the differences, or the lack thereof, among all personas. Statistically significant difference implies unique preferences, and insignificant difference implies shared preferences. MNL interaction models with different base categories were used, as the panel effect does not prove to be significant, to test the statistical significance of the differences among personas, as shown in Table A-3-2, Appendix A.

Table 3-6, elicited from the MNL interaction models in Table A-3-2, Appendix A, presents a mosaic of the statistically significant and insignificant differences among all seven personas, arranged with respect to each service attribute. The threshold for statistically significant differences is a 90% confidence level.

For instance, adopting an attribute-based interpretation (e.g., journey time) of the results presented in Table 3-6, Personas 01, 02, 05, 06, and 07 are not significantly different from each other; therefore, they share the same preference for journey time. Whereas, Persona 04 is significantly different from all other personas, and hence it has a unique preference for transit journey time. Also, Persona 03 is significantly different from Personas 01, 02, and 04 regarding most service attributes and insignificantly different than Personas 05, 06, and 07.

Table 3-6 Unique preferences versus shared preferences (symmetric).





Red Crossed: Significantly different (Unique preference) and Green: Not significantly different (Mindshare).

From a persona-based interpretation perspective, it could be argued that Personas 01 and 02 (both are transit users) have shared preferences regarding most service attributes, yet they have unique preference for walking time to/from bus stops. Personas 03 and 07 (both are full-time employees and car drivers) have shared preferences for many service attributes, but they have unique preferences regarding the number of transfers and walking time to/from bus stops. This might be attributed to their distinct PBC towards transit service and their different location of residence (i.e., suburbs and urban areas). Personas 02 and 05 (both are students) have shared preferences regarding all service attributes except for service headway and reducing the number of transfers from two to one per trip. Persona 07 has its own unique preference regarding the number of transfers with respect to other personas. As well, Persona 04 has a unique preference for journey time than other personas.

Overall, identifying shared preferences versus unique preferences among personas is crucial to transit agencies. Such identification enables service providers to better target their key customer segments and alter their marketing plans accordingly.

3.7 Conclusions

The study aimed at the following: *first,* Understanding the preferences of the dominant transit market segments considering a persona-based approach, and s*econd,* Advancing the use of the persona-based approach through quantifying personas' preferences and estimating their willingness to pay for service improvements. The study adopted an Error Component (EC) interaction model to investigate personas' preferences in a bus service desired quality choice experiment, while accounting for the panel effect, and to estimate the influence of each attribute on the overall transit utility with respect to each persona. The study adopted the preliminary seven personas, based on semi-structured interviews, that best describe the key groups of the targeted transit market within the city of Hamilton. The personas capture four main characteristics: travel behaviour, employment status, geographical distribution, and Perceived Behavioural Control (PBC). The study utilized a subsample size of 2907 respondents, pulled from a larger dataset (5238), which encompasses the seven personas.

The results of the EC interaction model show that all personas are, all else being equal, negatively affected by longer journey times, higher trip fares, longer service headways, while positively affected by reducing the number of transfers per trip and real-time information provision. Nevertheless, only Personas 02, 03, and 04 are negatively affected by walking time to/from bus stops while other personas are indifferent to walking time. To use precise distinctions:

- Persona 01 (Full-time employee, Transit user, Positive PBC, Live in urban areas) is the most influenced by higher trip fares ($\beta_{01-\text{Trip fare}}$: −0.541) among all personas.
- Persona 02 (Student, Transit user, Positive PBC, Live in urban areas) is the most impacted by longer service headways ($\beta_{02-\text{Service headway}}$: −0.042).
- Persona 03 (Full-time employee, Car driver, Neutral PBC, Live in urban areas) is the most affected by longer journey times ($\beta_{03-\text{Journey time}}$: −0.057) and longer walking times to/from bus stops ($\beta_{03-\text{Walking time}}$: −0.041).
- Persona 04 (Retiree, Car driver, Neutral PBC, Live in urban areas) is the least influenced by longer journey times ($\beta_{04-\text{Journey time}}$: −0.025), longer service headways ($\beta_{04-\text{Service headway}}$: −0.011), real-time information provision ($\beta_{04-\text{Onboard real-time}}$: 0.259 & $\beta_{04-\text{At-stop real-time}}$: 0.078), and reducing number of transfers from two to zero per trip ($\beta_{04-\text{Zero transfer}}$: 1.060)
- Persona 05 (Student, Car Driver/Passenger, Neutral PBC, Live in urban areas) is the highest influenced by at-stop real-time information provision ($\beta_{05-\text{At-stop real-time}}$: 0.486), while the least influenced by reducing number of transfers from two to one per trip ($\beta_{05-\text{One transfer}}$: 0.562).
- Persona 06 (Full-time employee, Car passenger, Neutral PBC, Live in urban areas) is among the least-affected personas regarding walking time to/from bus stops.
- Persona 07 (Full-time employee, Car driver, Negative PBC, Live in the suburbs) is the most influenced by reducing the number of transfers per trip ($\beta_{07-\text{Zero transfer}}$:

1.940 & $\beta_{07-\text{One transfer}}$: 1.230), and the least affected by higher trip fares ($\beta_{07-\text{Trip fare}}$: −0.306).

The willingness to pay (WTP) estimates for service improvements were calculated for each persona in CAD and based on the ratio of the population means. The WTP estimates show that, in general, potential users (Personas 03, 04, 05, 06, and 07) are more likely to have higher values compared to current users (Personas 01 and 02). For instance, Persona 07 has the highest WTP for all service improvements except for the at-stop real-time information provision, where the highest WTP belongs to Persona 05, which is also a potential user. This echoes the findings of [20] that the WTP estimates for potential users are greatly higher than the estimates for current users. However, current users (Personas 01 and 02) have higher WTP estimates for at-stop real-time information provision than some potential users (Personas 03 and 04). Additionally, it is worth noting that there is no consensus within the current users (Personas 01 and 02) nor within the potential users (Personas 03, 04, 05, 06, and 07) on WTP estimates for service improvements.

Shared and unique preferences for service attributes are identified in the light of the statistical significance of the differences among personas based on MNL interaction models. The results show that Personas 01 and 02 (both are transit users) have shared preferences regarding most service attributes, yet they have unique preferences for walking time to/from bus stops. Personas 03 and 07 (both are full-time employees and car drivers) have shared preferences for many service attributes, but they have unique preferences regarding the number of transfers and walking time to/from bus stops. This might be attributed to their distinct PBC towards transit service and their different location of residence (i.e., suburbs and urban areas). Personas 02 and 05 (both are students) have shared preferences regarding various service attributes except for service headway and reducing the number of transfers from two to one per trip.

In view of the findings of this study, transit agencies should be able to tailor their improvement plans as well as their marketing/educational campaigns with a better understanding of their key customers' needs and based on quantified measures.

3.8 Acknowledgments

The authors would like to thank the reviewers for their valuable comments. The authors would like to acknowledge the support received from the City of Hamilton, Public Transit Division (Project No. Hamtn-20010000).

3.9 Appendix A

Table A-3-1 EC model estimates for personas' interactions.

Variable	Coefficient(β)	β / Std. Err.	P−Value
Journey time	−0.0412	−9.490	0.000
Journey time × Persona 02	0.0025	0.352	0.725
Journey time × Persona 03	−0.0153	−2.390	0.017
Journey time × Persona 04	0.0167	2.210	0.027
Journey time × Persona 05	−0.0045	−0.408	0.683
Journey time × Persona 06	−0.0139	−0.906	0.365
Journey time × Persona 07	−0.0108	−0.808	0.419
Trip fare	−0.5410	−12.500	0.000
Trip fare × Persona 02	0.0756	1.140	0.254
Trip fare × Persona 03	0.0990	1.640	0.102
Trip fare × Persona 04	0.1840	2.640	0.008
Trip fare × Persona 05	0.1750	1.720	0.085
Trip fare × Persona 06	0.1420	1.030	0.305
Trip fare × Persona 07	0.2350	2.050	0.041
Walking time	−0.0069	−1.220	0.222
Walking time × Persona 02	−0.0224	−2.410	0.016
Walking time × Persona 03	−0.0346	−4.040	0.000
Walking time × Persona 04	−0.0224	−2.250	0.024
Walking time × Persona 05	−0.0172	−1.110	0.266
Walking time × Persona 06	0.0035	0.156	0.876

Variable	Coefficient(β)	β / Std. Err.	P−Value
Walking time × Persona 07	0.0023	0.140	0.888
Service headway	−0.0385	−11.200	0.000
Service headway × Persona 02	−0.0030	−0.539	0.590
Service headway × Persona 03	0.0046	0.921	0.357
Service headway × Persona 04	0.0271	5.060	0.000
Service headway × Persona 05	0.0172	1.980	0.047
Service headway × Persona 06	0.0080	0.790	0.430
Service headway × Persona 07	0.0107	1.270	0.203
Number of transfers (2 transfers base category)			
One transfer	0.8840	16.100	0.000
One transfer × Persona 02	−0.0052	−0.057	0.955
One transfer × Persona 03	0.0103	0.121	0.903
One transfer × Persona 04	−0.1150	−1.190	0.233
One transfer × Persona 05	−0.3220	−2.110	0.035
One transfer × Persona 06	−0.2430	−1.310	0.191
One transfer × Persona 07	0.3440	2.020	0.044
Zero transfer	1.1600	14.900	0.000
Zero transfer × Persona 02	0.0324	0.256	0.798
Zero transfer × Persona 03	0.3840	3.290	0.001
Zero transfer × Persona 04	−0.0922	−0.708	0.479
Zero transfer × Persona 05	−0.0610	−0.305	0.760
Zero transfer × Persona 06	0.0997	0.386	0.700
Zero transfer × Persona 07	0.7820	3.440	0.001
Real-time information (No info. Base category)			
Real-time info. Onboard	0.3880	8.340	0.000
Real-time info. Onboard × Persona 02	0.1160	1.470	0.141
Real-time info. Onboard × Persona 03	−0.0665	−0.934	0.351
Real-time info. Onboard × Persona 04	−0.1280	−1.560	0.118
Real-time info. Onboard × Persona 05	0.1160	0.867	0.386
Real-time info. Onboard × Persona 06	−0.0584	−0.395	0.693
Real-time info. Onboard × Persona 07	0.0800	0.595	0.552
Real-time info. at-stop	0.3430	6.500	0.000
Real-time info. at-stop × Persona 02	0.0262	0.302	0.762
Real-time info. at-stop × Persona 03	−0.1240	−1.530	0.125
Real-time info. at-stop × Persona 04	−0.2650	−2.890	0.004
Real-time info. at-stop × Persona 05	0.1430	1.020	0.307
Real-time info. at-stop × Persona 06	0.0395	0.231	0.818
Real-time info. at-stop × Persona 07	0.0457	0.308	0.758
Error Component	0.0158	1.150	0.252
Log-Likelihood		−11580.86	
Log-Likelihood ratio test		2570.716	
Rho-square		0.106	

Table A-3-2 The estimation of MNL interaction models.

Variable	**Persona 01 (Ref.)**	**Persona 02 (Ref.)**	**Persona 03 (Ref.)**	**Persona 04 (Ref.)**	**Persona 05 (Ref.)**	**Persona 06 (Ref.)**	**Persona 07 (Ref.)**
Journey time × Persona 01	−0.041***	−0.003	0.015**	−0.017**	0.005	0.014	0.011
Journey time × Persona 02	0.003	−0.039***	0.018**	−0.014*	0.007	0.016	0.013
Journey time × Persona 03	−0.015**	−0.018**	−0.057***	−0.032***	−0.011	−0.001	−0.004
Journey time × Persona 04	0.017**	0.014*	0.032***	−0.025***	0.021*	0.031**	0.028**
Journey time × Persona 05	−0.005	−0.007	0.011	−0.021*	−0.046***	0.009	0.006
Journey time × Persona 06	−0.014	−0.016	0.001	−0.031**	−0.009	−0.055***	−0.003
Journey time × Persona 07	−0.011	−0.013	0.004	−0.028**	−0.006	0.003	−0.052***
Trip fare × Persona 01	−0.541***	−0.076	−0.099*	−0.184***	−0.175*	−0.142	−0.235**
Trip fare × Persona 02	0.076	−0.466***	−0.023	−0.109	−0.099	−0.066	−0.159
Trip fare × Persona 03	0.099*	0.023	−0.442***	−0.085	−0.076	−0.043	−0.136
Trip fare × Persona 04	0.184***	0.109	0.085	−0.357***	0.010	0.043	−0.051
Trip fare × Persona 05	0.175*	0.099	0.076	−0.010	−0.367***	0.033	−0.060
Trip fare × Persona 06	0.142	0.066	0.043	−0.043	−0.033	−0.400***	−0.094
Trip fare × Persona 07	0.235**	0.159	0.136	0.051	0.060	0.094	−0.306***
Walking time × Persona 01	−0.007	0.022**	0.035***	0.022**	0.017	−0.004	−0.002
Walking time × Persona 02	−0.022**	−0.029***	0.012	0.000	−0.005	−0.026	−0.025
Walking time × Persona 03	−0.035***	−0.012	−0.041***	−0.012	−0.017	−0.038*	−0.037**
Walking time × Persona 04	−0.022**	0.000	0.012	−0.029***	−0.005	−0.026	−0.025
Walking time × Persona 05	−0.017	0.005	0.017	0.005	−0.024*	−0.021	−0.020
Walking time × Persona 06	0.004	0.026	0.038*	0.026	0.021	−0.003	0.001
Walking time × Persona 07	0.002	0.025	0.037**	0.025	0.020	−0.001	−0.005
Service headway × Persona 01	−0.039***	0.003	−0.005	−0.027***	−0.017**	−0.008	−0.011
Service headway × Persona 02	−0.003	−0.042***	−0.008	−0.030***	−0.020**	−0.011	−0.014
Service headway × Persona 03	0.005	0.008	−0.034***	−0.022***	−0.013	−0.003	−0.006
Service headway × Persona 04	0.027***	0.030***	0.022***	−0.011**	0.010	0.019	0.016*
Service headway × Persona 05	0.017**	0.020**	0.013	−0.010	−0.021***	0.009	0.006
Service headway × Persona 06	0.008	0.011	0.003	−0.019	−0.009	−0.030***	−0.003
Service headway × Persona 07	0.011	0.014	0.006	−0.016*	−0.006	0.003	−0.028***
Number of transfers (2 transfers base category)							
One transfer × Persona 01	0.884***	0.005	−0.010	0.115	0.322**	0.243	−0.344**
One transfer × Persona 02	−0.005	0.879***	−0.016	0.110	0.317**	0.238	−0.349**
One transfer × Persona 03	0.010	0.016	0.894***	0.125	0.332**	0.253	−0.334**
One transfer × Persona 04	−0.115	−0.110	−0.125	0.769***	0.207	0.128	−0.459***
One transfer × Persona 05	−0.322**	−0.317**	−0.332**	−0.207	0.562***	−0.079	−0.666***
One transfer × Persona 06	−0.243	−0.238	−0.253	−0.128	0.079	0.641***	−0.587***
One transfer × Persona 07	0.344**	0.349**	0.334**	0.459***	0.666***	0.587***	1.230***
Zero transfer × Persona 01	1.160***	−0.032	−0.384***	0.092	0.061	−0.100	−0.782***

Variable	**Persona 01 (Ref.)**	**Persona 02 (Ref.)**	**Persona 03 (Ref.)**	**Persona 04 (Ref.)**	**Persona 05 (Ref.)**	**Persona 06 (Ref.)**	**Persona 07 (Ref.)**
Zero transfer × Persona 02	0.032	1.190***	−0.352***	0.125	0.093	−0.067	−0.750***
Zero transfer × Persona 03	0.384***	0.352***	1.540***	0.476***	0.445**	0.284	−0.398*
Zero transfer × Persona 04	−0.092	−0.125	−0.476***	1.060***	−0.031	−0.192	−0.875***
Zero transfer × Persona 05	−0.061	−0.093	−0.445**	0.031	1.100***	−0.161	−0.843***
Zero transfer × Persona 06	0.100	0.067	−0.284	0.192	0.161	1.260***	−0.683**
Zero transfer × Persona 07	0.782***	0.750***	0.398*	0.875***	0.843***	0.683**	1.940***
Real-time information (No info. base-category)							
Real-time info. Onboard × Persona 01	0.388***	−0.116	0.067	0.128	−0.116	0.058	−0.080
Real-time info. Onboard × Persona 02	0.116	0.503***	0.182**	0.244***	−0.001	0.174	0.036
Real-time info. Onboard × Persona 03	−0.067	−0.182**	0.321***	0.062	−0.183	−0.008	−0.146
Real-time info. Onboard × Persona 04	−0.128	−0.244***	−0.062	0.259***	−0.245*	−0.070	−0.208
Real-time info. Onboard × Persona 05	0.116	0.001	0.183	0.245*	0.504***	0.175	0.036
Real-time info. Onboard × Persona 06	−0.058	−0.174	0.008	0.070	−0.175	0.329**	−0.138
Real-time info. Onboard × Persona 07	0.080	−0.036	0.146	0.208	−0.036	0.138	0.467***
Real-time info. at-stop × Persona 01	0.343***	−0.026	0.124*	0.265***	−0.143	−0.040	−0.046
Real-time info. at-stop × Persona 02	0.026	0.369***	0.150*	0.291***	−0.117	−0.013	−0.020
Real-time info. at-stop × Persona 03	−0.124*	−0.150*	0.219***	0.141	−0.267**	−0.163	−0.170
Real-time info. at-stop × Persona 04	−0.265***	−0.291***	−0.141	0.078	−0.408***	−0.304*	−0.311**
Real-time info. at-stop × Persona 05	0.143	0.117	0.267**	0.408***	0.486***	0.104	0.098
Real-time info. at-stop × Persona 06	0.040	0.013	0.163	0.304*	−0.104	0.382**	−0.006
Real-time info. at-stop × Persona 07	0.046	0.020	0.170	0.311**	−0.098	0.006	0.388***
Log-likelihood	−11,580.88						
Log-likelihood ratio test	2387.56						
Rho-square	0.0934						

Note: ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

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CHAPTER 4

Consumers Oriented Investments in Transit Service Quality Improvements: The Best Bang for Your Buck

Preamble

This chapter addresses the fifth objective of this dissertation, which questions the notion of applying willingness to pay (WTP) values for service improvements for the entire population without considering the significant degree of preference heterogeneity. First, this chapter unveils the heterogeneity in transit customers' preferences based on a prior classification approach. Then, it examines its implications on willingness to pay values for service improvements for various user groups.

The submitted manuscript included in this chapter is:

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4.1 Abstract

Targeted transit quality improvement is essential to maintain ridership and attract car users. However, there remain the question about what are the best investments to increase the likelihood of transit utilization. This study aims at unveiling the broad-spectrum of transit users' preferences as well as their willingness to pay (WTP) for six service attributes. The study employed a multinomial logit (MNL) interaction models and a random parameter logit (RPL) model to unveil preference heterogeneity in a choice experiment. The results revealed significant heterogeneity on customers' preferences and WTP towards service improvements due to variations in customers' socioeconomic characteristics, travel behaviour and attitudes. For instance, females are willing to pay more to reduce service headway and the number of transfers, while males would pay more for at-stop real-time information provision. In a nutshell, effective transit quality improvements cannot ignore such heterogeneity, and should be tailored based on the targeted user type.

4.2 Introduction and background

Ensuring efficient and high-quality public transit service is of utmost importance to retain current transit users and attract potential users. The research in transit service quality focuses on identifying the most critical aspects of public transit efficiency and attractiveness. It is evident that the preferences towards public transit service quality are highly influenced by various subjective factors such as customers' habits and attitudes towards public transit (Fu, Zhang, & Chan, 2018) as well as their previous experience (Lai and Chen, 2011; Susilo and Cats, 2014; Diab, van Lierop, & El-Geneidy, 2017). Furthermore, there is an apparent heterogeneity in customers' preferences for transit service quality, which is associated with three primary reasons as advocated by (Cirillo, et al., 2011; Bordagaray, et al., 2014): the differences in the socioeconomic demographics, the uniqueness of tastes and attitudes, and lastly, the qualitative nature of several service quality aspects.

The literature of transit service desired quality is, generally, centred around investigating the preferences of current transit users (del Castillo and Benitez, 2013; Li, et al., 2018; Fu et al., 2018; Machado, et al., 2018; Sam, et al., 2018). However, service improvements geared towards satisfying current transit users might not be sufficient to attract potential users such as private vehicle users (Mahmoud and Hine, 2016; Eldeeb and Mohamed, 2020; de Oña, et al., 2021). That said, recent research has concentrated on investigating the preference heterogeneity in the public transit market to target different user groups (e.g. de Oña and de Oña, 2015; Allen, et al., 2018; Bellizzi, et al., 2020; Eldeeb and Mohamed, 2020). For example, Eldeeb and Mohamed (2020) confirmed preference heterogeneity among Hamilton Street Railway customers and identified three latent user classes: direct trip enthusiastic, cost-sensitive, and real-time information supporter. Also, Bellizzi, et al. (2020) identified three latent classes among current transit users in the City of Santander, Spain, and two latent classes for potential transit users. Each class (segment) exhibits significantly different preferences towards transit service that requires tailored quality improvement intervention.

Additionally, some other research adopted a prior classification approach to better understand transit preferences. In this respect, the population is often classified based on socioeconomic characteristics and public transit frequency of use (dell'Olio, et al., 2011;

Mahmoud and Hine, 2013; Deb and Ali Ahmed, 2018; de Oña et al., 2021), geographical distribution (Grisé and El-Geneidy, 2017; Eboli, et al., 2018; Kieu, et al., 2018; Güner, 2018; Nikel, et al., 2020; Eldeeb and Mohamed, 2020b), and public transit captivity (Jacques, et al., 2013; Venter, 2016; Lierop and El-Geneidy, 2017). For instance, Grisé and El-Geneidy (2017) developed a novel spatial segmentation approach that incorporates geographical distribution, personal traits and service satisfaction levels. Furthermore, Kieu, et al., (2018) developed a spatial-behavioural transit market segmentation algorithm, namely Spatial Affinity Propagation, based on spatial and behavioural features of current transit users.

Findings from previous literature highlight that reduced journey times, a limited number of transfers, and real-time information provision are essential for attracting potential users (dell'Olio, et al., 2011; Eldeeb and Mohamed, 2020). The importance of service providers' responsiveness (customer interface) for potential transit users is also highlighted by Abenoza et al., (2017). Further, the willingness to pay for service improvements is much higher for potential users compared to current users (Bellizzi, et al., 2020; Eldeeb and Mohamed, 2020). Current transit users are highly influenced by operational aspects such as service frequency, punctuality and trip fare (Nesheli, et al., 2017; Fu et al., 2018; Machado et al., 2018). Choice transit users are more concerned about reliability, comfort, trip fare and walking time, while captive users care more about waiting time and number of transfers (Krizek and El-Geneidy, 2007; Venter, 2016).

The findings of these studies indeed help public transit agencies to understand the broad spectrum of the transit market and develop service improvement policies for satisfying current users and persuading potential users into public transit use. However, there are some additional contributions to be made. Previous studies fall short in understanding the variation of consumer preferences and their willingness to pay within the same user category (current & potential). Further, recommendations are made for the entire population, which overlook the fact that a significant degree of preference heterogeneity exists.

Towards that end, the primary goal of this study is to inform transit providers on the best investments to increase transit ridership based on identifying cost-effective service improvement plans tailored to market segments. As such, this study aims at 1) Investigating preference heterogeneity in transit service desired quality by adopting a prior classification approach based on customers socioeconomic characteristics and travel behaviour attributes, 2) Estimating willingness to pay values for service improvements for each user categorization, and 3) Examining the differences between interaction effects and random parameter logit models in unveiling preference heterogeneity.

The study utilizes Multinomial Logit (MNL) interaction models along with Random Parameter (RPL) Logit model. MNL interaction models are adopted to independently investigate transit preferences of various users' categories with respect to socioeconomic characteristics, travel behaviour and attitudinal attributes. The RPL model examines the existence of unobserved taste heterogeneity around each attribute and quantifies the spread of such heterogeneity if any.

The utilization of the two aforementioned models provides precious information into understanding transit users' preferences through different lenses and hence tailor service improvements/strategies to satisfy transit users' needs and meet non-transit users' expectations as well as infer quality improvement through willingness to pay estimation for different users' categories.

It should be noted that there are very few studies that employed unlabelled stated preference experiment to investigate preference towards transit quality (Eboli and Mazzulla, 2008; dell'Olio et al., 2011; Bellizzi et al., 2020). The use of unlabelled stated preference experiments is well suited for examining the trade-offs between attribute (De Bekker-Grob et al., 2010), and establishing willingness to pay (WTP) values for service improvements (Hensher et al., 2016) compared to the labelled choice experiment. Further, the present study represents the first quantitative evidence on the willingness to pay of various user types, SEDs combination, and attitudinal orientations.

The remainder of this paper is arranged as follows: Section 2 describes the data used, stated preference experiment and the modelling techniques. Section 3 presents the results of the MNL interaction models as well as the RPL model. Section 4 provides some practical interventions, which is followed by a discussion and concluding remarks in Sections 5.

4.3 Data and methods

4.3.1 Survey data

The study utilized a dataset collected through a customer experience online survey in September 2018. The survey was part of Hamilton Street Railway (HSR) Public Engagement Efforts in the City of Hamilton, Ontario, Canada. HSR is the public transit provider for the City of Hamilton. HSR provides a service coverage area of 243 square kilometres and operates 35 regular bus routes (City of Hamilton, 2020). The survey is designed for all Hamiltonians and structured in four sections: 1) Socioeconomic demographic characteristics and travel behaviour, (2) Stated Preference (SP) experiments, (3) Service quality aspects, and (4) Attitudinal and behavioural characteristics. This study utilized the unlabelled SP experiment along with respondents' socioeconomic, behavioural and attitudinal characteristics, with a sample size of 979 respondents. The interested reader is referred to (Eldeeb and Mohamed, 2020) for a detailed description of the survey and the design process of the SP experiments.

The study employed a three-stage sequential process (i.e., model specification, experimental design, and questionnaire) for the selection of SP experiment attributes and their corresponding levels (Bliemer and Rose, 2006). The final list of the unlabelled SP experiment attributes and the corresponding levels are presented in Table 4-1.

Table 4-1 Unlabelled SP experiment attributes and their associated levels (Eldeeb and Mohamed, 2020)

Service attributes	**Attribute levels**
One-way trip cost	$3, $4.5, and $6
One-way trip travel time	20, 30, and 40 minutes
Walking time to and from the bus stop	0, 5, 10, and 15 minutes
Service frequency	5, 10, 15, and 30 minutes
Number of transfers	0, 1, and 2 transfers
Real-time information	At-stop, on-board and none

The SP experimental design process resulted in twelve scenarios grouped into three blocks (i.e., four-choice situations per respondent). Each respondent was requested to choose from three unlabelled bus transit choices, as shown in Figure 4-1.

Trip & Service Attributes	Option - A	Option - B	Option - C
Bus Fare (one-way trip)	$ 3.00	$ 4.50	$ 3.00
Time Spent Travelling on Bus (one-way trip)	40 min	30 min	40 min
A Bus Departs from My Stop (at the start/end and transfer stops)	every 5 min	every 10 min	every 10 min
Walking Time to/from Bus Stop (includes walking time between transfer stops)	15 min	5 min	5 min
Number of Transfers Between Buses (during one-way trip)	2 Transfer	0 Transfer	1 Transfer
Real-time Trip Information (e.g. about delays)	None	At stop	On board
To Complete My Regular One-Way Trip, I would Choose	○	○	○

Figure 4-1 Example of the stated preference situations (Eldeeb and Mohamed, 2020)

Respondents' attitudes towards public transit were measured using three attitudinal statements; 1) I feel active when using transit, 2) I enjoy using transit, and 3) I think using transit is a good decision. These three attitudinal statements have a Cronbach's alpha of 0.774, which indicates an acceptable level of reliability. Respondents expressed their agreement with the accuracy of each statement on a 5-point Likert scale.

The study utilized a validated sample size of 906 respondents, where 73 invalid and unengaged responses were eliminated. Table 4-2 shows the sample distribution with respect to respondents' socioeconomic, behavioural, and attitudinal characteristics.

Table 4-2 Sample distribution (Eldeeb and Mohamed, 2020)

Category	**Sub-Category**	**Users (%)**	**Population (%)**
Gender	Male	49.34%	48.90%
	Female	50.66%	51.10%
Age	15 to 30 years old	24.72%	35.72%
	30 to 59 years old	51.55%	40.64%
	Over 60 years old	23.73%	23.64%
Income	Less than $40,000	17.33%	58.00%
	$40,000 to $79,999	27.48%	28.55%

Category	Sub-Category	Users (%)	Population (%)
	Over $80,000	42.05%	13.39%
	Prefer not to answer	13.13%	NA
Vehicle ownership	Zero Vehicle	10.82%	13.00%
	One Vehicle	51.10%	87.00%
	Two or more	38.08%	
Frequency of use HSR	Very frequent	27.04%	10.54%
	Med. Frequent	31.46%	89.46%
	Casual	41.50%	
Transit Captivity	Transit captive users	6.07%	NA
	Transit choice users	93.93%	NA
Car Captivity	Car captive users	5.85%	12.51%$^{+}$
	Car choice users	94.15%	87.49%$^{+}$

$^{+}$ spatially measured considering transit service area coverage in contrast with the residential land uses.

4.3.2 Methods

This study utilizes Multinomial Logit (MNL) interaction models and a Random Parameter Logit (RPL) logit model to investigate respondents' preferences towards public transit, and to estimate their willingness to pay (WTP) for service improvements.

First, MNL interaction models are used to independently investigate the preferences of users' categories, which are based on socioeconomic (i.e., sex, age, income, and vehicle ownership), behavioural (i.e., the frequency of using HSR, car and transit captivity) and attitudinal (i.e., transit attitude) attributes. The advantages of MNL interaction models, in addition to their simplicity, are their flexibility and concentricity in testing any specific categorization. The results of the MNL interaction models show the significant differences in transit service desired quality among different categories of users. The MNL model was developed based on the Random Utility Maximization (RUM) theory (Ben-Akiva and Lerman, 1985). RUM adopts a rational decision-making approach, which assumes that individual i, picks the choice j, that maximizes their utility U_{ijt}, in the choice situation, t:

$$U_{ijt} = \beta X_{ijt} + \varepsilon_{ijt} \tag{4-1}$$

Where X_{ijt} is the observable component of the utility function, which is a vector of explanatory variables and β is a vector of estimated fixed parameters. The explanatory variables might include choice attributes as well as interaction variables regarding individuals' characteristics. And ε_{ijt} is the error term, which is assumed to be identically and independently distributed (IID). The probability for individual i, selecting a choice j, in a situation t, based on MNL formulation is expressed as follows:

$$P_{ijt} = \frac{e^{\beta X_{ijt}}}{\sum_{j=1}^{J} e^{\beta X_{ijt}}} \tag{4-2}$$

Second, the Random Parameter Logit (RPL), or mixed logit, model accounts for the unobserved taste heterogeneity between individuals and the correlations between repeated choices by an individual (i.e., panel effect). RPL assumes continuous probability distribution for the random parameters. For RPL models, the random utility function U_{ijt}, is restated in a more general form as follows:

$$U_{ijt} = \beta_i X_{ijt} + \varepsilon_{ijt} \tag{4-3}$$

Where β_i is the vector of estimated parameters for each individual utility i, X_{ijt} is a vector of explanatory variables, and ε_{ijt} is the error term. The parameters vary across individuals according to a density function assumed by the analyst. The RPL model formula for calculating the unconditional probability of individual i, selecting a choice j, is expressed as follows:

$$P_{ij} = \int \prod_{t=1}^{T_q} \left[\frac{e^{\beta_i X_{ijt}}}{\sum_{j=1}^{J} e^{\beta_i X_{ijt}}} \right] f(\beta)\, d(\beta) \tag{4-4}$$

Where T_q is the number of choice situations of individual q and $f(\beta)$ is the density function.

RPL model estimates the mean value of random parameters as well as their standard deviations. The latter reflects the degree of heterogeneity around an attribute. As argued by Greene and Hensher (2003), the RPL model is the most flexible and significant choice model regarding the range of captured heterogeneity. The interested reader is referred to (McFadden and Train, 2000; Hensher and Greene, 2003) for more information.

The integration between the two models provides valuable insights into unveiling transit preference heterogeneity of users on different levels. MNL interaction models capture the sample preference heterogeneity based on a prior classification approach considering specific socioeconomic, behavioural, or attitudinal attributes. While, the RPL model reveals the spread of preference heterogeneity around each attribute. Such details enable transit practitioners to better understand the transit market and hence, tailor their strategies/marketing plans to satisfy transit customers and increase ridership.

4.4 Modelling results

4.4.1 MNL interaction models

Various MNL interaction models were developed to explain different service quality preferences associated with different classifications. Each MNL interaction model targets a specific category, and the categorization is based on gender, age, frequency of use, transit and car captivity, vehicle ownership, and transit attitude. This categorization is motivated by findings from previous studies such as dell'Olio, et al., (2011). Appendix A shows the detailed results of these models, which include service attributes and interactions along with their significance level, as well as goodness-of-fit measures such as log-likelihood, log-likelihood ratio test, and rho-squared.

A base MNL model is shown in Table 4-3 without any interactions and considering only service attributes. All the estimated parameters are statistically significant at a 95% confidence level, and the signs are informative. The negative coefficients represent a disutility where the utility tends to decrease with increasing, for instance, journey time. Using the same analogy, a reduction in travel time, all else being equal, results in an increase in the utility. This also applies for trip fare, walking time, and service headway.

Table 4-3 Multinomial logit model estimation for the base model

Base model (No interaction)			
Variable	**Coefficient(β)**	**β / Std. Err.**	**P-Value**
Journey time	-0.038	-9.620	0.000
Trip fare	-0.378	-11.210	0.000
Walking time	-0.010	-1.990	0.050
Service headway	-0.020	-6.340	0.000
Number of transfers (2-transfers base-category)			
One Transfer	0.122	4.830	0.000
Zero Transfer	0.323	9.100	0.000
Real-time information (No info. base-category)			
Real-time information At-stop	0.069	2.770	0.010
Real-time information On-board	0.149	6.240	0.000
Log-Likelihood	***-3773.636***		
Log-Likelihood ratio test	***415.470***		
Rho-squared	***0.0520***		

Number of respondents = 906, number of observations = 3624

As rational utility maximizers, 1) Respondents prefer, ceteris paribus, shorter journey times, shorter walking times, lower fares, and higher service frequencies as opposed to longer journey times, lengthier walking times, higher fares, and lower service frequencies,2) Respondents appreciate on-board real-time information more than at-stop real-time information, and both (i.e. on-board and at-stop) are more preferred than no-real-time information provision at all, and 3) They express a high preference for direct trips (i.e. zero transfer) over multiple transfers based trips.

MNL interaction models disclosed the heterogeneities among different user classifications. Table 4-4 shows the significant interactions at a 95% confidence level, corresponding to each MNL interaction model.

With respect to socioeconomic interactions, females prefer direct trips and are more sensitive to cost and service frequency than males. Old respondents (i.e., over 60 years old) prefer a lower cost, shorter walking times, and direct trips than young (i.e., less than 30 years old) and middle-aged (i.e., from 30 to 60 years old) respondents. The low-income class prefers shorter travel times and direct trips than high- and middle-income classes. Also, the low-income class is more sensitive to trip fare than the middle- and high-income classes, whereas the high-income class appreciates at-stop real-time information more than the middle-income class. Respondents with two or more vehicles are more sensitive to travel time and appreciate direct trips more than other respondents, while they are less sensitive to trip fare.

Table 4-4 List of MNL interaction models

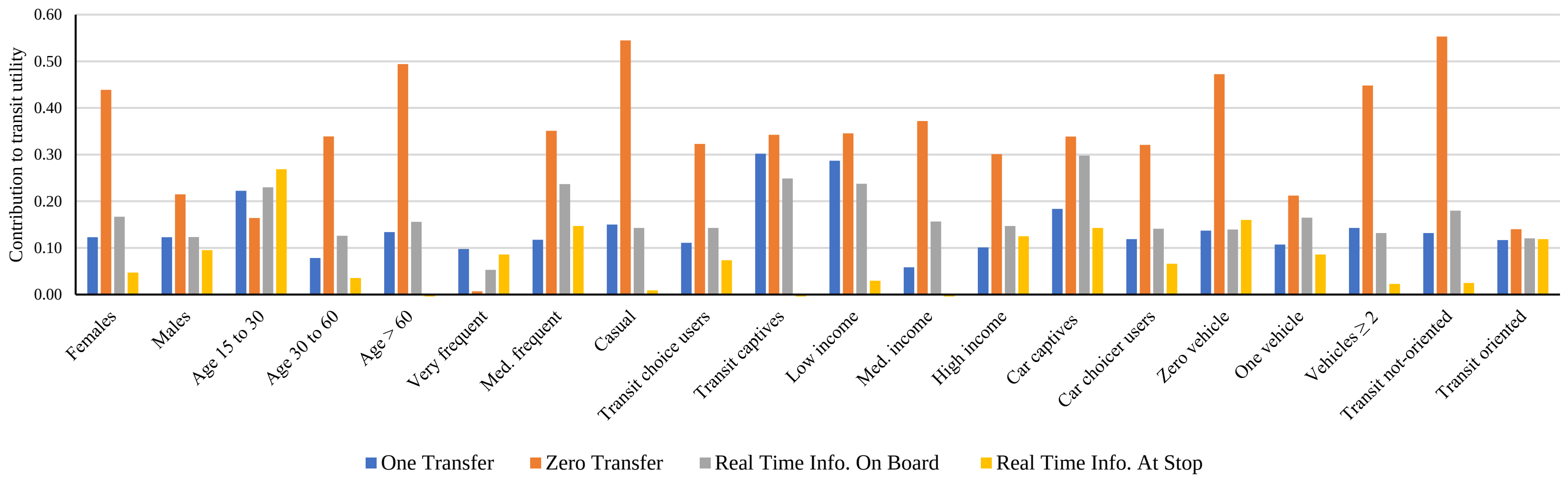
Model	Significant interactions
Gender interaction	Trip fare (β_{female}: -0.436; β_{male}: -0.330) Frequency (β_{female}: -0.028; β_{male}: -0.013) Zero transfer (β_{female}: 0.443; β_{male}: 0.213)
Age interaction	Trip fare ($\beta_{Age > 60}$: -0.655; $\beta_{Age\ 30\ to\ 60}$: -0.358; $\beta_{Age < 30}$: -0.203) Walking time ($\beta_{Age > 60}$: -0.043; $\beta_{Age\ 30\ to\ 60}$: -0.008; $\beta_{Age < 30}$: 0.015) Zero transfer ($\beta_{Age > 60}$: 0.496; $\beta_{Age\ 30\ to\ 60}$: 0.329; $\beta_{Age < 30}$: 0.179)
Income interaction	One transfer ($\beta_{high\text{-}\&med\text{-}income}$: 0.084; $\beta_{low\text{-}income}$: 0.291) Trip fare ($\beta_{high\text{-}income}$: -0.262; $\beta_{med\text{-}income}$: -0.390; $\beta_{low\text{-}income}$: -0.639) Journey time ($\beta_{high\text{-}\&med\text{-}income}$: -0.039; $\beta_{low\text{-}income}$: -0.057) At-stop real-time information ($\beta_{high\text{-}income}$: 0.128; $\beta_{med\text{-}income}$: -0.036)
Vehicle ownership interaction	Journey time ($\beta_{Vehicles > 2}$: -0.048; $\beta_{one\text{-}vehicle}$: -0.033; $\beta_{zero\text{-}vehicles}$: -0.028) Zero transfer ($\beta_{Vehicles > 2}$: 0.438; $\beta_{one\text{-}vehicle}$: 0.224)

Model	Significant interactions
	Trip fare ($\beta_{2\text{ or more Vehicles}}$: -0.389; $\beta_{\text{zero-vehicle}}$: -0.555)
Frequency of use interaction	Journey time (β_{casual}: -0.057; β_{frequent}: -0.033; $\beta_{\text{very frequent}}$: -0.023) Walking time ($\beta_{\text{casual}}$: -0.034; $\beta_{\text{frequent \& very frequent}}$: 0.002) Zero transfer ($\beta_{\text{casual}}$: 0.568; β_{frequent}: 0.335; $\beta_{\text{very frequent}}$: -0.012)
Transit captivity interaction	Frequency (β_{choice}: -0.019; β_{captive}: -0.044) One transfer (β_{choice}: 0.111; β_{captive}: 0.300)
Car captivity interaction	Journey time ($\beta_{\text{car-choice}}$: -0.039; $\beta_{\text{car-captive}}$: -0.017) Trip fare ($\beta_{\text{car-choice}}$: -0.392; $\beta_{\text{car-captive}}$: -0.151) On-board real-time information ($\beta_{\text{car-choice}}$: 0.139; $\beta_{\text{car-captive}}$: 0.319)
Transit attitude interaction	Journey time ($\beta_{\text{not-transit-oriented}}$: -0.055; $\beta_{\text{transit oriented}}$: -0.025) Trip fare ($\beta_{\text{not-transit oriented}}$: -0.518; $\beta_{\text{transit oriented}}$: -0.283) Walking time ($\beta_{\text{not-transit-oriented}}$: -0.031; $\beta_{\text{transit oriented}}$: 0.004) Zero transfer ($\beta_{\text{not-transit oriented}}$: 0.558; $\beta_{\text{transit oriented}}$: 0.135)

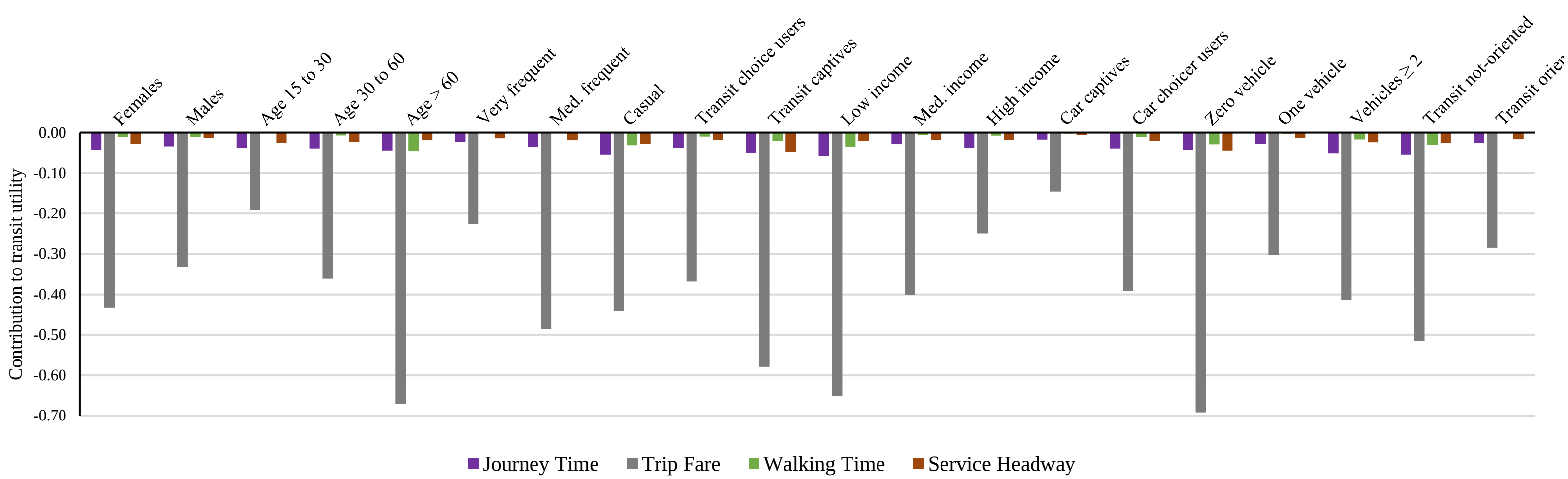
* The detailed results of each interaction model are presented in Appendix A

Considering travel behaviour interactions, casual transit users prefer shorter journey and walking times and direct trips than other users (i.e., frequent and very frequent users). Moreover, transit captive users prefer higher service frequency than choice users while the latter appreciate direct trips more. Car choice users are more sensitive to journey time and trip fare than car captives, while car captives appreciate real-time information more.

Regarding transit attitude interaction, transit-oriented respondents are more lenient regarding journey time, trip fare, walking time and number of transfers comparing to non-transit-oriented respondents. Figure 4-2 illustrates the contribution of each variable to the transit utility for all categories of the MNL-interactions.



(a) Variables with positive influence on transit utility



(b) Variables with negative influence on transit utility

Figure 4-2 Sensitivity of transit utility functions across different users' categorizations

That being said, it is worth noting that the MNL interaction models are not feasible for depicting the underlying classification of the population. The results should be interpreted only with respect to each interaction. Hence, a more in-depth analysis is required to investigating the wide spectrum of respondents' preference heterogeneity. The RPL model is the most suited choice model for investigating the range of customers' preference heterogeneity as advocated by Greene and Hensher (2003).

4.4.2 Random parameter logit model

Defining the RPL model specification is a laborious task because of the numerous possibilities of different distributional assumptions (i.e., normal, lognormal, triangular, and uniform) of the considered random parameters. RPL model specification considered: 1) The significance of random parameters and the associated standard deviations (STDs), 2) The Cholesky decomposition matrix, 3) Behaviorally plausible results (i.e., logical signs), and 4) Goodness-of-fit measures. The parameters associated with trip fare and zero transfer were proved to be random, while the rest remained fixed.

For zero-transfer (dummy variable) random parameter, a uniform distribution was considered as advised by Hensher and Greene, (2003). With the uniform distribution, the parameter β is distributed uniformly between (μ - s) and (μ + s), where the mean μ and spread s are estimated. For trip fare (continuous variable) a normal, lognormal, and triangular distributions were tested. The normal distribution is selected because it demonstrated a better goodness-of-fit compared to the triangle distribution, while the lognormal distribution failed to converge. The normal distribution is a bell-shaped density curve that is symmetrical around the mean μ. With the normal distribution, the distribution of parameter β starts at (μ - s), ascents gradually to μ and then declines to (μ + s). For more information, the reader is referred to by (Hensher and Greene, 2003; Train, 2003).

The error components of repeated choice situations for an individual are assumed to be correlated to account for the panel effect. Also, the correlation between the considered random parameters was permitted to unveil the unobserved effects, which might be a correlation between alternatives due to the correlation between random parameters. Through allowing the correlation between the random parameters, the Cholesky decomposition matrix isolates the contribution to the standard deviation estimates stemmed from the correlation between the random parameters, and the contribution resulted exclusively from the heterogeneity around the mean of each random parameter (Hensher and Greene, 2003). The model was estimated considering a range of Halton intelligent draws (e.g., 50, 100, 500, 1000), and the stability of each model was checked. The Halton draws method provides considerable advances over the pseudo-random method regarding the accuracy, number of required draws, and computational time (Bhat, 2001).

As shown in Table 4-5, the RPL model shows a significant improvement over the base MNL model (likelihood ratio test statistic of 202.2402 with 2 degrees of freedom) regarding goodness-of-fit measures. The two estimated random parameters and their corresponding standard deviations are significant at a 99% confidence level as well as the fixed parameters. Highly significant standard deviations prove the existence of preference heterogeneity and validate the use of RPL models. All estimated parameters have the expected signs and prove behaviorally plausible results.

Table 4-5 Random parameter logit model estimation

Variable	Coefficient(β)	β / Std. Err.	P-Value
Journey time	-0.04972	-10.750	0.0000
Trip fare	-0.58579	-12.380	0.0000
Trip fare (standard deviation)	0.61162	12.550	0.0000
Walking time	-0.02487	-4.240	0.0000
Service headway	-0.03008	-7.720	0.0000
Number of transfers (2-transfers base-category)			
One Transfer	0.18917	6.220	0.0000
Zero Transfer	0.43278	9.030	0.0000
Zero Transfer (standard deviation)	1.20339	14.290	0.0000
Real-time information (No info. base-category)			
Real-time information At-stop	0.12056	3.990	0.0001
Real-time information On-board	0.13643	4.550	0.0000
Diagonal values in the Cholesky matrix			
Trip fare (standard deviation)	0.61162	12.550	0.0000
Zero Transfer (standard deviation)	1.19316	14.810	0.0000
Log-Likelihood	***-3672.51590***		
Log-Likelihood ratio test	***617.71007***		
Rho-squared	***0.0775750***		

Number of respondents = 906, number of observations = 3624

RPL model results are consistent with the MNL model results except for real-time information provision, where RPL shows that respondents also prefer at-stop real-time information nearly as on-board real-time information. A kernel density estimator is used to graph the distribution of trip fare and zero-transfer random parameters, as shown in Figure 4-3.

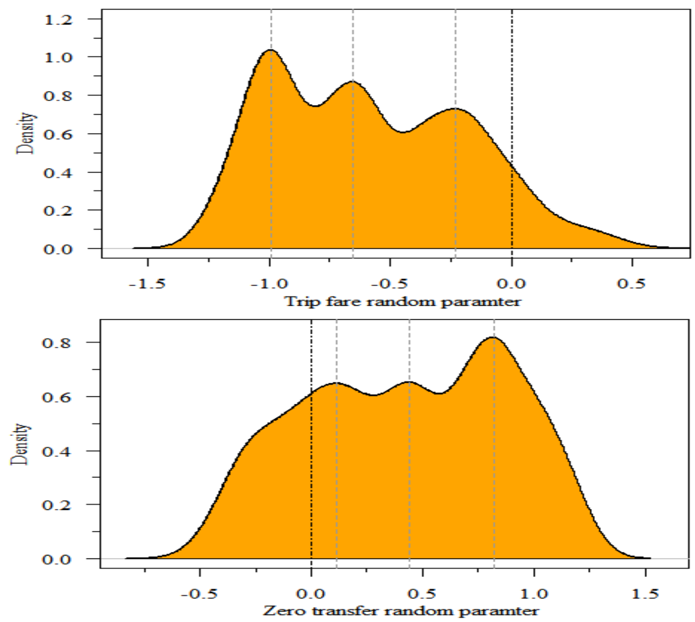


Figure 4-3 Kernel densities for the considered random parameters.

Regarding trip fare random parameter ($\beta_{trip\ fare}$: -0.58579), it reflects the general preference of respondents for trip fare, while the unconfounded standard deviation ($\sigma_{trip\ fare}$: 0.61162) implies a relatively high degree of heterogeneity. The distribution of the trip fare random parameter seems to be a multimodal, which confirms the existence of pronounced preferences. The major mode lies around -0.99, and the intermediate mode is around -0.655, while the minor mode exists around -0.23. Only 8.16% of the sample prefers (or tolerant with) trip fare increase.

With respect to zero-transfer random parameters ($\beta_{zero\text{-}transfer}$: 0.43278), it reveals that respondents, in general, prefer direct trips but their preferences are highly heterogeneous as depicted from the unconfounded standard deviation ($\sigma_{zero\text{-}transfer}$: 1.19316). For the distribution of the zero-transfer random parameter, the main mode of the sample lies around 0.82, while the two other agglomerations are around 0.44 and 0.11. The distribution confirms that most respondents, albeit not at the same level, prefer zero-transfer trips, while 20.75% of the sample is lenient towards multiple transfer trips.

Based on the density distributions, it could be said that some respondents are indifferent about trip fare (i.e., positive value), or they did not consider the trip fare in the decision-making process to alleviate the complexity of making a choice. The same also applies to the number of transfers attribute (i.e., a negative value for zero transfer parameter) where some respondents seem to be tolerant with transfers-based trips.

It is worth noting that the parameters associated with some service attributes (e.g., journey time) do not prove to be random; however, it proved to be significantly affected by respondents' characteristics, such as vehicle ownership and frequency of using public transit, as proved by the MNL interaction models. Consequently, adopting interaction effects in revealing preference heterogeneity has its own strengths in revealing heterogeneity and the reasons behind it.

4.4.3 Willingness to pay (WTP)

WTP values for various service improvements were calculated for the MNL and RPL models, as shown in Table 4-6. The comparison among the WTP estimates, which emerged from different models, allows selecting more robust values. WTP estimates are based on the trip fare attribute coefficient and calculated in CAD$ for the significant attributes only. The WTP estimates were derived based on the ratio of population means using the formula $WTP = -\beta_x/\beta_{cost}$ as advised by Hensher, et al. (2016). For the RPL model, the WTP estimates were derived using the ratio of population means, and a simulation-based method which utilizes all the information in the parameters' distributions (Hensher et al., 2016).

Table 4-6 WTP estimates based on MNL and RPL models

Service improvement	MNL	RPL (Std. Dev.)	
		Pop. means	Simulated
Reduction in Journey time (CDN$ per minute)	$0.1006	$0.0848	$0.0669 (2.286)
Reduction in Walking time (CDN$ per minute)	$0.0274	$0.0424	$0.0334 (1.1438)
Reduction in Service headway (CDN$ per minute)	$0.0530	$0.0512	$0.0404(1.3834)
Trip with Zero transfer (CDN$ per trip)	$0.855	$0.738 (1.951)	$1.318 (52.24)
Trip with One transfer (CDN$ per trip)	$0.324	$0.323	$0.276 (33.78)
Provision of Real time info. At-stop (CDN$ per trip)	$0.183	$0.206	$0.162 (5.545)
Provision of Real-time info. On-board (CDN$ per trip)	$0.395	$0.233	$0.183 (6.274)

WTP varies based on the model and technique used in the estimation process; these differences may be classified as optimistic and conservative estimates. For journey time, respondents would pay around $1 to save 10 minutes based on the MNL model while $0.669 considering the RPL simulated WTP estimates. The WTP to save 5 minutes of walking time ranges from $ 0.137 to $0.167 based on MNL and RPL, respectively.

Regarding transit service headway, respondents' WTP to decrease the headway by 5 minutes ranges from $0.265 based on MNL to $0.202 based on RPL. Respondents would pay $0.855 based on MNL or $0.738 based on RPL for zero transfer trips and avoiding two transfer trips. While respondents would pay $0.324 (MNL) or $0.276 (RPL) for one-transfer trips comparing to two transfer trips. For real-time information provision, respondents are willing to pay $0.183 (MNL) or $0.162 (RPL) for at-stop real-time information provision while they would pay $0.395 (MNL) or $0.183 (RPL) for on-board real-time information provision.

4.4.4 Reflected heterogeneity on the WTP

The willingness to pay values for service improvements were estimated for each MNL interaction model to depict the heterogeneity in willingness to pay for different customer groups, as shown in Table 4-7. This depiction is indeed of benefit to service providers/marketing teams where they can identify cost-effective market segments and service improvements.

With respect to socioeconomic-based classifications, female customers are willing to pay more than male customers to reduce service headway and the number of transfers, while males would pay more for at-stop real-time information provision. For instance, WTP values for reducing the number of transfers from 2 to 1 per trip is $1.014 for females and $0.648 for males. Young customers (i.e., 15 to 30 years old) have a higher willingness to pay than other age groups for reducing journey time, service headway and the number of transfers, and real-time information provision. Old customers (i.e., over 60 years old) have the highest WTP ($0.349) for 5 minutes reduction in walking time.

The high-income class is willing to pay more than others for reducing journey time, service headway, and the number of transfers to zero, and real-time information provision. However, the low-income class would pay more for 5 minutes reduction in walking time ($0.272) and for reducing the number of transfers from 2 to 1 per trip ($0.441). Customers with two or more vehicles would pay more than others for reducing journey time and the number of transfers to zero per trip, while customers with zero vehicles have the highest WTP for reducing walking time and service headway. Customers with one vehicle having the highest WTP for real-time information provision.

Regarding customers' travel behaviour, casual (i.e., yearly) transit users are willing to pay more for reducing journey time, walking time and number of transfers. For example, Casual transit users would pay $1.236 for reducing the number of transfers from 2 to 0 per trip. Very frequent (i.e., daily) transit users would pay more for reducing service headway and at-stop real-time information provision.

For customers' accessibility to travel modes, choice transit users are willing to pay more than captive transit users for reducing journey time and the number of transfers and at-stop real-time information provision. In contrast, captive transit users would pay more for reducing walking time, service headway, and on-board real-time information provision. For instance, choice transit users would pay $0.878 for reducing the number of transfers from 2 to 0 per trip while it is $ 0.591 for transit captives. Car captives would pay more for reducing journey time and number of transfers, and real-time information provision. At the same time, car choice users are willing to pay more for reducing walking time and service headway.

Table 4-7 WTP estimates for all considered classifications.

Variable	Reduction in Journey time (CDN$/minute)	Reduction in Walking time (CDN$/minute)	Reduction in Service headway (CDN$/minute)	Reducing no. of transfers from 2 to 0 (CDN$/trip)	Reducing no. of transfers from 2 to 1 (CDN$/trip)	Provision of Real-time info. At-stop (CDN$/trip)	Provision of Real-time info. On-board (CDN$/trip)
SEDs							
Females	$0.099	$0.025	$0.064	$1.014	$0.284	$0.109	$0.386
Males	$0.102	$0.033	$0.039	$0.648	$0.371	$0.287	$0.371
Age 15 to 30	$0.198	$0.000	$0.133	$0.854	$1.159	$1.399	$1.197
Age 30 to 60	$0.109	$0.020	$0.063	$0.939	$0.217	$0.098	$0.349
Age > 60	$0.068	$0.070	$0.027	$0.736	$0.200	$0.000	$0.233
Low income	$0.090	$0.055	$0.032	$0.531	$0.441	$0.046	$0.365
Med. income	$0.071	$0.016	$0.046	$0.927	$0.145	$0.000	$0.390
High income	$0.153	$0.030	$0.075	$1.209	$0.406	$0.502	$0.590
Zero vehicle	$0.064	$0.042	$0.066	$0.683	$0.198	$0.231	$0.201
One vehicle	$0.090	$0.013	$0.043	$0.702	$0.355	$0.285	$0.546
Vehicles ≥ 2	$0.125	$0.040	$0.058	$1.080	$0.345	$0.055	$0.318
Transit Usage Frequency							
Very frequent	$0.103	$0.000	$0.063	$0.031	$0.432	$0.381	$0.235
Med. frequent	$0.072	$0.000	$0.038	$0.723	$0.242	$0.303	$0.488
Casual	$0.125	$0.071	$0.062	$1.236	$0.340	$0.020	$0.324
User Type							
Transit choice users	$0.101	$0.027	$0.050	$0.878	$0.302	$0.200	$0.389
Transit captives	$0.087	$0.036	$0.083	$0.591	$0.522	$0.000	$0.430
Car captive users	$0.119	$0.018	$0.043	$2.321	$1.257	$0.980	$2.041
Car choicer users	$0.100	$0.028	$0.053	$0.819	$0.304	$0.168	$0.360
Transit Attitude							
Transit not oriented	$0.106	$0.059	$0.050	$1.074	$0.256	$0.048	$0.350
Transit oriented	$0.090	$0.000	$0.058	$0.491	$0.410	$0.417	$0.424

** The heatmap represents variations in the WTP estimates across all values (Green represents higher WTP and Red represents lower WTP)*

For customers' attitudes, transit-oriented customers are willing to pay more for reducing service headway and real-time information provision. While transit not-oriented customers would pay more reducing journey time, walking time and number of transfers. For example, transit not-oriented customers would pay \$1.074 for reducing the number of transfers from 2 to 0 per trip compared to \$0.491 for transit-oriented customers.

Explained another way, the data in Table 4-7 highlights the significant variation on the willingness to pay for the same service improvements across different user type, SEDs, and attitudinal orientation. This, in turn, means that the same quality improvement will not have similar impacts on the entire population. Reacting to that, service quality improvements should be carried out in three steps. First, is to identify the targeted user type: current, potential, captive, and choice users or the targeted SED group. Second, from the WTP estimates, locates the service improvement corresponding to the highest WTP values for each user type. Third, is to prioritize quality improvements based on maximizing the return over investment.

For example, our results indicate that for captive users providing direct trips and real-time information on board is the most effective quality improvement to attract them to transit. While for younger generations (15-30 years old), real-time information provision at stop and on-board are likely to significantly change their transit usage followed by reducing the number of required transfers.

4.5 Practical interventions: an illustrative example

Three scenarios were considered to examine the overall performance of transit routes based on the WTP estimates for the whole sample. The scenarios compare annual operating costs versus annual revenues. For simplicity, the considered scenarios focus on improvements concerning service operating aspects such as journey time and service frequency. Based on our WTP estimates extracted from the RPL model, a conservative WTP estimate of CAN$0.202 was used, corresponding to five minutes reduction in service headway. While a value of CAN$0.335 was used, corresponding to five minutes reduction in journey time.

Remix transit planning platform was used to calculate annual operating costs, based on CAN$115 per hour, due to travel time and frequency changes. The A-line express and 16-Ancaster routes were used as an example; A-line express is a north-south express route that travels from downtown Hamilton to the Hamilton international airport in around 40 minutes. For 16-Ancaster, it is a local route that serves the community of Ancaster and travels from Meadowlands transit terminal to the shopping complex at Garner road in Ancaster in around 25 minutes (City of Hamilton, 2020; Nikel et al., 2020). A-Line express runs on weekdays from early morning to early evening, and the average ridership is 668 passengers per working day as indicated by HSR Automatic Passenger Count (APC) data. While 16-Ancaster local route runs on weekdays and Saturdays from early morning to late evening, and the average ridership is 255 passengers per day.

The considered scenarios are 1) Reducing service headway by five minutes, 2) Reducing journey time by 5 minutes, and 3) Reducing service headway by five minutes and journey time by five minutes simultaneously.

Table 4-8 shows the A-line route’s existing conditions, altered trip fares, annual revenues and operating costs, and the required fleet size based on the adopted scenarios. The existing conditions of the A-line route show that the annual revenues to the annual operating cost ratio is around 31% (i.e., 69% subsidies). This value is used as a benchmark to evaluate the considered scenarios.

Table 4-8 Practical demonstration for A-line express transit route

Scenarios	Fares (CAN$)	Revenues (CAN$/year)	Fleet size	Operating cost (CAN$/year)	Revenues/ Cost (R/C)
A-Line Express					
0. Existing conditions	$3.00	$480,960	6	$1,545,140	0.311
1. Headway, H (-5 mins)	$3.20	$513,345	7	$1,789,170	0.287
2. Journey time, T (-5 mins)	$3.34	$534,667	5	$1,273,050	0.420
3. T (-5 mins) & H (-5 mins)	$3.54	$567,052	6	$1,548,360	0.366
16 – Ancaster Local					
Existing condition	$3.00	$220,320	3	$742,555	0.297
1. Headway, H (-5 mins)	$3.20	$235,155	3	$754,055	0.312
2. Journey time, T (-5 mins)	$3.34	$244,922	2	$530,265	0.462
3. T (-5 mins) & H (-5 mins)	$3.54	$259,757	2	$598,115	0.434

For A-Line Express, the results show that the best financial performance and consequently the most significant change in subsidies is corresponding to the second scenario as there is a 34.93% increase in R/C ratio and a 17.61% decrease in annual operating costs comparing to the existing conditions. Moreover, the fleet size decreased to 5 instead of 6 buses. Regarding the third scenario, the financial performance is better than the existing condition by 11.97%, and fleet size is the same. Although the altered trip fares for the third scenario (CAN$3.54) is higher than the second scenario (CAN$3.34), the financial performance of the second scenario is higher by 13.36% than the third scenario. A similar trend is observed for Local Route 16.

From an overall transit utility, scenario one will contribute to an overall 0.85% change in transit utility, while scenarios two and three will contribute to an overall change of transit utility of 1.27% and 2.12%, respectively. The results of this example showcase that transit agencies should focus on reducing journey time more than increasing service frequency to improve transit agencies' financial performance and hence decrease the required subsidies.

It should be noted that reducing travel time might not be feasible for all routes, especially where stop spacing, and traffic conditions hinder the reduction in travel time. In this case, additional measures (e.g., dedicated bus lanes, transit signal priority, and stop rationalization) are encouraged, which should be associated with measures to reduce transit travel time.

This illustrative example shows how transit agencies could prioritize their service improvement plans based on data-driven willingness to pay values. This example could be enlarged to examine more challenging service improvements for the network as a whole, such as reducing the number of transfers and the provision of real-time information onboard and at stops.

4.6 Discussion and concluding remarks

The study aims to unveil the heterogeneity in transit customers' preferences based on a prior classification and examine its implications on willingness to pay values for service improvements for various classifications of customers. The study questions the notion of applying WTP values for the entire population, without considering the significant degree of preference heterogeneity.

The study utilized an unlabelled choice experiment from a public engagement survey with a sample size of 906 respondents. The sample represents the transit market in the City of Hamilton by 58.50% current HSR users and 41.50% potential HSR users. The study employed multinomial logit interaction models and a random parameter logit model to unveil preference heterogeneity in the transit market. The integration between the two models provides valuable insights into unveiling transit preference heterogeneity of users on different levels and highlights the strengths of each model in disclosing preference heterogeneity. MNL interaction models capture the sample preference heterogeneity based on a specific socioeconomic, behavioural, and attitudinal attribute. And the RPL model reveals the spread of preference heterogeneity around each attribute.

The results of the MNL interaction models proved preference heterogeneity towards service attributes due to variations in customers' socioeconomic characteristics, travel behaviour and attitudes. In addition, the MNL interaction models highlighted the dire need to significantly reduce journey time, walking time and the number of transfers to attract casual users. The results are aligned with the findings of (dell'Olio et al., 2011; de Oña, et al., 2020), which indicates that casual (potential) users are more sensitive to journey time, intramodality, comfort, and waiting time than frequent and very frequent users. Additionally, the results showed that transit attitude profoundly affects people's perceptions of transit service attributes which are consistent with the findings of Susilo and Cats (2014), and Lierop and El-Geneidy (2018) regarding the effect of attitudes on travel satisfaction.

Further, the RPL model investigated preference heterogeneity around all attributes and concluded the significant spread of preference heterogeneity around trip fare and zero transfer attributes. The RPL model was also used by Eboli and Mazzulla (2011b) where it confirmed preference heterogeneity around bus stop facilities characteristics and bus crowding. While for Venter (2016), the RPL confirmed preference heterogeneity around in-vehicle travel time and walking time to bus stops. The RPL defines the agglomerations of users' preferences regarding trip fare, and zero transfer attributes separately. For trip fare, the multimodal density distribution depicts the wide spectrum of users' preferences and concludes the variant, yet important, influences of trip fare on public transit. Regarding zero transfer, the density distribution confirms that most respondents, albeit at different rates, prefer zero-transfer trips while around 20% of the sample is tolerant with multiple transfer trips.

It is worth mentioning that MNL interaction models have revealed preference heterogeneity for some attributes (e.g., journey time), which were masked in the RPL model. This shows the strengths of the interaction effects in testing preference heterogeneity for specific categorizations.

The results of estimating willingness to pay values for service improvements for different customer groups affirm the presence of WTP heterogeneity. Unveiling WTP heterogeneity is of utmost importance to transit providers where they can tailor service improvements and identify cost-effective market segments. For instance, females are willing to pay more to reduce service headway and the number of transfers, while males would pay more for at-stop real-time information provision. In addition, casual transit users are willing to pay more for reducing journey time, walking time and number of transfers. In contrast, very frequent transit users would pay more for reducing service headway and at-stop real-time information provision.

With respect to practical contributions, the findings of this paper will help public transit service providers and policymakers to better understand their customers and to address the needs of current users along with attracting non-transit (potential) users. Practical interventions along with WTP estimates for service improvements were presented to show some promising avenues for enhancing public transit service quality while maintaining the service operating cost.

Lastly, to answer the question posed in the title of the study "*the best bang for your buck*" it depends on the targeted user type, which varies across service providers. The main issue is to measure/acknowledge preference heterogeneity and its impacts on the WTP for service improvement for each user segment.

4.7 Appendix A

Table A-4-1 Multinomial logit model estimation for gender interaction

Gender interaction			
Variable	**Coefficient(β)**	**β / Std. Err.**	**P-Value**
Journey time	-0.043	-8.410	0.000
Journey time × Gender	0.010	1.500	0.130
Trip fare	-0.436	-10.480	0.000
Trip fare × Gender	0.106	2.290	0.020
Walking time	-0.011	-2.090	0.040
Service headway	-0.028	-6.250	0.000
Service headway × Gender	0.015	2.520	0.010
Number of transfers (2-transfers base-category)			
One transfer	0.123	4.830	0.000
Zero transfer	0.443	9.460	0.000
Zero transfer × Gender	-0.230	-4.060	0.000
Real-time information (No info. base-category)			
Real time info. On-board	0.145	6.050	0.000
Real-time info. at-stop	0.072	2.870	0.000
Log-Likelihood	***-3762.223***		
Log-Likelihood ratio test	***438.296***		
Rho-squared	***0.055***		

Number of respondents = 906, number of observations = 3624

Table A-4-2 Multinomial logit model estimation for age interaction

Age Interaction			
Variable	**Coefficient(β)**	**β / Std. Err.**	**P-Value**
Journey time	-0.040	-10.080	0.000
Trip fare	-0.655	-10.760	0.000
Trip fare × Age < 30	0.452	6.090	0.000
Trip fare × Age 30 - 60	0.297	4.620	0.000
Walking time	-0.043	-4.530	0.000
Walking time × Age < 30	0.058	4.590	0.000
Walking time × Age 30 - 60	0.035	3.340	0.000
Service headway	-0.022	-6.940	0.000
Number of transfers (2-transfers base-category)			
One transfer	0.099	3.380	0.000
One transfer × Age < 30	0.119	2.030	0.040
Zero transfer	0.496	7.800	0.000
Zero transfer × Age < 30	-0.317	-3.620	0.000
Zero transfer × Age 30 - 60	-0.167	-2.380	0.020
Real-time information (No info. base-category)			
Real time info. On-board	0.135	4.880	0.000
Real time info. On-board × Age < 30	0.089	1.590	0.110
Real-time info. at-stop	0.019	0.660	0.510
Real-time info. at-stop × Age < 30	0.247	4.430	0.000
Log-Likelihood	***-3732.28***		
Log-Likelihood ratio test	***498.182***		
Rho-squared	***0.063***		

Number of respondents = 906, number of observations = 3624

Table A-4-3 Multinomial logit model estimation for frequency of use interaction

Frequency of using transit interaction			
Variable	**Coefficient(β)**	**β/Std. Err.**	**P-Value**
Journey time	-0.057	-9.690	0.000
Journey time × Mid. Frequent	0.024	3.270	0.000
Journey time × Very Frequent	0.034	3.670	0.000
Trip fare	-0.464	-10.870	0.000
Trip fare × Very Frequent	0.248	3.770	0.000
Walking time	-0.034	-4.440	0.000
Walking time × Mid. Frequent	0.036	3.930	0.000
Walking time × Very Frequent	0.036	3.060	0.000
Service headway	-0.028	-5.950	0.000
Service headway × Mid. Frequent	0.010	1.360	0.170
Service headway × Very Frequent	0.014	1.820	0.070
Number of transfers (2-transfers base-category)			
One transfer	0.125	4.900	0.000
Zero transfer	0.568	11.190	0.000
Zero transfer × Mid. Frequent	-0.233	-3.910	0.000
Zero transfer × Very Frequent	-0.580	-8.120	0.000
Real-time information (No info. base-category)			
Real time info. On-board	0.146	3.980	0.000
Real time info. On-board × Mid. Frequent	0.088	1.620	0.110
Real time info. On-board × Very Frequent	-0.094	-1.580	0.110
Real-time info. at-stop	0.013	0.380	0.700
Real-time info. at-stop × Mid. Frequent	0.130	2.090	0.040

Real-time info. at-stop × Very Frequent	0.073	1.330	0.180
Log-Likelihood	***-3720.708***		
Log-Likelihood ratio test	***521.325***		
Rho-squared	***0.065***		

Number of respondents = 906, number of observations = 3624

Table A-4-4 Multinomial logit model estimation for transit captivity interaction

Transit captive interaction			
Variable	**Coefficient(β)**	**β/Std. Err.**	**P-Value**
Journey time	-0.038	-9.630	0.000
Trip fare	-0.372	-10.980	0.000
Trip fare × Captive users	-0.142	-1.560	0.120
Walking time	-0.011	-2.020	0.040
Service headway	-0.019	-5.800	0.000
Service headway × Captive users	-0.025	-1.810	0.070
Number of transfers (2-transfers base-category)			
One transfer	0.111	4.260	0.000
One transfer × Captive users	0.189	2.060	0.040
Zero transfer	0.325	9.160	0.000
Real-time information (No info. base-category)			
Real time info. On-board	0.149	6.230	0.000
Real-time info. at-stop	0.069	2.760	0.010
Log-Likelihood	***-3768.867***		
Log-Likelihood ratio test	***425.007***		
Rho-squared	***0.053***		

Number of respondents = 906, number of observations = 3624

Table A-4-5 Multinomial logit model estimation for income interactions

Income interaction			
Variable	**Coefficient(β)**	**β / Std. Err.**	**P-Value**
Journey time	-0.039	-7.240	0.000
Journey time × Low income	-0.018	-1.860	0.060
Journey time × Med. Income	0.011	1.550	0.120
Trip fare	-0.262	-6.490	0.000
Trip fare × Low income	-0.377	-4.750	0.000
Trip fare × Med. Income	-0.128	-2.580	0.010
Walking time	-0.007	-1.220	0.220
Walking time × Low income	-0.027	-2.040	0.040
Service headway	-0.019	-5.620	0.000
Number of transfers (2-transfers base-category)			
One transfer	0.084	2.770	0.010
One transfer × Low income	0.207	3.490	0.000
Zero transfer	0.331	8.760	0.000
Real-time information (No info. base-category)			
Real time info. On-board	0.152	5.350	0.000
Real time info. On-board × Low income	0.084	1.260	0.210
Real-time info. at-stop	0.128	3.520	0.000
Real-time info. at-stop × Low income	-0.102	-1.470	0.140
Real-time info. at-stop × Med. Income	-0.164	-3.040	0.000
Log-Likelihood	***-3249.513***		
Log-Likelihood ratio test	***417.838***		
Rho-squared	***0.060***		

*All missing values were excluded from the analyses & Number of respondents = 787, number of observations = 3148

Table A-4-6 Multinomial logit model for car captivity interactions

Car captive interaction			
Variable	**Coefficient(β)**	**β / Std. Err.**	**P-Value**
Journey time	-0.039	-9.720	0.000
Journey time × Car captives	0.022	1.630	0.100
Trip fare	-0.392	-11.480	0.000
Trip fare × Car captives	0.241	2.870	0.000
Walking time	-0.010	-1.990	0.050
Service headway	-0.021	-6.460	0.000
Service headway × Car captives	0.016	1.240	0.210
Number of transfers (2-transfers base-category)			
One transfer	0.122	4.820	0.000
Zero transfer	0.322	9.080	0.000
Real-time information (No info. base-category)			
Real time info. On-board	0.139	5.630	0.000
Real time info. On-board × Car captives	0.180	1.950	0.050
Real-time info. at-stop	0.071	2.830	0.000
Log-Likelihood	***-3765.962***		
Log-Likelihood ratio test	***430.818***		
Rho-square	***0.054***		

Number of respondents = 906, number of observations = 3624

Table A-4-7 Multinomial logit model estimation for vehicle ownership interactions

Vehicle ownership interaction			
Variable	**Coefficient(β)**	**β / Std. Err.**	**P-Value**
Journey time	-0.048	-8.770	0.000
Journey time × One vehicle	0.015	2.400	0.020
Journey time × Zero vehicle	0.020	1.890	0.060
Trip fare	-0.389	-8.690	0.000
Trip fare × One vehicle	0.054	1.080	0.280
Trip fare × Zero vehicle	-0.166	-1.910	0.060
Walking time	-0.011	-2.020	0.040
Service headway	-0.020	-6.360	0.000
Number of transfers (2-transfers base-category)			
One transfer	0.123	4.840	0.000
Zero transfer	0.438	8.620	0.000
Zero transfer × One vehicle	-0.214	-3.520	0.000
Zero transfer × Zero vehicle	-0.042	-0.410	0.680
Real-time information (No info. base-category)			
Real time info. On-board	0.150	6.280	0.000
Real-time info. at-stop	0.011	0.300	0.770
Real-time info. at-stop × One vehicle	0.088	1.830	0.070
Real-time info. at-stop × Zero vehicle	0.112	1.430	0.150
Log-Likelihood	***-3756.448***		
Log-Likelihood ratio test	***449.846***		
Rho-square	***0.056***		

Number of respondents = 906, number of observations = 3624

Table A-4-8 Multinomial logit model estimation for transit attitudinal interactions

Transit attitudinal interaction			
Variable	**Coefficient(β)**	**β / Std. Err.**	**P-Value**
Journey time	-0.055	-8.820	0.000
Journey time × Transit-oriented	0.030	3.670	0.000
Trip fare	-0.518	-9.380	0.000
Trip fare × Transit-oriented	0.235	3.510	0.000
Walking time	-0.031	-3.780	0.000
Walking time × Transit-oriented	0.035	3.400	0.000
Service headway	-0.026	-5.610	0.000
Frequency × Transit-oriented	0.009	1.410	0.160
Number of transfers (2-transfers base-category)			
One transfer	0.124	4.880	0.000
Zero transfer	0.558	10.440	0.000
Zero transfer × Transit-oriented	-0.423	-6.540	0.000
Real-time information (No info. base-category)			
Real time info. On-board	0.181	5.190	0.000
Real time info. On-board × Transit oriented	-0.060	-1.250	0.210
Real-time info. at-stop	0.026	0.690	0.490
Real-time info. at-stop × Transit oriented	0.092	1.860	0.060
Log-Likelihood	***-3744.215***		
Log-Likelihood ratio test	***474.312***		
Rho-square	***0.06***		

Number of respondents = 906, number of observations = 3624

4.8 References

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CHAPTER 5

How Psychological Factors Sway Customers' Preferences Towards Transit Service Attributes?

Preamble

This chapter investigates the role of subjective psychological factors in shaping potential transit customers' perception towards transit service attributes (i.e., the sixth objective) using an Error Components (EC) logit model and Confirmatory Factor Analysis (CFA). The chapter also examines the association between customers' socioeconomic characteristics and subjective psychological tendencies (i.e., the seventh objective).

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5.1 Abstract

The study aims at quantifying the influence of subjective psychological factors on shaping customers' preferences towards transit service attributes. In addition, the study examines the association between customers' subjective psychological tendencies and socioeconomic characteristics. A dataset of 1,241 potential transit users is explored through an Error Components (EC) logit model with systematic taste variations and multivariate analysis of variance (MANOVA). The results quantified the influence of subjective psychological aspects on customers' preferences towards various transit service attributes and concluded the power of psychological aspects in explaining preference heterogeneity. For instance, environmentally conscious customers are more tolerant towards walking time to/from bus stops and have a higher appreciation of at-stop real-time information provision than others. Further, the multivariate analysis of variance highlighted that customers' psychological factors vary significantly across their socioeconomic characteristics. For example, young customers are more environmentally conscious and have higher perceived behaviour control and social norms towards transit than old and middle-aged customers. Overall, the findings provide research-based evidence to practitioners and policymakers on the dire need to jointly considering both psychological and utilitarian aspects in evaluating the desired quality from public transit.

5.2 Introduction

Understanding the demands of public transit customers is a necessity for transit agencies to satisfy transit users and attract new riders. An efficient and desirable public transit service is vital for reshaping travel behaviour in urban areas into an environmentally friendly travel pattern (Saelens et al., 2003; Leslie et al., 2007; Mariel et al., 2018; Eldeeb and Mohamed, 2020b). Luring people out of their cars into public transit is a complex endeavour that requires a deep comprehension of the driving factors behind individuals' desired quality of public transit service. As argued by Eboli and Mazzulla (2011), the qualitative nature of various service quality aspects, subjective psychological factors, and customers' diverse socioeconomic characteristics are an added challenge to unveiling the heterogeneity of public transit desired quality.

The literature on public transit service quality is rooted in two main approaches: investigating preferences towards service quality aspects such as travel time, service frequency, comfort and reliability (Grujičić et al., 2014; Nwachukwu, 2014; Morton et al., 2016; Allen et al., 2018; Sam et al., 2018; Machado et al., 2018; Eldeeb and Mohamed 2020a), and examining the role of subjective psychological factors (e.g., attitudes, habits, subjective norm) on customers' satisfaction, loyalty and intention to use the service (Lai and Chen, 2011; Susilo and Cats, 2014; Fu and Juan, 2017b; Diab et al., 2017; Fu et al., 2018; Li et al., 2018). Additionally, in an effort to better understand transit customer' preferences and psychological tendencies, it is a common practice in the literature to classify the public transit market into current and potential users (dell'Olio et al., 2011; Mahmoud and Hine, 2013; Deb and Ali Ahmed, 2018) or into captive and choice users (Krizek & El-Geneidy, 2007; Venter, 2016). Other studies have adopted more parsimonious approaches in classifying transit customers, such a latent class choice model (Eldeeb and Mohamed 2020a) and spatial segmentation (Kieu et al. 2018; Nikel et al., 2020).

In this respect, the significant role of subjective psychological factors in shaping the overall satisfaction towards public transit service and its ridership is confirmed by various studies (e.g., Carreira et al., 2014; Şimşekoğlu et al., 2015; Fu et al., 2018; J. de Oña, 2021). However, how subjective psychological factors affect transit customers' perceptions towards service attributes? and how psychological factors and socioeconomic characteristics are related? are questions worthy of investigating.

Therefore, we argue on the pressing need to investigate/quantify the influence of subjective psychological aspects on shaping customers' perceptions towards utilitarian public transit service attributes. This integration is unlike the common practice of independently investigating the role of psychological factors or the role of service quality attributes on public transit use behaviour, satisfaction, and/or loyalty (e.g., Susilo and Cats, 2014; Deb and Ali Ahmed, 2018; Li et al., 2018); it is rather quantifying the influence of psychological aspects (e.g., environmental consciousness) on perceiving various service quality attributes (e.g., walking time to/from bus stops). The proposed two-fold approach enables transit agencies to better understand the actual reasons behind their customers' desired quality. In addition, we argue that understanding the interdependencies between customers' socioeconomic characteristics and their subjective psychological factors is a step towards unveiling the underlying causes for their psychological tendencies.

Towards that end, the aim of this study is twofold: 1) Investigating how subjective psychological aspects of potential transit users affect their perceptions towards utilitarian public transit service attributes, and 2) Examining the interrelationships between potential users' socioeconomic attributes and their subjective psychological aspects. In particular, this study simultaneously examines the influence of five subjective psychological aspects (Car Reliance, Transit Stigma, Perceived Behavioural Control, Social Norm, and Environmental Consciousness) in shaping transit service desired quality from potential users' perspectives. Potential users are defined herein as respondents who do not consider public transit as their primary travel mode.

The remainder of this paper is arranged as follows. In section 2, a review of the relationship between subjective psychological factors and public transportation use behaviour is presented. Section 3 describes the data used in this research. Then, section 4 presents the methods for the analysis. The results are introduced in section 5, which is followed by a discussion and conclusions section.

5.3 Literature review

In the literature, there is a plethora of studies focusing on understanding the broad spectrum of public transit users' preferences towards service quality aspects and how to increase public transit ridership (e.g., Krizek and El-Geneidy, 2007; Mahmoud and Hine, 2016; Abenoza et al., 2017; Eldeeb and Mohamed, 2020b). The rationale is to facilitate targeting particular types of users with directed service improvements. However, besides the conventional service quality aspects that are well-documented in the literature, other studies highlighted the significant role of subjective psychological aspects (e.g., attitudes, social norm, perceived behavioural control, and habits) in explaining consumers travel behaviour (Flannelly and McLeod, 1989; Ajzen, 1991; Ben-Akiva et al., 2002; Chen and Chao, 2011; Eboli and Mazzulla, 2011), and affirmed that their inclusion advances the predictive power of public transit quality assessment models (Domarchi et al., 2008; Galdames et al., 2011; Muenrit et al., 2017).

For utilitarian service quality aspects, the literature highlights that both transit users and non-transit (potential) users are concerned about travel time, reliability, service frequency, trip fare (Mahmoud and Hine, 2016; Abenoza et al., 2017; Deb and Ahmed, 2018). Whereas potential users are more concerned about service operational aspects such as travel time, waiting time, reliability, punctuality, safety and travel cost (Mahmoud and Hine, 2016; De Oña et al., 2017; Machado et al., 2018) as well as service attractiveness, comfort, staff attitude, and customer interface (Krizek and El-Geneidy, 2007; Abenoza et al., 2017). For instance, Abenoza et al. (2017) examined the determinants of public transit use for different travellers' segments in Sweden. They concluded that length of trip time, service frequency and network design are the most significant factors to increase public transit satisfaction among non-transit users.

Additionally, the recent work in Eldeeb and Mohamed (2020a) confirmed the existence of preference heterogeneity towards public transit service quality aspects and emphasized that reducing journey time and the number of transfers along with real-time information provision are essential improvements to attract potential users (Eldeeb and Mohamed, 2020b). They also concluded that at-stop real-time information provision is of utmost importance for frequent transit users (Eldeeb and Mohamed, 2020a). Other studies identified park and ride facilities, flexible fare policies, and accessibility as essential to satisfy current users and to lure potential users out of their cars (Mahmoud and Hine, 2013; Grisé and El-Geneidy, 2017).

With respect to subjective psychological factors, the theory of planned behaviour (TPB), developed by Ajzen, 1991, is commonly used for explaining travel behaviour (Idris, 2013; Muñoz et al., 2016; Mohamed et al., 2016; Kaewkluengklom et al., 2017). TPB is an established widely-used psychological theory for explaining and predicting intentional/deliberate human behaviour (Ajzen, 1991; Ajzen, 2013). The theory states that actual behaviour is determined by behavioural intention, which is a function of three main determinants: 1) Attitude: refers to the favourable or unfavourable attitudes towards behaviour, service or product, 2) Social norm: refers to the perceived social pressure for engaging or not engaging in a behaviour, and 3) Perceived behavioural control refers to how easy or difficult performing a specific behaviour (Ajzen, 1991; Ajzen, 2002; Chen and Chao, 2011).

The literature provides solid evidence that public transit use is highly influenced by users' behavioural and attitudinal aspects (Lai and Chen, 2011; Fu and Juan, 2017; Fu et al., 2018). Previous studies emphasized the importance of subjective psychological factors such as attitudes towards public transit (Zhao et al., 2013; Susilo and Cats, 2014; Eldeeb and Mohamed, 2020a), subjective/social norm (Fu and Juan, 2017), perceived behavioural control (Fu and Juan, 2017; Eldeeb and Mohamed, 2020b), travel habits and previous experience (Susilo and Cats, 2014; Fu and Juan, 2017), private vehicle use habit (Şimşekoğlu et al., 2015), and public transit image (van Lierop and El-Geneidy, 2018) in predicting public transportation use behaviour and forming users' overall satisfaction towards service quality.

For example, Fu and Juan (2017) examined how a group of psychological factors affect public transit use behaviour in Shaoxing City, China. They concluded that travel habits and social norms are the most significant predictors of public transit use behaviour. Furthermore, individuals' past travel experience and travel-related attitudes are proved to highly influence their travel satisfaction (Susilo and Cats, 2014). Another research by Şimşekoğlu et al. (2015) concluded that habitual private vehicle use is negatively associated with public transit use. For attitudes, positive attitudes towards public transit service and its attributes are associated with higher public transit mode choice as advocated by (Zhao et al., 2013; Eldeeb and Mohamed, 2020a). For service image, van Lierop and El-Geneidy (2018) affirmed the strong relationship between public transit image and users' loyalty and intention of use.

In this respect, the literature emphasizes the significance of the subjective psychological factors in shaping individuals' public transit use behaviour and their overall satisfaction towards the service. Nevertheless, the role of subjective psychological factors in shaping individuals' preferences towards public transit service attributes is yet to be sufficiently investigated. Further, the interrelationships between individuals' socioeconomic characteristics and their attitudinal and behavioural attributes are also worth investigating.

Reaching that target, this study aims at: 1) Investigating how subjective psychological factors (i.e., attitudinal and behavioural attributes) of potential transit users affect their perceptions towards utilitarian public transit service attributes, and 2) Examining the association between potential users' socioeconomic attributes and their transit-related subjective psychological tendencies. In the present study, we investigate the role of five subjective psychological aspects in shaping transit service desired quality from potential users' perspectives, namely: Car Reliance, Transit Stigma, Perceived Behavioural Control, Social Norm, and Environmental Consciousness. The study utilizes an Error components logit model with systematic taste variation along with factor analysis and multivariate analysis of variance to achieve the aforementioned objectives.

5.4 Data and Survey Instrument

The paper utilizes a primary dataset elicited from an online survey. The survey was part of Hamilton Street Railway (HSR) Public Engagement efforts in the City of Hamilton, Ontario, Canada. HSR is the municipal public transit provider for the City of Hamilton and provides a service coverage area of 243 square kilometres through 35 regular bus routes (City of Hamilton, 2020). The general purpose of the survey is to benchmark the service quality provided by HSR based on Hamiltonians' preferences and expectations. As mentioned in (Eldeeb et al., 2019), the survey is designed for both current and potential transit users and structured in four independent sections; 1) Socioeconomic demographic characteristics and travel behaviour, 2) Stated Preference (SP) experiments, 3) Service quality aspects, and 4) Attitudinal and behavioural characteristics.

This paper focuses on HSR potential users' transit service desired quality. Towards that end, the paper utilized the unlabelled SP experiment, socioeconomic attributes, and attitudinal and behavioural (subjective psychological) characteristics components of the survey. The total number of respondents who answered the online survey by April 2019 was 5781 Hamiltonians. However, the total number of potential HSR users who provided valid answers to the whole four sections of the survey is 1241 respondents.

The design of the SP experiment adopted a three-stage sequential process (i.e., model specification, experimental design, and questionnaire) for the selection of the attributes and their associated levels (Bliemer & Rose, 2006). The final list of attributes and the associated levels are presented in Table 5-1.

Table 5-1 Unlabeled SP experiment attributes and their associated levels (Eldeeb and Mohamed 2020a)

Service attributes	**Attribute levels**
One-way trip cost	\$3, \$4.5, and \$6
One-way trip travel time	20, 30, and 40 minutes
Walking time to and from the bus stop	0, 5, 10, and 15 minutes
Service headway	5, 10, 15, and 30 minutes
Number of transfers	0, 1, and 2 transfers
Real-time information	At-stop, on-board and none

The efficient experimental design approach was utilized to improve the statistical efficiency and maximize the amount of information extracted from the SP experiment (Kuhfeld et al., 1994). For the interested reader, a detailed description of the design process of the unlabelled SP experiment is introduced in (Eldeeb and Mohamed, 2020). Overall, the experimental design produced twelve scenarios grouped into three blocks. Each respondent faced four scenarios and chose an option from three unlabelled bus transit alternatives, as shown in Figure 5-1.

Trip & Service Attributes	Option - A	Option - B	Option - C
Bus Fare (one-way trip)	$ 3.00	$ 4.50	$ 3.00
Time Spent Travelling on Bus (one-way trip)	40 min	30 min	40 min
A Bus Departs from My Stop (at the start/end and transfer stops)	every 5 min	every 10 min	every 10 min
Walking Time to/from Bus Stop (includes walking time between transfer stops)	15 min	5 min	5 min
Number of Transfers Between Buses (during one-way trip)	2 Transfer	0 Transfer	1 Transfer
Real-time Trip Information (e.g. about delays)	None	At stop	On board
To Complete My Regular One-Way Trip, I would Choose	○	○	○

Figure 5-1 Example of a stated preference scenario (Eldeeb and Mohamed 2020a)

In addition to the SP experiment, the paper utilizes the attitudinal and behavioural components of the survey, where potential users were asked, as shown in Table 5-2, about their perceived behavioural control, attitudes, and social norm regarding public transit as well as their environmental orientation. Additionally, potential users were asked about their preferences, habits, and symbolic motives associated with car use. Well-established psychometric scales and studies were used to inform the development of the attitudinal and behavioural statements such as (Ajzen, 2013; Montgomery, 2002, Ersche et al., 2017), for TPB constructs (American Psychiatric Association, 2017), for car-preference and habitual use, and (Anable, 2005; Schuitema et al., 2013) for symbolic motives. Respondents were asked to assess their agreement on the accuracy of each statement on a 5-point Likert scale.

Table 5-2 The attitudinal and behavioural statements

Item	Statements	Mean	Std. D.
Car Reliance			

Item	Statements	Mean	Std. D.
Item 01	I choose my car for all my trips (work, leisure, shopping, visiting family, etc.)	3.218	1.506
Item 02	Even if transit is reliable, fast and free, I would continue using my car for most trips	2.136	1.302
Item 03	If I do not use my car for all my trips, I feel uncomfortable.	1.873	1.156
Item 04	I have been driving for a long time; I do not need to think about any other modes.	1.748	1.110
Environmental Awareness			
Item 05	I believe HSR should promote the use of electric buses to reduce Greenhouse Gases	3.940	1.123
Item 06	I am willing to use HSR if all buses are electric because I will help the environment	3.244	1.204
Social Norm			
Item 07	People around me think I should use transit for my commute.	2.239	1.208
Item 08	My close friends think I should use transit on a regular basis.	2.096	1.137
Item 09*	My colleagues at school/work are using transit for their commute.	2.615	1.354
Perceived Behavioural Control			
Item 10*	Finding routes and schedules for my trip does not require too much effort.	3.226	1.324
Item 11	It is easy to travel around the city using the HSR transit service.	2.911	1.234
Item 12	Transferring between routes is easy	2.981	1.097
Transit Stigma			
Item 13*	Transit is for those who are less fortunate than me.	1.811	1.115
Item 14	I would not want others to know that I use transit.	1.407	0.795
Item 15	I see driving as more fashionable.	1.924	1.188
Item 16	I express myself through my car.	1.642	1.070
Item 17	Transit is old fashion	1.457	0.836

* Items dropped due to low loading values.

The distribution of the considered sample (1,241 potential HSR users) is shown in Table 5-3. The sample represents females by 56% and males by 41.42%, while the percentage of gender self-identified (e.g., agender, non-binary, prefer not to answer) respondents is 2.58%. Respondents from 30 to 59 years old (i.e., middle-aged) are the most represented (60.03%), while the representation of respondents from 15 to 30 years old and over 60 years old is 20.79% and 19.18%, respectively. The sample represents full-time employees by around 53%, part-time employees by 8.14%, and students by 10.23%. For vehicle ownership, respondents with two or more vehicles are about 52%, while respondents without private vehicles are only 8.86%.

Table 5-3 Sample distribution

Category	Sub-Category	Sample (%)
Total	Total	1241 (100%)
Gender	Male	514 (41.42%)
	Female	695 (56.00%)
	Self-identity	32 (2.58%)
Age	15 to 30 years old	258 (20.79%)
	30 to 59 years old	745 (60.03%)
	Over 60 years old	238 (19.18%)
Employment Status	Full-time	659 (53.10%)
	Part-time	101 (8.14%)
	Student	127 (10.23%)
	Others	354 (28.53%)
Vehicle ownership	Zero vehicle	110 (8.86%)
	One vehicle	487 (39.24%)
	Two or more	644 (51.89%)

5.5 Methodology

First, this study utilizes an Error Components (EC) with systematic taste variations model and Factor Analysis (FA) to explore the role of subjective psychological aspects and socioeconomic attributes in shaping potential users' preferences towards transit service desired quality. The EC model with systematic taste variations estimates the bearing of each service attribute on the overall transit utility, with respect to the considered psychological and socioeconomic attributes, while accounting for the panel effect due to the SP experiment.

The EC model is a Mixed Logit (ML) model with fixed coefficients and error components (McFadden and Train, 2000). The EC model utilizes the Random Utility Maximization (RUM) theory (Ben-Akiva and Lerman, 1985; McFadden, 1998), which assumes a rational decision-making process where an individual i, picks the choice j, that maximizes their utility U_{ijt}, in the choice situation, t:

$$U_{ijt} = \beta X_{ijt} + \eta_{ijt} Y_{ijt} + \varepsilon_{ijt} \tag{5-1}$$

Where X_{ijt} is the observable component of the utility function, which is a vector of explanatory variables, and β is a vector of estimated fixed parameters. While η_{ijt} is a vector of random elements with a distribution with zero mean and Y_{ijt} is a vector of unknown attributes. And ε_{ijt} is the error term, which is assumed to be identically and independently distributed (IID). The explanatory variables include the SP experiment attributes as well as attitudinal and socioeconomic characteristics as interaction terms. This approach adopts the systematic taste variations specification suggested by (Rizzi and Ortúzar, 2003; Ortúzar and Willumsen, 2011). The unconditional choice probability, as mentioned in (Hensher and Greene, 2003), for individual i, selecting a choice j, based on the EC formulation, is expressed as follows:

$$P_{ij} = \int \prod_{t=1}^{T_q} \left[\frac{e^{\beta X_{ijt} + \eta_{ijt} Y_{ijt}}}{\sum_{j=1}^{J} e^{\beta X_{ijt} + \eta_{ijt} Y_{ijt}}} \right] f(\eta)\, d(\eta) \tag{5-2}$$

The EC model is estimated using a range of Modified Latin Hypercube Sampling (MLHS) draws (e.g. 100, 500, 1000, 2000) using Pandas Biogeme (Bierlaire, 2018). The MLHS outperforms other types of Quasi-random number sequences, such as Halton draws (Hess et al., 2006).

For Factor Analysis (FA), it is a statistical technique used to describe the underlying structure among observed variables (i.e., attitudinal and behavioural statements) in terms of a fewer number of latent (unobserved) variables with a minimal information loss (Hair et al., 2010; Mohamed and Bromfield, 2017). The FA's primary purpose is to condense the information obtained from the attitudinal and behavioural statements into a precise number of latent variables (factors) that could be used in subsequent analysis. The Maximum Likelihood (ML) extraction method was used along with the Promax method for oblique rotation. The validity of the Exploratory Factor Analysis (EFA) is assessed using the cumulative variance explained, Kaiser-Meyer-Olkin (KMO), Bartlett's test of sphericity, and Cronbach's alpha (Hair et al., 2010; Field, 2013). Then, a Confirmatory Factor Analysis (CFA) is conducted to further validate and confirm the structure of the developed constructs using Average Variance Explained (AVE) as a measure of convergent validity ($AVE \geq 0.5$), squared inter-correlation between constructs less than AVE as a measure of discriminant validity, and Construct Reliability as a measure of internal consistency ($CR \geq 0.7$) (Hooper et al., 2008; Mohamed et al., 2016).

The factor scores resulted from the FA are used as explanatory variables, in an interaction terms form, in the EC interaction model. The use of latent variables as interactions helps to investigate how latent variables affect the preferences towards service attributes (Raveau et al., 2010; Tudela et al., 2011; Fernández-Antolín et al., 2016).

Second, the study utilizes a multivariate analysis of variance (MANOVA) to investigate the statistical differences in the latent variables (i.e., subjective psychological constructs) with respect to the socioeconomic attributes. MANOVA could be seen as a repeated univariate analysis of variance (ANOVA) with multiple continuous dependent variables (Hair et al., 2010; Field, 2013; Mahmoud and Hine, 2013). In our case, a full factorial MANOVA was carried out to simultaneously examine statistical differences on multiple dependent latent variables (i.e., car reliance, transit stigma, social norm, perceived behavioural control, environmentally consciousness) with reference to multiple independent grouping variables (i.e., vehicle ownership, age, education, gender, employment status) as well as their interactions.

5.6 Modelling Results

A statistically validated factor analysis (FA) was conducted to identify and enhance the structure of the considered psychological constructs associated with HSR potential users' travel behaviour. The KMO measure of sampling adequacy is 0.762, and Bartlett's test of sphericity is significant ($p \leq 0.0001$), which confirms the validity of the factor analysis (Kaiser, 1974; Field, 2013). The factors pattern matrix (variable loading) is presented in Table 5-4.

Table 5-4 The pattern matrix of the Exploratory Factor Analysis (EFA)

Statement	**Factors**				
	Car Reliance	Transit Stigma	Social Norm	PBC	Environmental Consciousness
Item 04: I have been driving for a long time; I do not need to think about any other modes.	0.808				
Item 03: If I do not use my car for all my trips, I feel uncomfortable.	0.767				
Item 02: Even if transit is reliable, fast and free, I would continue using my car for most trips	0.728				
Item 01:I choose my car for all my trips (work, leisure, shopping, visiting family, etc.)	0.569				
Item 15: I see driving as more fashionable.		0.811			
Item 14: I would not want others to know that I use transit.		0.673			
Item 17: Transit is old fashion.		0.642			
Item 16: I express myself through my car.		0.603			
Item 08: My close friends think I should use transit on a regular basis.			0.908		
Item 07: People around me think I should use transit for my commute.			0.863		
Item 11: It is easy to travel around the city using the HSR transit service.				0.906	
Item 12: Transferring between routes is easy				0.735	
Item 06: I am willing to use HSR if all buses are electric because I will help the environment					0.929
Item 05: I believe HSR should promote the use of electric buses to reduce Greenhouse Gases					0.663

* Coefficients below the 0.3 level were suppressed.

The CFA model supports the structure of the considered psychological factors in terms of convergent validity, discriminant validity and construct reliability. As shown in Table 5-5, for all phycological constructs, the attitudinal and behavioural statements have Cronbach's alpha and Construct Reliability greater than 0.70, which indicates internal consistency for the developed latent constructs (Hair et al., 2010). The average shared variance (AVE) is greater than 0.5 for all constructs except for the transit stigma construct (0.482), and the square root of AVE is higher than the inter-correlation between constructs. The factor scores of the developed latent variables are used as explanatory variables in the EC interaction model.

Table 5-5 Confirmatory Factor Analysis (CFA) Validity Examinations

	Cronbach's Alpha	CR	AVE	MSV	Car Reliance	Transit Stigma	Social Norm	PBC	Environ. Conscious.
Car Reliance	0.803	0.817	0.529	0.326	0.728				
Transit Stigma	0.776	0.788	0.482	0.326	0.571	0.694			
Social Norm	0.872	0.876	0.780	0.127	-0.356	-0.098	0.883		
PBC	0.791	0.794	0.659	0.033	-0.181	-0.095	0.161	0.812	
Environ. Consciousness	0.749	0.748	0.598	0.071	-0.267	-0.171	0.214	0.107	0.773

* CR: Construct Reliability, AVE: Average Variance Explained, and MSV: Maximum Shared Variance.

The EC model with systematic taste variations was developed to investigate how psychological and socioeconomic attributes influence potential users' preference towards public transit service attributes. Table 5-6 presents the estimation results of 1) Base EC model, 2) EC model with socioeconomic interactions (EC-SED), and 3) EC model with both psychological and socioeconomic interactions (EC-Inclusive).

Without any interactions and considering only service attributes, a base EC model was developed with a –4915.70 log-likelihood at convergence. Table 5-6 shows only the statistically significant parameters at, at least, a 90% confidence level. The error component does not prove to be significant; however, it is retained as a precautionary measure to account for the panel effect.

The EC-SED and EC-Inclusive models show a statistically significant improvement, at a 99% confidence level, over the base EC model regarding goodness-of-fit measures (likelihood ratio test of 142.80 with 21 degrees of freedom for the EC-SED model, and likelihood ratio test of 236.12 with 25 degrees of freedom for the EC-Inclusive model). In the same way, the EC-Inclusive model shows a statistically significant improvement, at a 99% confidence level, over the EC-SED model with a likelihood ratio test of 93.32 and 4 degrees of freedom which validates the inclusion of subjective psychological factors to the EC-SED model.

Table 5-6 Error Components interaction model estimation

Variable	**Base EC**	**EC-SED**	**EC-Inclusive**
Journey time	-0.0442***	-0.0275***	-0.0274***
Journey time × Age 30 to 60	—	-0.0191***	-0.0200***
Journey time × Age 15 to 30	—	-0.0293***	-0.0296***
Trip fare	-0.3830***	-0.3620***	-0.4170***
Trip fare × Full-time	—	0.1060**	0.1110***
Trip fare × Age 15 to 30	—	-0.1940***	-0.1700***
Trip fare × One-vehicle	—	-0.1090***	—
Trip fare × Car-reliance	—	—	0.0625***
Trip fare × PBC	—	—	-0.1050***
Walking time	-0.0243***	-0.0225***	-0.0208***
Walking time × Age 15 to 30	—	-0.0233**	-0.0253**
Walking time × Zero-vehicle	—	0.0280**	—
Walking time × Environ. Consciousness	—	—	0.0093**
Service headway	-0.0335***	-0.0172***	-0.0205***
Service headway × Age 30 to 60	—	-0.0153**	-0.0132**
Service headway × Age 15 to 30	—	-0.0161*	-0.0145*
Service headway × One-vehicle	—	-0.0109**	-0.0091*

Variable	Base EC	EC-SED	EC-Inclusive
Service headway × Car-reliance	—	—	0.0053**
Number of transfers (2-transfers base-category)			
One transfer	0.9360***	0.8430***	0.8550***
One transfer × Full-time	—	0.1730*	0.1660*
One transfer × Self-identity	—	0.8330**	0.8080**
Zero transfer	1.5100***	1.4200***	1.400***
Zero transfer × Full-time	—	0.3650***	0.3480***
Zero transfer × Male	—	-0.1350*	-0.1380*
Zero transfer × Self-identity	—	0.7190**	0.6280**
Zero transfer × Zero-vehicle	—	-0.4310***	—
Zero transfer × PBC	—	—	-0.1010**
Zero transfer × Social norm	—	—	-0.1070***
Real-time information (No info. base-category)			
Real-time information On-board	0.3280***	0.3250***	0.3300***
Real-time information On-board × Self-identity	—	0.5620***	0.5480***
Real-time information At-stop	0.2340***	0.1470***	0.1570***
Real-time information At-stop × Part-time	—	-0.2430**	-0.2700**
Real-time information At-stop × Student	—	-0.3600*	-0.3190*
Real-time information At-stop × Age 15 to 30	—	0.3030***	0.2670***
Real-time information At-stop × One-vehicle	—	0.1520**	0.1240*
Real-time information At-stop × Environ. consciousness	—	—	0.0708*
Error Component (EC)	0.0061	-0.0077	-0.0066
Log-Likelihood	**-4915.700**	**-4844.30**	**-4797.64**
Rho-squared	**0.0986**	**0.1120**	**0.1200**

No. of respondents = 1,241 and No. of observations = 4,964 & Note: ***, **, and * indicate significance at 1%, 5%, and 10% levels

The results show that, in general, HSR potential users: 1) prefer, ceteris paribus, shorter journey times, shorter walking times, lower fares, and higher service frequencies, 2) appreciate real-time information provision, and 3) express a high preference for direct trips (i.e., zero transfer) over multiple transfers-based trips.

For SED characteristics, old respondents (i.e., over 60 years old) are less sensitive to journey time and service headway than young (i.e., 15 to 30 years old) and middle-aged (30 to 60 years old) respondents. While young respondents are the most sensitive to trip fare and walking time to/from bus stops, and they prefer at-stop real-time information provision more than others. Gender self-identified, and female respondents have higher preferences towards direct trips than male respondents. Also, gender self-identified respondents appreciate on-board real-time information provision than others.

Full-time employees are less sensitive to trip fare compared to others, while they have higher preferences towards direct trips (i.e., reducing the number of transfers). Students and part-time employees are less sensitive to at-stop real-time information provision than full-time employees. Respondents with one vehicle prefer at-stop real-time information and higher service frequencies than others. Moreover, according to the EC-SED, Respondents with zero vehicles are less sensitive to walking time and number of transfers than others. In contrast, respondents with one vehicle are more sensitive to trip fare. It is worth noting that those interactions come to be insignificant when the attitudinal variables were introduced in the EC-Inclusive model, which confirms the importance of the subjective psychological factors in explaining respondents' preferences. This behaviour is worth more investigation as it implies a possible association between private vehicle ownership and shaping people's perception of public transit.

Regarding the subjective psychological factors, respondents with high car reliance are less sensitive to trip fare and service frequency than other respondents. Potential transit users with high perceived behavioural control (PBC) are less sensitive to the number of transfers while more sensitive to trip fare than others with low PBC towards transit. Environmentally conscious respondents are less sensitive to walking time and have higher preferences to at-stop real-time information provision than others with low environmental consciousness. Moreover, potential users with high social norm attitudes towards transit are less sensitive about the number of transfers than others with low social norm attitudes. It is noteworthy that transit-stigma does not prove significant in explaining potential users' preferences towards the considered service attributes.

5.7 How attitudes and SEDs are linked?

The results of the EC interaction models indicated that some SED's interactions became statistically insignificant once the subjective psychological factors were introduced in the model. This behaviour validates the importance of the attitudinal and behavioural variables in explaining respondents' heterogeneity and suggests possible interdependencies between socioeconomic attributes and subjective psychological factors, which calls for further investigation.

Therefore, the variations on the five considered latent variables across various socioeconomic attributes (i.e., vehicle ownership, age, education level, employment status, and gender) were assessed through MANOVA, as shown in Table 5-7.

The validity of the MANOVA was assessed using several multivariate test statistics such as Pillai's Trace and Wilks' Lambda, Hotelling's Trace, and Roy's Largest Root. It is worth noting that the Box's Test statistic is significant, which indicates a violation of the assumption of homogeneity of the variance-covariance matrices; however, this might be attributed to the large sample size as advocated by Field, (2013). A bootstrap of 2000 random samples was performed to validate the robustness of the estimates. The results confirmed statistically significant differences in the considered latent variables across three socioeconomic attributes, namely: vehicle ownership, age and education level. The distribution of the latent psychological variables across significantly grouping socioeconomic attributes is presented in Figure 5-2.

Table 5-7 Multivariate Analysis of Variance by SEDs

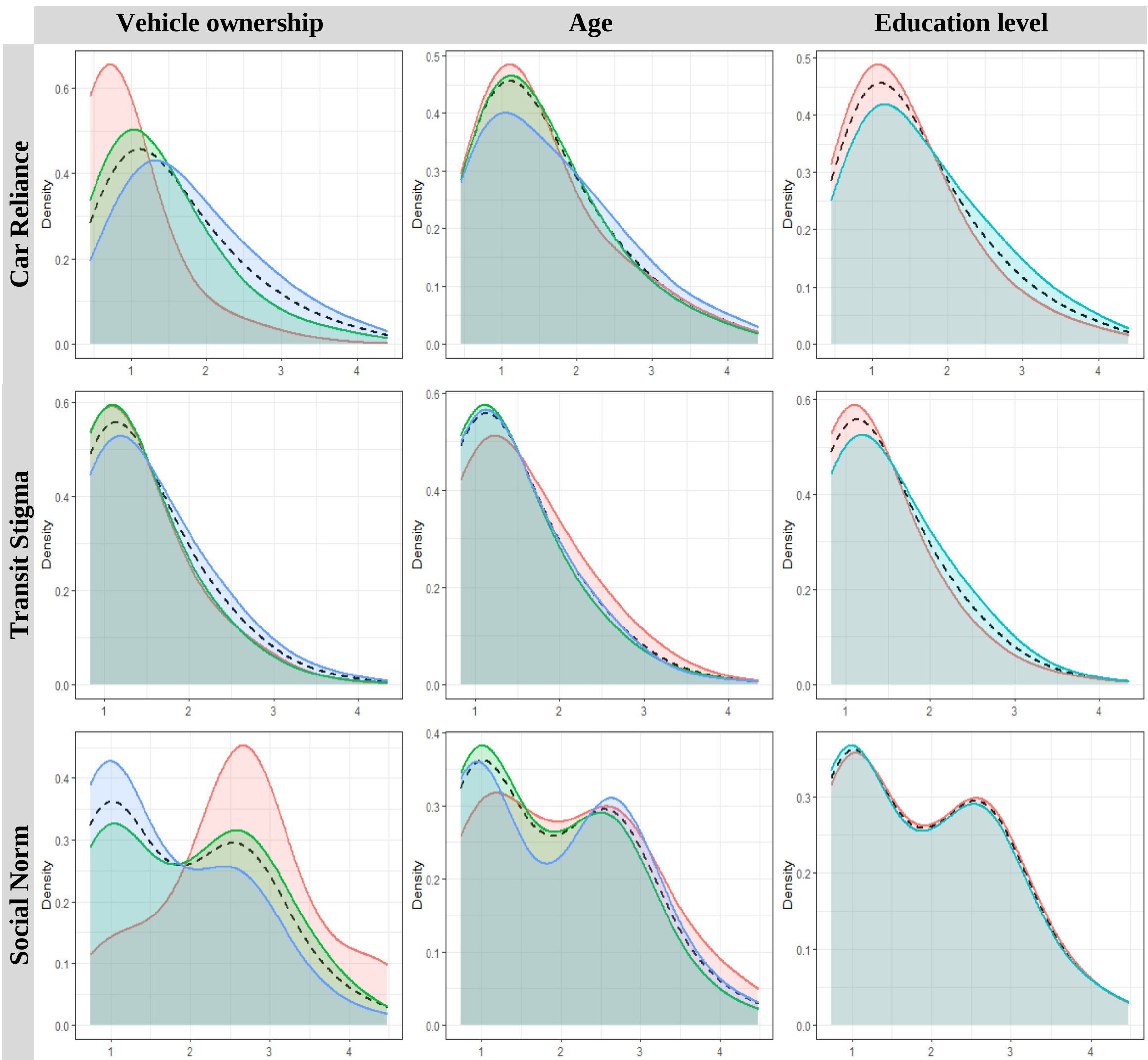
Independent variable	Dependent variable	Significance
Vehicle ownership	Car Reliance	0.000
	Transit Stigma	0.000
	Social Norm	0.000
	Perceived Behavioural Control	0.000
	Environmental Consciousness	0.000
Age	*Car Reliance*	*0.186*
	Transit Stigma	0.000
	Social Norm	0.001
	Perceived Behavioural Control	*0.416*
	Environmental Consciousness	0.000
Education	Car Reliance	0.000
	Transit Stigma	0.000
	Social Norm	*0.377*
	Perceived Behavioural Control	0.000
	Environmental Consciousness	*0.060*
Age × Education	Car Reliance	0.000
	Transit Stigma	*0.286*
	Social Norm	*0.056*
	Perceived Behavioural Control	*0.622*
	Environmental Consciousness	0.027

The analysis shows that all subjective psychological factors are highly sensitive to vehicle ownership, indicating a strong correlation between private vehicle ownership and people's perception towards public transit. Additionally, this finding calls into question the possible causality between private vehicle ownership and perceptions towards public transit service attributes. As shown in Figure 2, zero vehicle ownership is associated with the highest social norm and perceived behavioural control towards transit as well as high environmental consciousness. In contrast, two-vehicle ownership is associated with the highest car reliance and transit stigma attitudes. It is worth mentioning that zero vehicle ownership is associated with higher transit stigma than in the case of one vehicle ownership.

For potential users' age, the results show that age is a significant clustering variable for transit stigma, social norm towards transit, and environmental consciousness latent variables. This implies a strong correlation between age and those latent psychological variables. For instance, young respondents (Gen-Z) have the highest social norm towards transit and, interestingly, the highest transit stigma. They also have the highest environmental consciousness attitudes, while middle-aged respondents (Millennials and Gen-X) have the lowest. It is worth mentioning that car reliance attitude and perceived behavioural control towards transit are not sensitive to age.

With respect to education, the analysis shows that car reliance, transit stigma and perceived behavioural control towards transit are sensitive to education level. Figure 5-2 shows that respondents with university/college degrees have lower car reliance, transit stigma, and perceived behavioural control towards transit than others. It is worth pointing out that social norms towards transit and environmental consciousness are not associated with the education level.

The significant interactions between age and education level show that car reliance and environmental consciousness are sensitive to the six groups of combinations of young, middle-aged, and old respondents with and without university/college degrees. In other words, we can conclude that significant differences in car reliance and environmental consciousness across age are dependent on the education level. In contrast, differences in transit stigma and social norm latent variables across age are not dependent on education levels, and differences in perceived behavioural control across educational levels are not dependent on age.



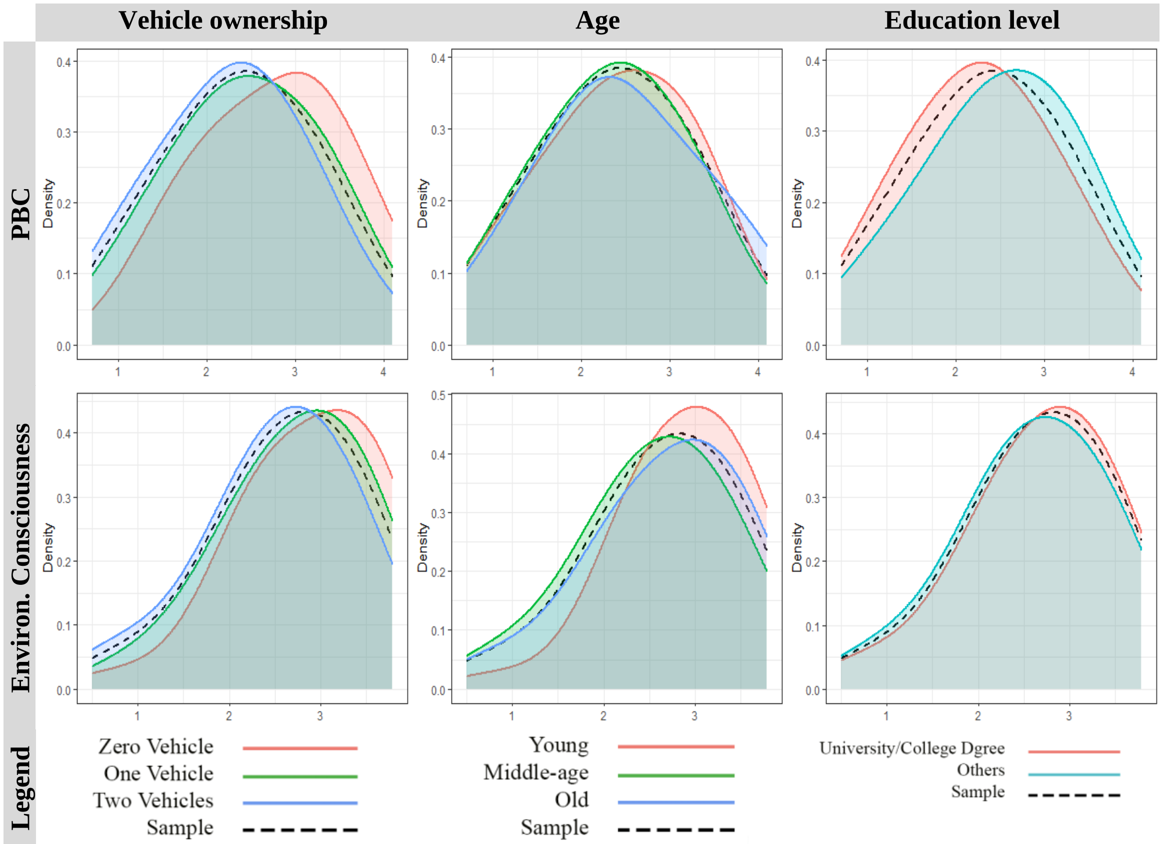


Figure 5-2 The distribution of the latent variables across SED attributes

It should be noted that the MANOVA results highlight the exitance of significant variations between different SEDs across the five laten construct. However, the model should not be interpreted in terms of causality. The key messages of the MANOVA results are 1) There is indeed a significant variance in the subjective phycological orientation of different SEDs groups, and 2) This variation is manifested across age, education, and vehicle ownership spectrums.

5.8 Discussion and Conclusions

The study aimed to investigate how potential users' subjective psychological factors affect their perception of public transit service attributes and examine the association between potential users' socioeconomic attributes and subjective psychological aspects. The study utilized a dataset of 1,241 potential transit users elicited from an online survey that was part of Hamilton Street Railway's (HSR) public engagement efforts. The study employed an Error Components (EC) logit model with systematic taste variations along with Factor Analysis (FA) to explore the role of subjective psychological aspects and socioeconomic attributes in shaping potential users' preferences towards transit service desired quality. In addition, the study utilized a multivariate analysis of variance (MANOVA) to investigate the statistical differences in the subjective psychological aspects across socioeconomic attributes. The study examined the influence of Car Reliance, Transit Stigma, Perceived Behavioural Control, Social Norm, and Environmental Consciousness in shaping potential users' transit service desired quality.

The results of the EC-Inclusive model show that young potential transit users are more sensitive to trip fare and walking time to/from bus stops more than middle-aged and old potential users. Moreover, young respondents appreciate at-stop real-time information provision more than others. The results are aligned with the results of (de Oña and de Oña, 2015; de Oña, 2021), which indicates that young customers have a higher sensitivity to trip fare and information provision than other age groups. Gender self-identified, and female potential users have higher preferences towards direct trips than male potential users. This finding is supported by the work of (Allen et al., 2018), which concluded that females express less satisfaction with multiple-transfers-based trips. Full-time employees are less sensitive to trip fare and more appreciable to direct trips and at-stop real-time information provision than other potential users. Respondents with one vehicle prefer at-stop real-time information and higher service frequencies than others.

It is worth noting that the EC-SED model revealed the low sensitivity of potential users without access to a private vehicle to walking time to/from bus stops and the number of transfers per trip. However, this revelation became insignificant when the subjective psychological factors were introduced into the model. This behaviour affirms the importance of subjective psychological aspects in explaining preferences and indicates the possible association between socioeconomic attributes and subjective psychological aspects.

In regard to subjective psychological factors, potential users with high car reliance are less sensitive to trip fare and service frequency than potential users with low car reliance. In contrast, potential transit users with high perceived behavioural control (PBC) are less sensitive to the number of transfers and more sensitive to trip fare than others with low PBC towards transit. Moreover, potential users with high social norms towards transit are less sensitive to the number of transfers than others with low social norms.

For environmental consciousness, environmentally conscious potential users are less sensitive to walking time and have higher preferences to at-stop real-time information provision than others with low environmental consciousness. It is noteworthy that transit-stigma does not prove significant in explaining potential users' preferences towards the considered service attributes.

The results of the MANOVA confirm statistically significant differences in the considered subjective psychological latent variables across vehicle ownership, age, and education level attributes. For vehicle ownership, there is a strong correlation between vehicle ownership and all the considered subjective psychological latent variables. Potential users with zero vehicle ownership have the highest social norm and perceived behavioural control towards transit as well as the highest environmental consciousness. Potential users with two or more vehicles have the highest transit stigma attitudes.

Regarding age, MANOVA confirmed a significant correlation between potential users' age and their social norm towards transit, environmental consciousness, and transit stigma latent variables. This finding indicates a generational shift in transit attitude and calls for further analysis to profile the gaps/traits of different generations (e.g., boomers, Gen-X, millennials, and Gen-Z).

Young potential users have the highest social norm towards transit, and environmental consciousness attitudes, yet they have the highest transit stigma. With respect to education, the results show that the educational level of potential users is significantly associated with car reliance, transit stigma and perceived behavioural control towards transit. Potential users with university/college degrees have lower car reliance and transit stigma than others. Regarding the interaction between age and education level, we can conclude that statistically significant differences in car reliance, social norm, and environmental consciousness across potential users' age are dependent on their education level. Based on the findings of this research, several key remarks are concluded:

For scholars, the study clearly demonstrates the impacts of subjective psychological orientation on the utilitarian preferences of transit service quality. This finding opens the gate for future studies to investigate the joint, mediated and directional relationship between these two dominant measures.

For policymakers, the findings highlight the existence of significant differences between generations in their subjective psychological tendencies and their assessment of transit service quality. Potential transit quality improvement policies must acknowledge this variation and enable policies that appeal to the unique requirements of each group.

Lastly, transit agencies should put more emphasis on investigating the subjective psychological factors of their customers because of the decisive role they play in shaping public transit customers' perception towards conventional transit service attributes (e.g., travel time and service frequency). Equipped with a better comprehension of their potential customers' subjective psychological attributes, transit agencies should tailor their marketing and improvement plans. More importantly, they can pinpoint the underlying causes behind potential users' reluctance to use transit.

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CHAPTER 6

Built for active travel?
Investigating the contextual effects of the built environment on transportation mode choice

Preamble

This chapter focuses on the eighth and ninth objectives of the dissertation. The chapter examines the role of the built environment attributes and their contextual effects on travel behaviour. A Nested Logit (NL) model and a quadratic polynomial trend surface were utilized to spatially examine the influence of built environment on travel behaviour while accounting for socioeconomic characteristics. The chapter explains how city geography moderates the impact of built environment attributes on mode choice behaviour.

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6.1 Abstract

The study investigates the role of the built environment attributes and their contextual effects on travel behaviour. The study utilized a dataset of 4,739 respondents elicited from an online survey distributed in Hamilton City, Canada. A Nested Logit (NL) model and a quadratic polynomial trend surface are employed to spatially investigate the determinants influencing mode choice behaviour. The study contributes to our understanding of how geography moderates the impact of built environment attributes on mode choice behaviour. Socioeconomic demographics are found to play a pivotal role in explaining Hamiltonians' mode choice behaviour. For built environment attributes, sidewalk density is positively associated with walking and public transit use. Moreover, bike lane density is positively associated with biking and negatively associated with public transit use. Regarding land-use entropy (mix), the results show that high land-use entropy is negatively associated with choosing the car as a passenger travel mode. From a contextual perspective, the results affirmed that the influence of built environment attributes is not equally efficacious across the city. Improving the built environment attributes across the city reveals a substantial increase in walking and biking while decreasing the probability of choosing other modes. However, it is noteworthy to mention that the influence of improving the built environment is not homogeneous over geography.

6.2 Introduction

Understanding transportation mode choices is of utmost importance to plan efficient, sustainable, and safe mobility in our cities. An efficient and well-harmonized urban transportation system is a fundamental building block in making our urban communities environmentally sustainable and economically viable. Transportation is responsible for approximately 25% of greenhouse gas (GHG) emissions in Canada and globally (Natural Resources Canada, 2020), and much of this is attributed to motorized road transportation. Urban areas are often associated with a higher percentage of GHG emissions due to their demographic weight, reduced speeds, and traffic congestion (Urban Mobility Task Force, 2020).

The factors that influence mode choices cover a broad spectrum of disciplines, including geography, economics, and social psychology (De Witte et al., 2013; van Acker et al., 2010). Generally, these factors could be broadly classified into four main categories: 1) socioeconomic and demographic characteristics; 2) trip and travel modes characteristics; 3) spatial and built environment aspects; and 4) attitudinal and psychological factors (Buehler, 2011; De Witte et al., 2013; Foth et al., 2014, Eldeeb et al., 2015). That said, the relevance of the various determinants used to explain mode choice behaviour depends on the research context. From the geographical and planning perspectives, for example, there has been much interest in the role of the built environment in influencing the use of different modes since this aspect is a key modifiable component for encouraging modal shift (e.g., Cervero, 2002; Chen et al., 2008; Ding et al., 2017).

The relationship between the built environment and travel behaviour has been extensively researched, increasingly with a focus on active travel (e.g., Rodríguez and Joo, 2004; van Acker et al., 2013; Khan, et al., 2016; Aziz et al., 2018; Cheng et al., 2019; Martín and Páez, 2019). However, as research using spatial analytical approaches makes clear, it is possible that relationships between covariates are non-stationary over space

(Cheng et al., 2019; Liu et al., 2016; Páez, 2006). In this research, we study the built environment's role on mode choice and investigate its contextual (spatial) effects across an urban area. Succinctly, our research question is: does infrastructure for travel influence mode choice uniformly in a region, or are there variations in the dose-response relationship?

Adopting a spatial analytical approach enables the capturing of the geographical nature of transportation systems, including behavioural variations over space (Loidl et al., 2016; Páez and Scott, 2004). We aim to investigate the impacts of built environment attributes, Socioeconomic and demographic (SED) characteristics on mode choice. Furthermore, the spatial expansion method is used to quantify the spatial variation of the impacts of built environment attributes on mode choice. In this way, the study contributes to our understanding of the extent to which city geography moderates the impact of built environment attributes on mode choice while considering SEDs traits.

The research is based on a case study (the City of Hamilton), which is part of the Greater Toronto and Hamilton Area, the largest metropolitan region in Canada. The analysis develops a Nested Logit (NL) model along with spatial expansion variables. The study utilizes a dataset of 4,739 respondents elicited from an online survey that was part of Hamilton Street Railway (HSR) Public Engagement efforts, weighted by mode to achieve a representative sample of the population of the region.

The analysis includes five main transportation modes, namely walk, bike, public transit, car as a driver, and car as a passenger. Additionally, the analysis incorporates a broad spectrum of socioeconomic demographic characteristics and built environment attributes (i.e., bike lanes density, sidewalks density, and land use mix). A geographical analytical approach allows us to obtain detailed spatial variations in the probability of choosing different modes of transportation.

After this brief introduction, section two provides some relevant background to this study. Next, we describe the data collection process, the dataset, and the modelling approach. Section four presents the results of the analysis, as well as the contextual variations of mode choice behaviour across Hamilton. Finally, section five provides a discussion and concluding remarks.

6.3 Background

Previous research has identified a host of factors that influence the use of different modes of transportation. First, socioeconomic demographic (SED) characteristics (e.g., age, gender, employment status, income, car ownership) influence travel mode selection. In some cases, SEDs are the only statistically significant determinant of mode choice behaviour, as in the work of Nkeki and Asikhia (2019). Some SEDs are found to be more critical and commonly significant for mode choice behaviour than others. For instance, income and car ownership are the most important determinants affecting mode choice among SED characteristics (Limtanakool et al., 2006; Nurul Habib et al., 2009; Yu et al., 2018; Aziz et al., 2018; Srinivasan et al., 2019), where the probability of driving a private vehicle increases with the increase of income and number of vehicles per household and vice versa.

Second, trip characteristics (e.g., trip type, distance, departure and return times, weather conditions) and travel mode characteristics (e.g., travel time, cost, comfort, reliability) have profound impacts on mode choice. Travel cost and travel distance/time are the most studied factors compared to other characteristics (Ton et al., 2019). For example, long travel distance is highly associated with the selection of motorized travel modes (Sun et al., 2017). In contrast, the probability of active travel modes (i.e. Walking and Biking) diminishes when the travel distance increases (Muñoz et al., 2016; Winters et al., 2017). Additionally, weather conditions are important but not extensively studied in the literature. Moderate (i.e. dry and warm) weather conditions are positively affecting the use of active travel modes, while cold and hot weather adversely impacting active travel modes (Böcker et al., 2013; Wang et al., 2016). Moreover, Spinney, et al. (2019) proved that weather conditions along with travel distance influence children's mode choice to/from the school.

Third, spatial and built environment aspects explain the characteristics of the environment where the travel takes place. Those aspects include 1) Transportation infrastructure, such as roads network, sidewalks, bike lanes, public transit network, and parking availability (Santos, et al., 2013; Ferrer and Ruiz, 2018; Cheng et al., 2019), 2) Land use pattern, such as residential, industrial, and mixed land use (Litman, 2010), and 3) Geographical (spatial) variations, such as distance to the central business district (Morency et al., 2011; Martín and Páez, 2019). The broad spectrum of the built environment characteristics and their relation with travel behaviour could be condensed, albeit not conclusively, by the five Ds variables (i.e. Density, Diversity, Design, Destination, Distance to Transit) proposed by (Cervero and Kockelman, 1997; Ewing and Cervero, 2001). The relationship between travel behaviour and built environment characteristics is extensively investigated in the literature (Nkeki and Asikhia, 2019). However, the literature falls short on reaching a consensus regarding the impacts of different built environment variables on mode choice behaviour (Ewing and Cervero, 2010; Ding et al., 2017).

Fourth, psychological aspects are latent (i.e. unobserved) variables in nature, see Hair et al., (2010) for more information, that influence individuals' mode choice behaviour such as habits, previous experience, lifestyle, and attitudes (Anable, 2005; Mohamed et al., 2016; Mella Lira and Paez, 2021). Psychological aspects have a profound effect on mode choice behaviour and on how individuals perceive different service attributes (Fishbein and Ajzen, 1975; Ajzen, 1991; Ben-Akiva et al., 1999; Fujii and Kitamura, 2003). For instance, the influence of habitual behaviour is argued to override a rational travel mode choice in favour of a suboptimal one (Goodwin, 1977; Banister, 1978; Verplanken et al., 1997). Additionally, the work of Fatmi and Habib (2017) affirmed that people have a high tendency to preserve their past/familiar travel modes. Although frequently reported significant, psychological aspects are under-researched compared to other determinants of mode choice (De Witte et al., 2013), which might be attributed to the challenges of forecasting these aspects.

The dissensus in the impact of different mode choice determinants could be attributed to, among others, different contexts, modelling approaches, geographical scale, and the nonlinear effects of built environment attributes (Ding et al., 2017; Ding et al, 2018; Cheng et al., 2020). For instance, in the case of active travel modes, the high land-use mix is found to be a significant catalyst in Singapore (Mo et al., 2018), in Nanjing, China (L. Cheng et al., 2019), in Vitoria-Gasteiz, Spain (Martín and Páez, 2019), and in the Netherlands (Ton et al., 2019). While land-use mix, albeit significantly reducing travel time (Ewing and

Cervero, 2001; Ding et al., 2017), does not prove to be significantly affecting walking mode choice in Chengdu, China (Srinivasan et al., 2019), and in Shanghai, China (Wu et al., 2019).

Regarding active travel modes infrastructures, increasing sidewalk width and extending bike networks is found to increase the likelihood of using active travel modes in the San Francisco Bay Area, US (Kitamura et al., 1997), and in New York City, US (Aziz et al., 2018). Moreover, the existence of bicycle facilities is found to be associated with higher bicycle use in 13 US metropolitan areas (Le et al., 2019). Nonetheless, a study by Ton et al., (2019) in the Netherlands proved a limited relevance of active travel modes infrastructure (i.e. sidewalks and bike lanes) in explaining active travel mode choice. Additionally, the length of bike lanes was not found to correlate with daily bike trips in the City of Hamilton, Canada (Scott and Ciuro, 2019).

Active travel modes tend to be more popular near downtown (city centres with concentrated land uses) than in rural and suburban areas where land uses are dispersed (Schwanen et al., 2001). Distance to CBD is proved to be a significant predictor of mode choice and positively affects walking and biking travel volumes (Yang et al., 2017; Nkeki and Asikhia, 2019; Scott and Ciuro, 2019; Martín and Páez, 2019). For more information regarding the impact of built environment attributes on active travel modes (i.e. Walking and Biking), the reader is referred to (Ewing and Cervero, 2001; Van Acker and Witlox, 2005; Wang et al., 2016). Table A-6-1 - Appendix A provides a summary of the studies mentioned above, their methodological approach, geographical context, and sample size.

In this regard, investigating how the built environment attributes influence mode choice behaviour on a context-specific approach is essential for policymakers to understand their residents' travel behaviour better. Therefore, this study contributes to the existing growing literature by investigating the role of the built environment and its contextual/spatial effects on mode choice in the City of Hamilton, Ontario, Canada.

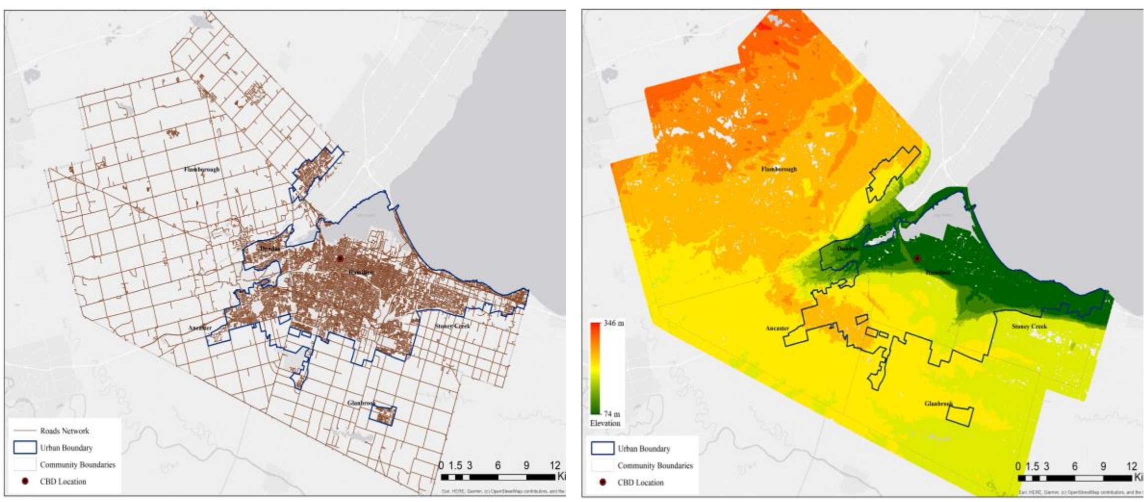
In the Hamilton context, Scott and Ciuro (2019) recently investigated the factors influencing bike sharing ridership in the City of Hamilton and affirmed that weather conditions and temporal aspects affect bike ridership significantly. While the mode choice analysis of McMaster University students in Hamilton shows that their travel behaviour is affected by cost, attitudes, street density and sidewalk density, as reported by (Whalen et al., 2013). Additionally, travel behaviour in Hamilton, reported by (Páez et al., 2007; Mercado and Páez, 2009; Roorda et al., 2010; Morency et al., 2011), shows a decrease in mobility when age increases along with a high degree of spatial heterogeneity in this behaviour.

6.4 Data and methods

6.4.1 Data description

The study utilizes a primary dataset collected through an online survey distributed in April 2019 and lasted for three months. The survey was part of the Hamilton Street Railway (HSR) Public Engagement efforts. HSR, the municipality-operated transit service, provides a service coverage area of 243 square kilometres through 35 regular bus routes. This is in addition to Disabled and Aged Regional Transportation System (DARTS) and Trans-Cab services (City of Hamilton, 2020).

The City of Hamilton, shown in Figure 6-1, is in the Golden Horseshoe at the west end of Lake Ontario. As of 2016, it had a population of around 747,545 people and covers an area of 1,372 square kilometres (Statistics Canada, 2017). The city consists of three main regions: 1) Lower city, which is located below the Niagara Escarpment and includes the downtown area, high density and old neighbourhoods, and McMaster University, 2) Upper city (mountain), which is located on top of the Niagara Escarpment and includes relatively new (post-war) developments and Mohawk College, and 3) Suburbs, which is composed of the former municipalities of Dundas, Ancaster, Stoney Creek, Glenbrook, and Flamborough. This study focuses on the urban area of the city, as shown in Figure 6-1.



(a) Road network (b) Elevation model

Figure 6-1 City of Hamilton Map; outlines show the area under examination

The general purpose of the survey was to benchmark the quality of HSR service based on users' preferences and expectations (Eldeeb and Mohamed, 2020b). The survey was designed for all Hamiltonians (i.e., both current and potential transit users) and structured in four sections: (1) Socioeconomic demographic characteristics and travel behaviour, (2) Stated Preference (SP) experiments, (3) Service quality aspects, and (4) Attitudinal and behavioural characteristics. This study focuses on Hamiltonians' travel behaviour. The respondents were asked: what is your primary travel mode during weekdays? The study also utilized respondents' geographic location and socioeconomic characteristics components of the survey. Furthermore, the surrounding built environment characteristics associated with each respondent were estimated. For more information about the survey, the reader is referred to (Eldeeb et al., 2019; Eldeeb and Mohamed, 2020a; Nikel et al., 2020).

Overall, the survey includes a sample of 5,238 respondents with valid responses. The analysis in this study is based on the five travel modes: collectively, these five travel modes account for around 99% of all trips in Hamilton. Excluded travel modes due to their marginal use rates are carpooling, paid rideshares, institutional buses, and DARTS. The number of respondents who use the aforementioned five travel modes and agreed to report their six digits homes' postal codes is 4,739 (referred hereafter as the sample).

Socioeconomic and travel behaviour characteristics of the sample versus those of the City of Hamilton population are presented in Table 6-1. As seen in the table, the shares of the various modes are different in the sample compared to the population. This is a consequence of the sampling framework, which was stratified by mode to ensure that sufficient samples were obtained from HSR users.

For this analysis, we used a sample weighting approach to correct the nonproportional sampling. According to Lerman and Manski (1976), for the choice model to be representative, the sample and population distributions should fulfill the following condition:

$$P(i, X|\theta) = f(i, X|\theta) \tag{6-1}$$

where P and f are the population and sample characteristics, i is the individual's travel choice, X is a vector of the individual's characteristics, and θ is the model parameters. The sample was weighted using the "anesrake" raking algorithm (Pasek, 2018) to correct the nonproportional sampling based on established accurate population proportions for gender, age, and travel mode according to the Census of Canada. In this way, we were able to obtain a representative weighted sample of the population (fifth column in Table 6-1). The framework for calculating the sampling weights was the Census of Canada.

After weighting, we see that 11.84% of respondents use HSR as their primary mode of travel, while around 72.93% and 8.02% of respondents are drivers and passengers of private vehicles, respectively. Additionally, walking and biking are the main travel modes for 5.19% and 2.03% of the sample, respectively. The sample represents more females (49.74%) than males (47.79%) and also represents self-identity gender by 2.45%. A plurality of respondents, around 47.35%, are between 30 to 59 years old, while respondents over 60 years old represent nearly 28.28%, and respondents between 15 to 30 years old represent about 24.37% of the sample. The percentage of personal vehicle ownership is high, with around 90.65% of respondents owning/leasing a vehicle; also, around 90.80% of respondents have a valid driving license. Regarding employment status, full-time and part-time workers represent 55.81% of the sample, while 32.44% of the sample are retirees, homemakers, self-employed, or unemployed. Additionally, students form nearly 11.75% of the sample.

Table 6-1 Sample distribution

Category	Sub-Category	Sample (%)	Population (%)	Weighted sample (%)
Total	Total	4739 (100%)	747545 (100%)	4739 (100%)
Gender	Male	1811 (38.21%)	48.90%	2265 (47.79%)
	Female	2789 (58.85%)	51.10%	2357 (49.74%)
	Self-identity	139 (2.93%)	—	116 (2.45%)
Age	15 to 30 years old	1396 (29.46%)	23.25 %	1155 (24.37%)
	30 to 59 years old	2476 (52.25%)	48.53%	2244 (47.35%)
	Over 60 years old	867 (18.29%)	28.22%	1340 (28.28%)
Employment Status	Full-time	2199 (46.4%)	60.20%	2254 (47.56%)
	Part-time	486 (10.26%)		391 (8.25%)
	Student	786 (16.59%)	—	557 (11.75%)
	Retired	678 (14.31%)	—	1054 (22.24%)
	Self-employed	206 (4.35%)	—	234 (4.94%)
	Housewife	136 (2.87%)	—	94 (1.98%)
	Not working	248 (5.23%)	—	156 (3.29%)
Driving license	Yes	3474 (73.31%)	—	4303 (90.8%)
	No	1265 (26.69%)	—	436 (9.2%)
Vehicle ownership	0	1063 (22.43%)	—	301 (6.35%)
	1	1919 (40.49%)	—	1881 (39.69%)
	Two or more	1757 (37.08%)	—	2557 (53.96%)
Travel mode	Walk	528 (11.14%)	4.63%	246 (5.19%)
	Bike	158 (3.33%)	1.80%	96 (2.03%)
	HSR	2091 (44.12%)	10.54%	561 (11.84%)
	Car-Driver	1728 (36.46%)	75.87%	3456 (72.93%)
	Car-Passenger	528 (11.14%)	7.16%	380 (8.02%)

6.4.2 Variables

The dependent variable under investigation is the primary travel mode of each respondent (based on daily travel) reported in the survey. As stated before, we consider five modes of travel, including Walk, Bike, HSR, Car-Driver, and Car-Passenger. The independent variables include socioeconomic and demographic characteristics, journey time, built environment characteristics, and geographic variables associated with each respondent's household.

The socioeconomic and demographic characteristics include age, employment status, gender, number of vehicles per household, and the ability to drive. The levels associated with each variable are shown in Table 6-1. Journey time, collected as a categorical variable, is classified into 1) 15 minutes or less, and 2) more than 15 minutes.

Built environment variables are land use entropy, sidewalk density, and bike lanes density around each respondent's place of residence. The sidewalk, land use, and bike lanes datasets required to calculate these variables were extracted from the City of Hamilton open data catalogue (City of Hamilton, 2019) and then processed using ArcGIS 10.7.1. Land use entropy for each respondent's origin was calculated based on a 400 meters buffer and using the following equation, following the work of (Frank and Pivo, 1994; Zahabi et al., 2012):

$$E_i = (-1) \times \sum_j \frac{P_j \, ln(P_j)}{ln(J)} \qquad (6\text{-}2)$$

Where E_i is the land use entropy for individual i, P_j is the proportion of land use j in a 400-meters buffer around individual i, and J is the number of land-use types in the area under consideration.

In this study, five primary land uses were considered: residential, commercial, institutional, industrial, and parks/open spaces. The sidewalk and bike lanes densities were calculated as the length of sidewalks/ bike lanes around each respondent within a 400 meters radius. A 400 meters buffer was used as it represents an acceptable walking distance and a suitable accessibility standard within urban areas (Murray and Wu, 2003; El-Geneidy and Levinson, 2006). Figure 6-2 shows the built environment attributes for the city of Hamilton.

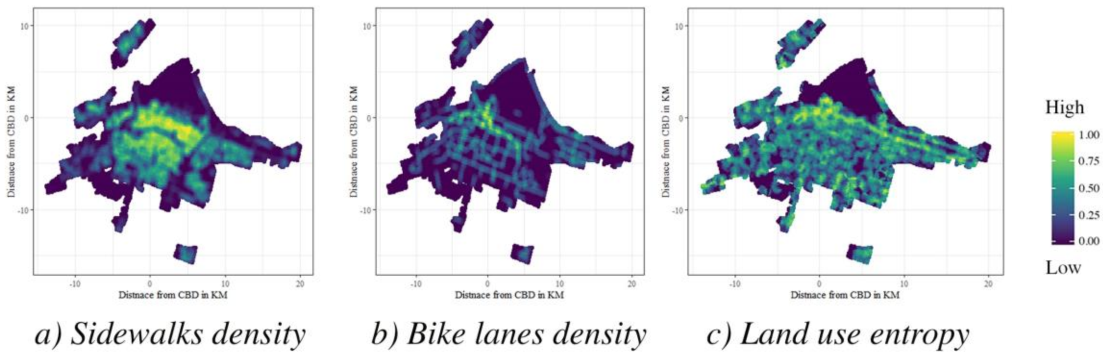
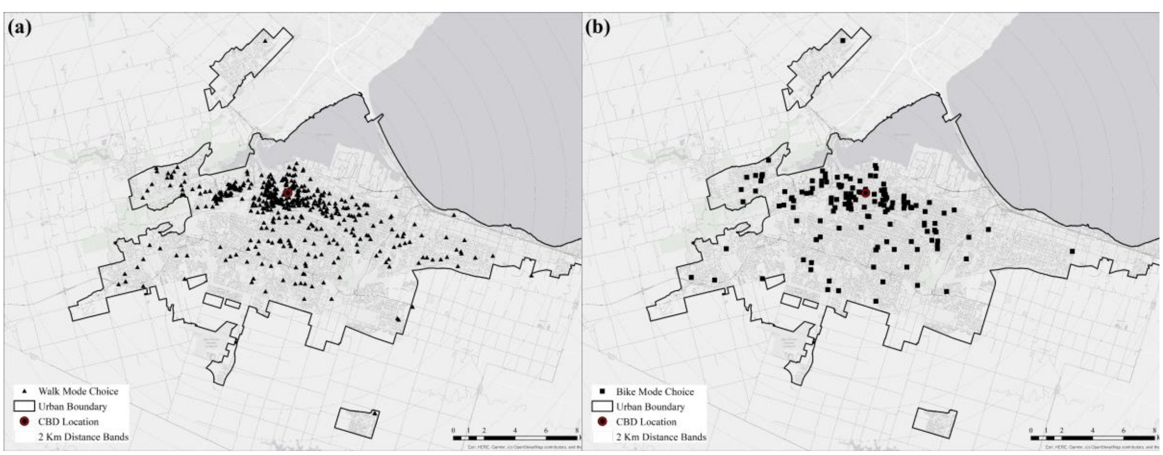
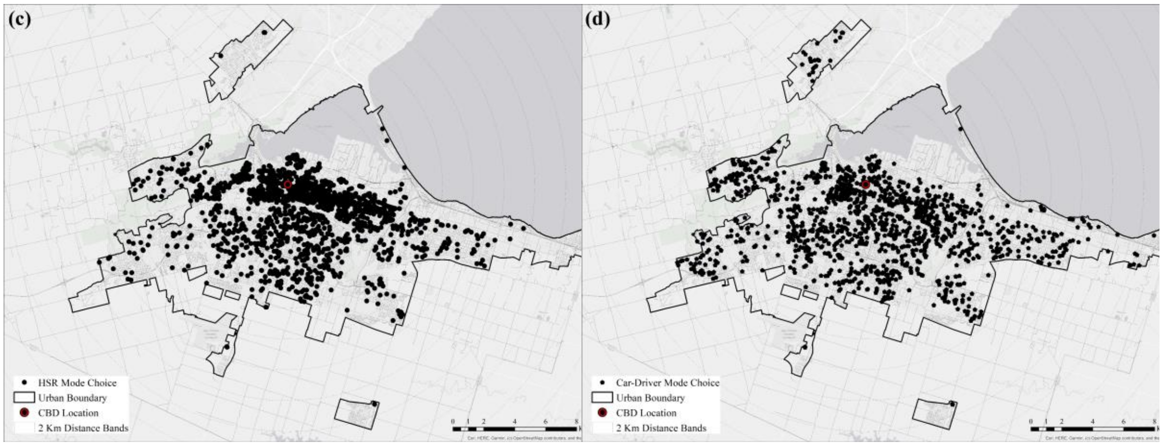


Figure 6-2 Built environment attributes over the City of Hamilton

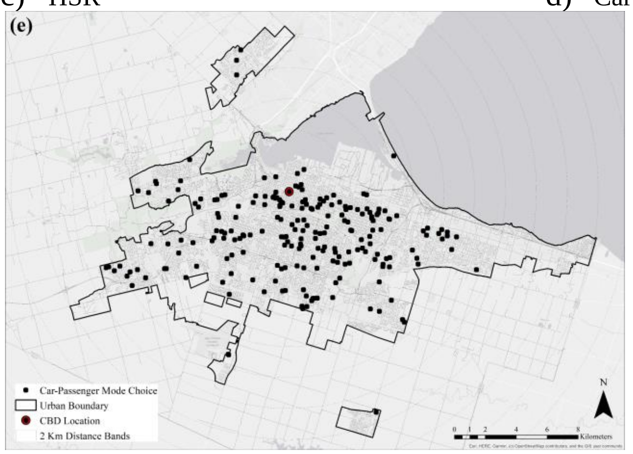
Place of residence was geocoded based on the voluntarily reported six digits postal codes. Geocoding was performed using a Python client geocoding application programming interface (API) for the Google Maps platform (GitHub, 2019). Respondents' geographical (contextual) variations are included in the analysis in reference to the central business district (CBD) of Hamilton. The geographical distribution of respondents' household locations with respect to their main travel modes is shown in Figure 6-3.



a) Walk b) Bike



c) HSR d) Car-Driver



e) Car-Passenger

Figure 6-3 Geographic distribution of respondents' mode choice

6.5 Modelling approach

This study utilizes discrete choice models along with a quadratic polynomial trend surface to investigate the spatial impact of the built environment attributes on mode choice behaviour for the City of Hamilton. We consider Multinomial Logit (MNL) and Nested Logit (NL) models. The MNL model is the most popular form of discrete choice models due to its simplicity and closed-form choice probability function (Ben-Akiva and Lerman, 1985). The MNL model was developed based on the random utility maximization (RUM) theory (Ben-Akiva and Lerman, 1985; McFadden, 1998). RUM adopts a rational decision-making approach, which assumes that individual i, picks the choice j, that maximizes their utility U_{ij}:

$$U_{ij}= \beta\ V_{ij}+ \varepsilon_{ij} \tag{6-3}$$

Where V_{ij} is the observable component of the utility function, which is a vector of explanatory variables, and β is a vector of estimated fixed parameters. And ε_{ijt} is the error term, which is assumed to be identically and independently distributed (IID). This leads to the independence assumption, where the choice of one mode is independent of any other modes, also known as the Independence from Irrelevant Alternatives (IIA) assumption. As mentioned in Ben-Akiva and Lerman (1985), the probability for individual i, selecting a choice j, based on the MNL formulation and expressed as follows:

$$P_{ij} = \frac{e^{\beta V_{ij}}}{\sum_{j=1}^{J} e^{\beta V_{ij}}} \tag{6-4}$$

If there is a correlation among specific alternatives (i.e., the IIA assumption is violated), the Nested Logit NL model is more appropriate as it relaxes the IID assumption by allowing nests of alternatives. As discussed in Train, (2002), for any two alternatives in the same nest, the ratio of probabilities is independent of all other alternatives, but for alternatives in different nests, the ratio of probabilities is not independent of other alternatives. In our case, there are two nests; motorized and non-motorized travel modes, as shown in Figure 6-4. For the NL model, the probability of respondent (i) choosing mode (j) is conditioned on choosing the nest (m) which mode (j) belongs to:

$$P_{ij} = P_{im} . P_{ij|m} \tag{6-5}$$

Where P_{im} is the probability of choosing nest m and $P_{ij|m}$ is the marginal probability of choosing mode (j) conditional on choosing nest (m). In this study, the NL model is estimated based on the RU2 normalization (Carrasco and Ortuzar, 2002). For more information, the interested reader is referred to (Hensher and Greene, 2002; Train, 2002; Ortúzar and Willumsen, 2011).

A number of approaches have been presented in the literature to model geographical variations in travel behaviour. Among others, Páez (2006) proposed the use of geographically weighted techniques. Wu and Hong (2017) used a spatial multilevel method to investigate commuting behaviour in Beijing. Lindner and Pitombo, (2018) drew from the geostatistical tradition to study mode choice in Sao Paulo, and Cheng et al. (2020) used indicator functions to capture spatial heterogeneity in the choice of public transportation.

Presently, we adopt the spatial expansion method of Casetti (1972) to obtain spatially varying coefficients and to identify the systematic spatial trends. In our case, built environment attributes were spatially expanded using a mixture of a quadratic polynomial trend surface and the distance to the CBD. An example of expanding coefficient β_j for variable V_{ij} would be as follows:

$$\beta_j = \beta_{0j} + \beta_{1j}X_i^2 + \beta_{2j}Y_i^2 + \beta_{3j}X_iY_i + \beta_{4j}X_i + \beta_{5j}Y_i + \beta_{6j}D_{i,CBD} \tag{6-6}$$

Where X_i is the CBD's longitude subtracted from individual i origin's longitude, Y_i is the CBD's latitude subtracted from the individual i origin's latitude, and $D_{i,CBD}$ is the distance to the CBD. $\beta_{0 \to 6j}$ are parameters to be estimated. Models were estimated using the Pandas Biogeme package (Bierlaire, 2018).

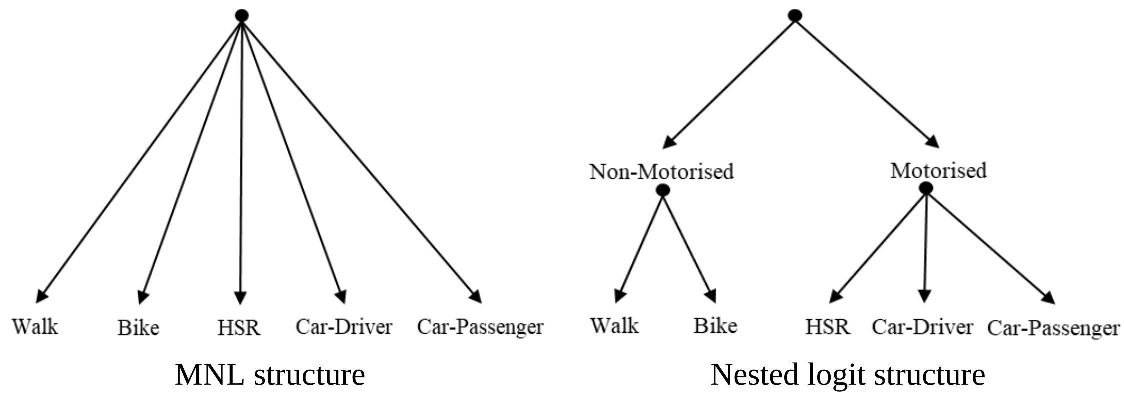


Figure 6-4 MNL and NL models structures

6.6 Results

6.6.1 Model assessment

MNL and NL models were estimated, as shown in Table 6-3. Walking is the reference category, and the independent variables are considered individual-specific variables. Additionally, all socioeconomic demographic characteristics and journey time are included in the model as indicator variables.

The results of the two models are consistent in terms of the correlation with the dependent variable and level of significance. Table 6-3 presents only statistically significant parameters at a 90% confidence level. The NL model shows a slight, yet insignificant, improvement over the MNL model based on the log-likelihood ratio test of 2.610 for 1 degree of freedom. The NL model is retained as a precautionary measure to account for the correlation among travel modes. The inclusive value (IV) parameter for the motorized nest ($IV_{motorised} = 1.2$) is found to be significant, which indicates the existence of marginal correlation among the motorized modes. While for the non-motorized nest, the IV value is set to 1 (fixed value) to remain within the boundaries of the discrete choice theory.

The predictive performance of the NL model is assessed using the Average Percentage Error (APE) and the Weighted Average Percentage Error (WAPE) metrics (Bogue, et al., 2017; Paez, et al., 2020). Using the same sample for estimating the models, the APE between the predicted shares (S_{Pj}) and observed shares (S_{Oj}) of each mode is estimated as follows:

$$APE_j = \left|\frac{S_{Pj} - S_{Oj}}{S_{Oj}}\right| \times 100 \tag{6-7}$$

The weighted average percentage error (WAPE) metric aggregates the APE for all travel modes as follows:

$$WAPE = \frac{\sum_j^J APE_j \times S_{Oj}}{\sum_j^J S_{Oj}} \tag{6-8}$$

Table 6-2 reports the predicted and observed shares of travel modes as well as the corresponding APE and WAPE. The lowest APE is corresponding to the car as a driver mode choice, while the highest is for biking. The WAPE is reasonably small (0.033%), which indicates a good predictive performance for the NL model.

Table 6-2 Predictive performance of the NL model

Travel mode	**Observed**	**Predicted**	**APE**
Walk	246	246.26	0.106%
Bike	96	95.67	0.339%
HSR	561	560.54	0.081%
Car-Driver	3456	3456.31	0.009%
Car-Passenger	380	380.21	0.056%
WAPE			**0.033%**

6.6.2 Model estimation results

The results of the NL model, in Table 6-3, show that middle age (i.e., from 30 to 59 years old) respondents are more likely to choose the car as a driver travel mode more than old (i.e., over 60 years old) and young (i.e., from 15 to 30 years old) respondents. Additionally, middle-aged respondents are less likely to walk or use transit compared to other age groups. While young respondents, all else being equal, tend to consider HSR or car as a passenger as their main travel mode more than others.

Students and part-time employees are less likely to drive compared to other employment groups. Unemployed respondents and students have a higher tendency to walk. Housemaker, unemployed and retired categories are the most probable to be passengers. Additionally, retirees and self-employed respondents are the least likely to choose HSR as their mode of travel. Also, retirees are less likely to consider biking as their main travel mode than other employment groups.

Table 6-3 MNL and NL models estimation results

Variable	Mode	MNL		NL	
		Beta	**t-stats**	**Beta**	**t-stats**
Alternative specific constants	Walk	—		—	
	Bike	-0.253	-0.408	-0.269	-0.437
	HSR	1.960	3.890	2.290	4.360
	Car-Driver	4.690	13.000	4.530	12.400
	Car-Passenger	2.990	5.930	3.150	6.380
Age (Over 60 years old base-category)					
Less than 30 years old	HSR	0.760	3.740	0.669	3.650
	Car-Passenger	0.685	3.550	0.604	3.540
From 30 to 59 years old	Walk	-1.430	-5.250	-1.430	-5.450
	HSR	-1.420	-5.360	-1.230	-4.640
	Car- Driver	0.708	4.140	0.581	3.140
Employment status (Unemployed base-category)					
Part-time employee	Car-Driver	-0.428	-2.510	-0.371	-2.470
Students	Walk	0.845	4.520	0.884	4.820
	Car-Driver	-1.530	-10.300	-1.300	-6.580
Retired	Bike	-0.928	-3.000	-0.901	-2.940
	HSR	-0.954	-4.380	-0.838	-3.900
	Car-Passenger	0.590	2.830	0.502	2.720
Self-employed	HSR	-0.808	-2.360	-0.700	-2.240

Housemaker	Car-Passenger	0.919	2.340	0.790	2.340
Not-working	Walk	1.020	2.830	1.000	2.810
	Car-Passenger	0.909	2.980	0.779	2.880
Gender (Female base-category)					
Male	Walk	0.484	3.170	0.461	3.050
	Bike	1.230	4.910	1.230	4.970
	HSR	0.734	5.920	0.547	3.170
	Car-Passenger	-1.250	-10.300	-1.140	-8.810
Self-identified	Walk	1.460	3.580	1.340	3.250
	HSR	1.500	4.780	1.280	4.160
Number of vehicles (≥ 2 vehicle base-category)					
Zero vehicle	HSR	0.891	4.040	0.556	1.830
One vehicle	HSR	0.547	3.640	0.440	2.930
	Car-Driver	-0.798	-7.320	-0.704	-6.260
Driving license (Not holding base category)					
Holding a driving license	Walk	-1.330	-8.570	-1.350	-8.860
	Bike	-0.564	-2.210	-0.641	-2.490
	HSR	-1.410	-9.440	-1.310	-8.230
	Car-Passenger	-1.380	-8.150	-1.230	-6.670
Journey time (> 15 minutes base-category)					
15 minutes or less	Walk	0.399	2.110	0.447	2.410
	HSR	-0.795	-4.430	-0.676	-3.720
	Car-Driver	-0.251	-1.990	-0.217	-1.930
Sidewalk density	Walk	0.097	6.510	0.096	2.770
	HSR	0.032	3.070	0.027	2.770
Sidewalk density × Distance to CBD	Walk	-0.203	-5.330	-0.202	-5.390
	HSR	-0.054	-2.600	-0.044	-2.250
Sidewalk density × X2 Distance to CBD	Walk	0.125	2.700	0.126	2.750
Sidewalk density × X Distance to CBD	Walk	-0.106	-6.010	-0.103	-6.030
	HSR	-0.031	-2.250	-0.028	-2.330
Sidewalk density × XY Distance to CBD	Walk	-0.407	-5.220	-0.401	-5.240
	HSR	-0.113	-2.160	-0.099	-2.180
Bike lanes density	Bike	0.125	1.830	0.132	1.950
	HSR	-0.104	-2.040	-0.084	-1.760
Bike lanes density × Y Distance to CBD	HSR	-0.626	-2.600	-0.530	-2.430
Bike lanes density × Y2 Distance to CBD	HSR	-1.180	-2.930	-0.984	-2.710
Land use entropy	Car-Passenger	-0.827	-2.280	-0.714	-2.250
Land use entropy × Distance to CBD	Walk	2.910	1.750	3.000	1.820
	Bike	-2.750	-2.390	-2.670	-2.350
	Car-Passenger	0.892	1.670	0.772	1.780
Land use entropy × X Distance to CBD	Bike	-2.880	-3.690	-2.860	-3.710
Land use entropy × X2 Distance to CBD	Walk	-3.080	-1.730	-3.110	-1.780
	Car-Passenger	-0.797	-1.670	-0.668	-1.620
Land use entropy × Y Distance to CBD	Walk	-2.350	-2.010	-2.210	-1.900
Land use entropy × Y2 Distance to CBD	Walk	-4.090	-2.200	-4.000	-2.170
IV (non-motorised)		—		1.000	—
IV (motorized)		—		1.200	8.060
Log-Likelihood		-2638.311		-2637.006	
Log-Likelihood ratio test		9553.001		9555.611	
Akaike Information Criterion		5390.622		5390.012	
Rho-square		0.644		0.644	

For gender, males are more likely to bike more than females and gender self-identified respondents. Self-identified and male respondents are more likely to choose Walking or

HSR as their main travel modes more than females. Additionally, male respondents are less likely to choose car-passenger compared to others.

Respondents without access to a private vehicle are more likely to use transit, and respondents with one vehicle have a higher tendency to use HSR than respondents with two or more vehicles. Respondents with two or more vehicles per household are more likely to drive than respondents with only one vehicle. Respondents with a driving license are less likely to consider HSR, car-passenger, walking, and biking as their main travel modes than respondents without a driving license. Respondents with trips shorter than 15 minutes are more likely to walk and less likely to choose the car as a driver or HSR.

Regarding built environment attributes and their variation over geography, sidewalk density is positively associated with the use of walk and HSR travel modes. The influence of sidewalk density on Walking and HSR travel modes decreases when the distance from the CBD increases: in other words, the efficaciousness of sidewalks for walking and using transit decreases away from the CBD. Bike lane density has a positive correlation with biking but a negative correlation with HSR. Land use entropy (mix) is negatively associated with the use of the car as a passenger travel mode. The effect of land use entropy on biking decreases when the distance from the CBD increases. While the influence of land use entropy on walking and car as a passenger increases when the distance to the CBD increases.

6.6.3 Simulation exercise

Mapping the probabilities of Hamiltonians' mode choices facilitates the comprehension of the contextual variations over space. Accordingly, a fine grid (100 meters × 100 meters) was superimposed on the study area. The distances from the square grids centroids to the CBD were used to simulate the probabilities using the NL model.

Additionally, as shown in Table 6-4, eight different Hamiltonians' profiles were defined to contrast the variations in mode choice behaviour in the simulation. The profiles represent the majority of the workers in Hamilton (i.e., full-time and part-time employees), as well as students and retirees. The student's profiles are also used to represent disadvantaged transportation groups without a vehicle, while retiree's profiles represent the most vulnerable age group. For simplicity, for all selected profiles, trips with more than 15 minutes of travel time are assumed, which also represents the majority of trips within the city.

Table 6-4 Six selective profiles used for the simulation.

Profile	**Employ. Status**	**Age**	**No. Vehicles**	**Gender**	**Shares (%)**
Profile 1	Full-time	Middle age	Two or more	Male	7.28%
Profile 2	Full-time	Middle age	Two or more	Female	9.37%
Profile 3	Part-time	Middle age	One	Male	0.25%
Profile 4	Part-time	Middle age	One	Female	0.55%
Profile 5	Student	Young	Zero	Male	0.36%
Profile 6	Student	Young	Zero	Female	0.11%
Profile 7	Retiree	Old	One	Male	3.59%
Profile 8	Retiree	Old	One	Female	3.78%

* Please note that each profile is a product of classifying/dissecting the population using five variables.

The probabilities of choosing travel modes across the city with respect to each profile are shown in Figure 6-5. It is worthwhile recalling that the trend surface was developed based on the respondents' household location.

The results indicate that the probability of choosing walking as a primary travel mode is higher near the CBD and in areas where built environment attributes are relatively high. Profiles 05 and 06 (i.e., part-time employees) have a higher tendency to walk. Profiles 07 and 08 (i.e., retirees) are next in order; however, it is worth noting that profile 07 (i.e., male retirees) have a noticeable higher tendency to choose walking than profile 08 (i.e., female retirees).

The probability of choosing biking as a primary travel mode is substantially low across the City of Hamilton except for the west of the city, where the probability is slightly higher. Profile 05 (i.e., male part-time employees) has the highest tendency to consider biking as their main travel mode, then comes profile 6 (i.e., female part-time employees) and profile 07 (i.e., male retirees).

Regarding public transit, the probability of choosing HSR as a primary travel mode is noticeably low across the city for all the considered profiles except for profiles 05 and 06 (i.e., students). For students with no access to a private vehicle, the probability of choosing HSR is relatively higher in the east, near the edge of the urban boundaries and near places where built environment attributes are favourable to this mode. Additionally, profile 03 (i.e., male part-time employees) and profile 07 (i.e., male retirees) have a higher tendency to use transit than their females' counterparts (i.e., profiles 04 and 08).

The probability of choosing the car as a driver is substantially high across the city of Hamilton, the highest among all travel modes. This probability is marginally lower in the downtown area and near places where built environment attributes favour other modes. Car as a driver travel mode is superior to other modes for all the considered profiles except for profiles 05 and 06, where there is no private vehicle access. It is worth noting that there is a systematic difference between males and females where female profiles (i.e., profiles 02, 04, and 08) have a higher likelihood to choose the car as a driver more than male profiles (i.e., profiles 01, 03 and 07).

The probability of being a passenger is generally low across the city; however, it is marginally higher in areas where built environment attributes are relatively low. Profiles 07 and 08 (i.e., retirees) have the highest probabilities of considering the car as a passenger travel mode. Additionally, profile 08 (i.e., female retirees) has a higher tendency to consider this travel mode more than male retirees (i.e., profile 07).

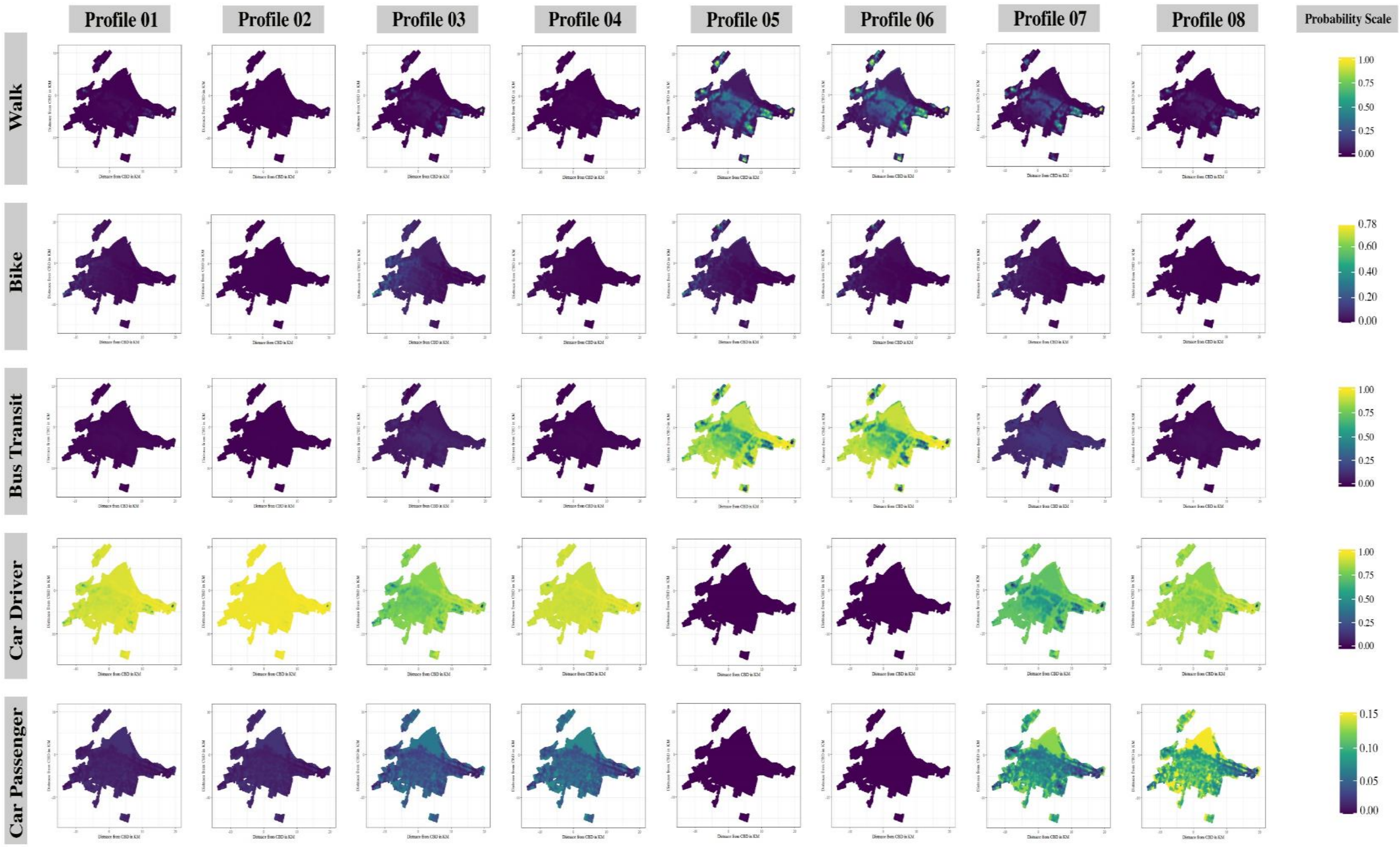


Figure 6-5 The probabilities of choosing travel modes across Hamilton for each profile

6.6.4 Estimated impact of improving built environment on mode choice

In order to examine the impact of improving built environment characteristics on mode choice while accounting for the geographical variations, we assumed significant built environment improvements (i.e., the highest existing values) to sidewalks density, land use entropy, and bike lanes density. Using the new values, we estimated the impact of such improvements on the probability of mode choice. The variations in mode choice probability due to improving sidewalks density, bike lanes density, and land use entropy, averaged over the City of Hamilton, are presented in Figure 6-6. The results show that, on average, improving built environment attributes for all the considered profiles can strongly increase the probability of walking and biking while decreasing the probability of choosing the car as a passenger, HSR, and car as a driver.

The probability simulation results show that improving the built environment positively affects the likelihood of choosing active transport modes as primary travel modes, especially in the east and west parts of the city. For walking, improving built environment attributes has its highest impact on profiles 05 and 06 (i.e., students with no access to a private vehicle) then profiles 07 and 08 (i.e., retirees). Additionally, in general, male profiles have a higher likelihood to walk more due to improving built environment than female profiles. While the lowest impact of improving the built environment will be on profiles 02 (i.e., female full-time employees) and 04 (i.e., female part-time employees). With respect to biking, profiles 05 and 06 (i.e., students with no access to a vehicle) and profile 03 (i.e., male part-time employees) are the most affected due to improving built environment while the least influenced are profiles 08 (i.e., female retirees) and 02 (i.e., female full-time employees).

Regarding public transit use, the results indicate that improving the built environment has a negative effect on public transit use for most considered profiles. Profiles 05 and 06 (i.e., students with no access to a private vehicle) are the most affected due to improving the built environment. This relatively high reduction in HSR use might be associated with a shift to more active transportation modes due to the improvement in the built environment. The least affected are profiles 01 and 02 (i.e., full-time employees) and profile 04 (i.e., female part-time employees).

In regard to the car as a driver mode, improving the built environment slightly decreases the likelihood of choosing car-driver as a primary travel mode for all the considered profiles. Profiles 07 (i.e., male retirees) and 03 (i.e., male part-time employees) are the most affected due to improving built environment, while profiles 02 (i.e., female full-time employee) and 04 (i.e., female part-time employee) are the least affected. It seems that improving built environment attributes will decrease the likelihood of using the car as a driver for male profiles than for female profiles.

For the car as a passenger travel mode, the likelihood of considering car-passenger as a primary travel mode declines due to improving the built environment attributes. Profiles 07 and 08 (i.e., retirees) are the most influenced by improving the built environment, while profiles 01 and 02 (i.e., full-time employees) are the least affected.

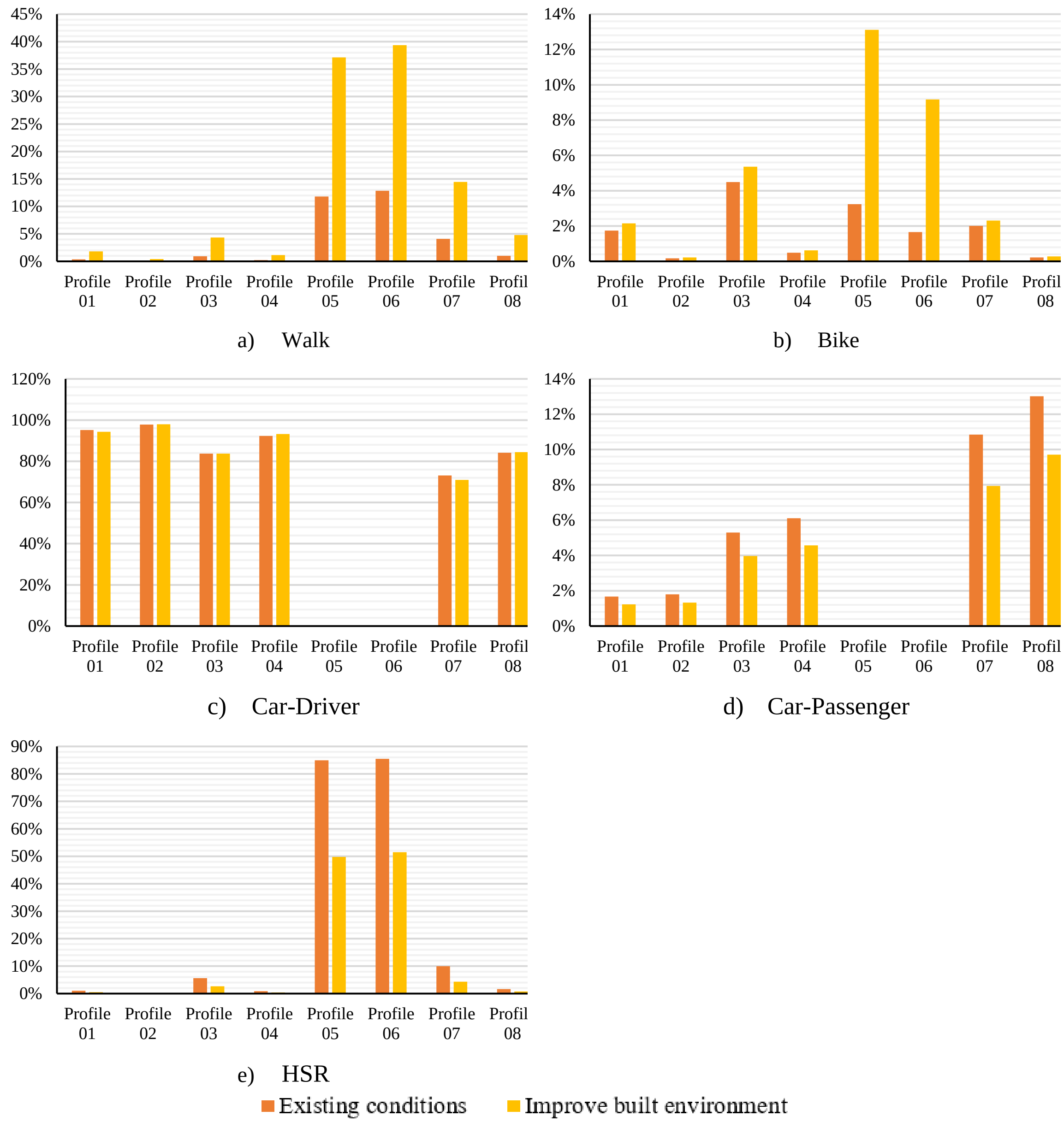


Figure 6-6 The change in mode choice probability due to various built environment improvements

In order to examine the spatial effects of improving built environment attributes, the probabilities of choosing different travel modes due to such improvements are estimated across the City of Hamilton for each profile, as shown in Figure 6-7. Compared to Figure 6-5, the results clearly demonstrate the varying magnitudes of the impact of built environment attributes over the geography of the city.

Improving the built environment across the city advances the likelihood of walking, especially in the east (Stoney Creek) and west (i.e., Dundas and Waterdown) parts of the city. For biking, improving the built environment increases the likelihood of biking as a main travel mode in the south-west part (i.e., Ancaster) of the city. The likelihood of using public transit is negatively affected by improving built environment attributes. The negative effect is higher in the peripheral neighbourhoods than in the core areas (e.g., downtown).

Improving the built environment negatively influences the probability of choosing Car-driver as the main travel mode. The highest negative effect appears in the east (i.e., Stoney Creek and Binbrook) and west ends (i.e., Dundas, Ancaster and Waterdown) of the city. For the car as a passenger travel mode, improving the built environment negatively affects the likelihood of considering car-passenger as the main travel mode in a spatially consistent way all over the city.

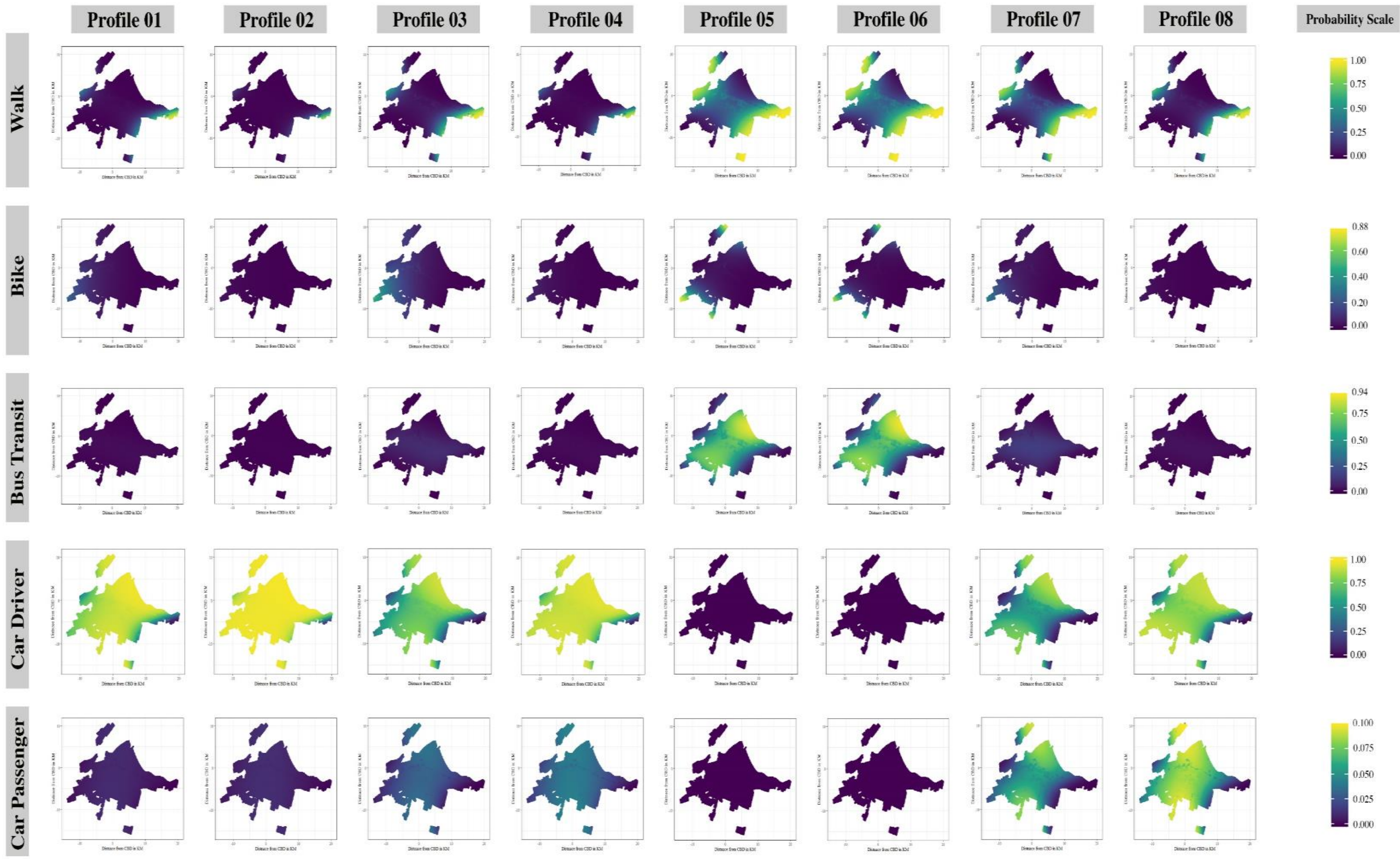


Figure 6-7 The simulated probabilities of improving all the built environment attributes for each profile

6.7 Discussion and concluding remarks

The study aimed to investigate the role of the built environment attributes and their contextual effects on travel behaviour in the City of Hamilton. The study utilized a dataset of 4,739 respondents elicited from an online survey that was part of Hamilton Street Railway (HSR) Public Engagement efforts. A sample weighting approach was used to correct the nonproportional sampling (i.e., over representing HSR users) and to achieve a representative sample of the population. The study employed a Nested Logit (NL) model along with a quadratic polynomial trend surface to spatially investigate the determinants influencing mode choice behaviour in the City of Hamilton. The study examined the association between the primary mode of travel (dependant variable) and socioeconomic demographics, trip characteristics, and surrounding built environment attributes along with their geographic variations as a set of independent variables. The built environment attributes were spatially expanded using the expansion method to identify their spatial impact on mode choice behaviour.

The results of the NL model reveal a tendency towards driving over other modes and indicate that there are several factors in play that impact travel behaviour in the City of Hamilton. Socioeconomic demographics are found to play a pivotal role in explaining Hamiltonians' mode choice behaviour. For instance, middle-aged respondents are more likely to be car drivers and less likely to use transit or walk than other age groups. For gender, females are less likely to consider walking or transit as a primary travel mode compared to males and gender self-identified respondents. For vehicle ownership, respondents with two or more vehicles per household are more likely to consider the car as a driver as their main travel mode than respondents with only one vehicle. The findings are consistent with the work of (Yu et al., 2018; Aziz et al., 2018; Srinivasan et al., 2019), which confirms the positive relationship between the number of private vehicles per household and driving a private vehicle.

From a trip characteristics perspective, journey time is a statistically significant explanatory variable for walking, public transit, and car as a driver travel modes. Car as a driver and HSR are less likely to be used for trips less than 15 minutes, while walking is more likely to be chosen for such trips. This finding is supported by the work of (Muñoz et al., 2016; Winters et al., 2017) which concluded that the probability of choosing active modes (i.e. walking) is negatively associated with travel time increase.

Regarding the built environment, the results indicate a positive relationship between sidewalks density and choosing walking and transit as main travel modes. The effect of sidewalks on boosting active travel modes has also been affirmed by (Aziz et al., 2018). For bike lanes density, the results show a positive correlation with biking while a negative correlation with public transit use. This finding is echoed by the work of (Santos, et al., 2013; Le et al., 2019) where they concluded that the existence of bicycle facilities is associated with higher bicycle use in 112 medium-size cities in Europe and 13 US metropolitan areas, respectively. It is worth noting that these aspects of the built environment are not equally efficacious in different parts of the city. For instance, the impact of sidewalk density decreases when the distance from the CBD increases. Regarding land use entropy, the NL model shows a negative correlation between land use entropy and considering car-passenger as a primary travel mode. From a contextual perspective, the influence of land use on biking lessens when the distance from the CBD increases. For walking and car as a passenger, the influence increases when the distance from the CBD increases.

The contextual variations in mode choice behaviour were mapped based on eight Hamiltonians' profiles. The profiles represent most of the working class (i.e., full-time and part-time employees) as well as students with no access to a private vehicle and retirees. The results show that the probability of choosing walking as the main travel mode is higher in the areas where built environment attributes are relatively high. This finding is supported by the work of (Ito et al., 2017; Mo et al., 2018; Martín and Páez, 2019; Cheng et al., 2019), where mixed land use is deemed to be correlated with more walking. While the probability of biking is slightly higher in the downtown and west neighbourhoods.

The probability of using public transit use is relatively low across the city for all profiles except for students with no access to a private vehicle, for whom this probability is higher in the east part of the city, and near places where built environment attributes are high. The probability of considering car-driver is high across the city; however, it is slightly lower in the downtown and near places where the built environment attributes are high. For the car as a passenger travel mode, the probability is marginally higher in areas where built environment attributes are relatively low.

A significant improvement to the built environment attributes across the city were imposed to examine the influence of such improvement on the mode choice behaviour. The results suggest that improving the built environment can substantially increase the probability of walking and biking as primary travel modes while decreasing the likelihood of choosing the car as a passenger, HSR, and car as a driver. From a geographical perspective, improving the built environment increases the likelihood of walking in the east and west parts of the city more than in other areas. While improving the built environment increases the likelihood of biking in the south-west part (i.e., Ancaster) of the city. For public transit, improving the built environment decreases the likelihood of using transit in the peripheral neighbourhoods than in the core areas (e.g., downtown). Improving the built environment negatively influences the likelihood of choosing the car as a driver in the east and west ends of the city than the rest of the city. While for the car as a passenger, the negative effect is spatially consistent all over the city.

It is worth noting that our results indicate that improving built environment attributes, albeit significant, will not drastically change travel behaviour in the City of Hamilton. However, the results also pinpoint locations for maximizing the impact of improving built environment attributes.

Lastly, it is worthwhile to recognize that the study has some limitations. First, the data were collected through the public transit provider (HSR), and the sample over-represents public transit users. Although a sample weighting technique was used to correct the nonproportional sampling, the actual (population) shares of some travel modes, such as biking and are vastly lower than the shares of car and transit travel modes. Further, travel time is collected as a categorical variable which hinders the investigation of mode choice behaviour across a continuous travel time variable.

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6.9 Appendix A

Table A-6-1 List of the studies mentioned in the background section.

Study	Context	Sample size	Method
1. (Cervero and Kockelman, 1997)	San Francisco Bay Area, US	50 neighbourhoods	Multiple regression and binomial logit models
2. (Kitamura et al., 1997)	San Francisco Bay Area, US	16346 respondents	Linear regression models
3. (Schwanen et al., 2001)	The Netherlands	7000 households	Multinomial logistic regression models
4. (Fujii and Kitamura, 2003)	Kyoto City, Japan	43 car drivers	Three phases experiment & analysis of variance test
5. (Anable, 2005)	National Trust, Northwest, UK	666 visitors	Factor analysis and k-means clustering procedure
6. (Limtanakool, et al., 2006)	The Netherlands	6330 trips	Binary logit models
7. (Páez et al., 2007)	City of Hamilton, Canada	10500 households	Mixed ordered probit models
8. (Mercado and Páez, 2009)	City of Hamilton, Canada	16190 individuals	Multilevel regression model
9. (Nurul Habib, et al., 2009)	Greater Toronto Area	102975 individuals	Joint discrete-continuous model
10. (Roorda et al., 2010)	Hamilton, Canada Toronto, Canada Montreal, Canada	22855 persons 126645 persons 150608 persons	Spatial ordered probit model
11. (Morency et al., 2011)	Hamilton, Canada Toronto, Canada Montreal, Canada	17944 persons 97465 persons 122420 persons	Multivariate regression (spatially expanded) model
12. (Santos, et al., 2013)	Medium Size European cities	112 cities	Multinomial logit, nested logit and mixed logit models
13. (Whalen et al., 2013)	City of Hamilton, Canada	1376 students	Multinomial logit model
14. (Khan, et al., 2016)	Windsor City, Canada	1260 travellers	Mixed logit model
15. (Ding et al., 2017)	Baltimore City, US	3519 households	Integrated structural equation and discrete choice model
16. (Fatmi and Habib 2017)	Halifax, Canada	289 households	Random parameter logit model
17. (Sun, et al., 2017)	Shanghai, China	857 individuals	Discrete-continuous joint copula model
18. (Yang et al., 2017)	Crittenden county, United States	3536 records	Geographically weighted regression
19. (Aziz et al., 2018)	New York City, US	3357 observations	Mixed logit model
20. (Ferrer and Ruiz, 2018)	Valencia and Granada, Spain	23 participants* 14 participants*	Thematic analysis

Study	Context	Sample size	Method
21. (Mo et al., 2018)	Singapore city, Singapore	23941 observations	Mixed logit model
22. (Yu, et al., 2018)	Shangxiasha, Shenzhen, China	512 households	Multinomial logit model
23. (Spinney, et al., 2019)	Halifax, Canada	1971 households	Mixed logit model
24. (Nkeki and Asikhia, 2019)	Benin City, Nigeria	1736 questionnaires	Geographically weighted logistic regression
25. (Cheng et al., 2019)	Nanjing, China	4474 persons	Two-step clustering and Propensity score matching
26. (Le et al., 2019)	13 metropolitan areas, US	5554 bicycle counts 5166 pedestrian counts	Multilevel mixed-effects models
27. (Martín and Páez, 2019)	Vitoria-Gasteiz, Spain	4192 individuals	Multinomial logit model
28. (Scott and Ciuro, 2019)	City of Hamilton, Canada	203427 trips	Random intercept multilevel models
29. (Srinivasan et al., 2019)	Chengdu, China	2,290 trips in 2005 2,464 trips in 2016	Multilevel and Binary logistic regression models
30. (Ton et al., 2019)	The Netherlands	1864 respondents	Multinomial and mixed logit models
31. (Wu et al., 2019)	Shanghai, China	2838 participants	Multinomial logistic regression analysis

* Focus groups.

6.10 References

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CHAPTER 7

Summary, Conclusions, and Future Research

7.1 Summary

The research presented in this dissertation aims at investigating the preference heterogeneity associated with transit customers' service desired quality and travel behaviour. A better understanding of transit customers' preferences is a necessity for an efficient and well-harmonized urban transportation system. This dissertation investigated the wide spectrum of transit customers' preferences through i) Quantifying preference heterogeneity in transit service desired quality due to customers' socioeconomic characteristics and travel behaviour, ii) Unveiling the latent heterogeneity in transit customers' preferences and identifying customers' latent classes, iii) Estimating willingness to pay values for service improvements for various user groups, iv) Employing and advancing the persona-based approach to better investigate the preferences of dominant transit market segments, v) Investigating the role of subjective psychological factors in shaping transit customers' preferences towards service attributes, and vi) Examining how built environment and its contextual effects influence mode choice behaviour while accounting for variations in socioeconomic characteristics.

The research utilized a primary dataset elicited from an online survey that was part of Hamilton Street Railway (HSR) Public Engagement efforts in the city of Hamilton, Ontario, Canada. The general purpose of the survey was to benchmark the service quality provided by HSR based on Hamiltonians' preferences and expectations. The survey is designed for all Hamiltonians (i.e., both transit and non-transit users) and structured in four independent sections: (1) Socioeconomic demographic characteristics and travel behaviour, (2) Stated Preference (SP) experiments, (3) Service quality aspects, and (4) Attitudinal and behavioural attributes.

In order to fully understand transit customers' preferences, the work presented in this dissertation utilized an Error Components (EC) logit model with systematic taste variations to investigate preference heterogeneity of transit customers' service desired quality with respect to their socioeconomic characteristics and travel behaviour. Then, a Latent Class choice Model (LCM) was used to unveil the latent heterogeneity in transit customers' preferences and identify customers' latent classes with homogenous preferences. Subsequently, the research employed a persona-based approach along with an EC logit model to investigate the preference of the key transit market segments and advance the persona-based approach beyond its qualitative nature by introducing quantified measures for preferences and willingness to pay for service improvements. Moreover, Multinomial Logit (MNL) interaction models were utilized to independently investigate transit preferences of various users' categories (i.e., considering a prior classification approach) and its implications on the willingness to pay for service improvements. Furthermore, a Random Parameter Logit (RPL) model is also used to examine the existence of unobserved taste heterogeneity around service attributes and quantifies the spread of such heterogeneity, if any.

Additionally, the research utilized an EC logit model with systematic taste variations, confirmatory factor analysis (CFA), and multivariate analysis of variance (MANOVA) to investigate the influence of subjective psychological aspects of transit customers on their preferences towards service attributes and to examine the association between customers' socioeconomic characteristics and subjective psychological attributes. Finally, a Nested Logit (NL) model and a quadratic polynomial trend surface were employed to investigate the spatial (contextual) effects of built environment attributes on customers' travel behaviour in the City of Hamilton.

7.2 Conclusions and contributions

The research presented in this dissertation provides a better understanding of the broad-ranging preferences of transit customers. The presented research quantified and unveiled the preference heterogeneity of transit customers through various techniques and specifications. The research also examined how subjective psychological factors affect customers' preferences towards service attributes. Furthermore, the research highlighted how city geography moderates the effects of built environment attributes on customers' travel behaviour. In this context, several conclusions and contributions associated with this dissertation are as follows:

- The Hamilton Street Railway (HSR) Public Engagement Survey was developed to benchmark the quality of HSR service based on customers' preferences and expectations. The survey gathered information about respondents' socioeconomic characteristics, travel behaviour, stated preferences and psychological aspects.

7.2.1 Conclusions and contributions from Chapter 2

The research, to the best of the authors' knowledge, is the first in the transit service quality literature to apply an Error Components (EC) logit model with systematic taste variations and a Latent Class choice Model (LCM) with an information processing heuristic to better understand transit customers preferences (i.e., Objective 1) and unveil the latent heterogeneity in the transit market (i.e., Objective 2).

- This research accentuated the effectiveness and superiority of the Latent Class choice Model (which is rarely utilized in transit quality literature) in investigating preference heterogeneity towards service quality aspects. Moreover, this research is the first in the transit quality literature to apply an information processing heuristic approach: Attribute Non-Attendance (ANA), which is valuable in deriving behaviourally plausible results.
- The Error Components (EC) with systematic taste variations model confirmed preference heterogeneity due to differences in customers' socioeconomic characteristics and travel behaviour attributes. Female customers are more sensitive to journey time, trip fare, walking time, number of transfers, and service frequency than males. Young customers (i.e., from 15 to 30 years old) appreciate at-stop real-time information provision more than others. Old customers (i.e., over 60 years old) are more sensitive to trip fare and walking time than others. Customers with two or more vehicles are the most sensitive to the journey time. Customers with one vehicle are less sensitive to trip fare, service headway, and direct trips than others.
- Very frequent (i.e., daily) transit users are less sensitive to journey time, direct trips and on-board real-time information provision. Frequent (i.e., weekly or monthly) transit users have the most sensitivity towards trip fare and at-stop real-time information provision.

- The Latent Class choice Model (LCM) unveiled the latent heterogeneity associated with customers' preferences towards transit service desired quality. Unlike traditional classifications of transit customers, the LCM classified the sample into three latent classes, namely: Direct Trips Enthusiastic (DTE), Cost-Sensitive (CS), and Real-time Information Supporter (RIS) respondents. Each latent class has homogenous (unique) preferences towards transit service quality aspects.
- Direct Trips Enthusiastic (DTE) class has the highest appreciation, compared to other classes, to direct trips over multiple transfers-based trips and frequent transit service. In addition, class members are also concerned about journey time and trip fare.
- Cost-Sensitive (CS) class has the highest sensitivity to trip fare, walking time and journey time with respect to other classes. Moreover, CS class members are in favour of direct trips over multiple transfers-based trips.
- Real-time Information Supporter (RIS) class is the only class that appreciates real-time information provision. RIS class members prefer at-stop real-time information provision more than the on-board option. Additionally, they are sensitive to service frequency and journey time.
- The latent class model indicates that conventional classifications (e.g., based on transit use) of the transit market, albeit beneficial, are not sufficient to capture transit customers' preference heterogeneity.

7.2.2 Conclusions and contributions from Chapter 3

The research proposes a framework that integrates the persona-based approach and discrete choice models to better understand the preferences of the key transit segments. The persona-based approach is utilized as a taxonomy tool of the transit market in the City of Hamilton (i.e., Objective 3). Additionally, the research advances the persona-based approach beyond its qualitative nature by introducing quantified preferences and willingness to pay estimates for each persona (i.e., Objective 4).

- The personas were developed through semi-structured workshops with Hamilton Street Railway (HSR) personnel and based on four primary characteristics: travel behaviour, employment status, geographical distribution, and Perceived Behavioural Control (PBC). Seven preliminary personas were identified to better describe the key groups of the targeted transit market.
- The analysis of the Error Components (EC) interaction model revealed that all personas are, all else being equal, negatively affected by longer journey times, higher trip fares, longer service headways, while positively affected by reducing the number of transfers per trip and real-time information provision. Distinctions between personas could be described as follows:
  - Persona 01 (Full-time employee, Transit user, Positive PBC, Live in urban areas) is the most sensitive to trip fare.
  - Persona 02 (Student, Transit user, Positive PBC, Live in urban areas) has the highest sensitivity to service headway and is negatively influenced by longer walking times.

- Persona 03 (Full-time employee, Car driver, Neutral PBC, Live in urban areas) is the most sensitive to longer journeys and walking times.
- Persona 04 (Retiree, Car driver, Neutral PBC, Live in urban areas) is the most lenient towards journey time, service headway, real-time information provision and the number of transfers. However, persona 04 is negatively affected by longer walking times.
- Persona 05 (Student, Car Driver/Passenger, Neutral PBC, Live in urban areas) has the highest appreciation for at-stop real-time information provision.
- Persona 06 (Full-time employee, Car passenger, Neutral PBC, Live in urban areas) is lenient towards walking time to/from bus stops.
- Persona 07 (Full-time employee, Car driver, Negative PBC, Live in the suburbs) has the highest appreciation for reducing the number of transfers per trip and is the most lenient towards higher trip fares.

• The willingness to pay estimates show that non-transit users (Personas 03, 04, 05, 06, and 07) are more likely to have higher values compared to current transit users (Personas 01 and 02). Persona 07 has the highest WTP for all service improvements except for the at-stop real-time information provision, where the highest WTP belongs to Persona 05.

• The analysis shows that Personas 01 and 02 (both are transit users) have shared preferences regarding most service attributes, yet they have unique preferences for walking time to/from bus stops. Personas 03 and 07 (both are full-time employees and car drivers) have shared preferences for various service attributes. However, they have unique preferences regarding the number of transfers and walking time to/from bus stops. This might be attributed to their distinct PBC towards transit service and their different location of residence (i.e., suburbs and urban areas). Personas 02 and 05 (both are students) have shared preferences regarding various service attributes except for service headway and reducing the number of transfers from two to one per trip.

7.2.3 Conclusions and contributions from Chapter 4

The research aims at investigating the notion of considering the willingness to pay (WTP) values for service improvements for the entire population without accounting for preference heterogeneity embedded in the transit market (i.e., Objective 5). The study investigated the heterogeneity in transit customers' preferences based on a prior classification approach and estimated WTP for service improvements for various classes of customers.

- The multinomial logit (MNL) model confirmed the existence of preference heterogeneity towards service attributes due to differences in socioeconomic characteristics, travel behaviour, access to travel modes and transit attitude. For instance, casual transit users have higher preferences towards reducing journey time, walking time, and the number of transfers than frequent (i.e., weekly or monthly) and very frequent (i.e., daily) users.
- The random parameter logit (RPL) confirmed the significant spread of preference heterogeneity around trip fare and zero transfer attributes. The density distribution of the trip fare random parameter depicts the wide spectrum of users' preferences and concludes the variant, yet important, influences of trip fare on transit customers.

For the zero random transfer parameter, the density distribution confirms that most customers, albeit at different rates, prefer direct trips. At the same time, around 20% of the sample is tolerant with multiple transfer trips.

- The utilization of the MNL interaction model and the RPL model provides precious information into understanding transit customers' preferences through different lenses; however, it is worth noting that the MNL interaction models have revealed preference heterogeneity for specific service attributes (e.g., journey time), which were masked in the RPL model. This shows the strengths of the interaction effects in testing preference heterogeneity for specific categorizations.
- This research estimated the willingness to pay for service improvements for different customer groups based on the MNL interaction models. This depiction of the WTP heterogeneity is of benefit to transit providers/marketing teams where they can identify cost-effective market segments and service improvements as follows:
    - Female customers are willing to pay more than male customers to reduce service headway and the number of transfers, while males would pay more for at-stop real-time information provision.
    - Young customers (i.e., 15 to 30 years old) have a higher willingness to pay than other age groups for reducing journey time, service headway and the number of transfers, and real-time information provision. Old customers (i.e., over 60 years old) have the highest WTP for reducing walking time to/from bus stops.
    - The high-income class is willing to pay more than others for reducing journey time, service headway, and the number of transfers to zero, and real-time

information provision. However, the low-income class would pay more for reducing walking time and the number of transfers from 2 to 1 per trip.

- Customers with two or more vehicles would pay more for reducing journey time and the number of transfers to zero per trip, while customers with zero vehicles would pay more for reducing walking time and service headway. Customers with one vehicle have the highest WTP for real-time information provision.
- Casual (i.e., yearly) transit users are willing to pay more for reducing journey time, walking time and number of transfers. Very frequent (i.e., daily) transit users would pay more for reducing service headway and at-stop real-time information provision.
- Choice transit users are willing to pay more than captive transit users for reducing journey time and the number of transfers and at-stop real-time information provision. In contrast, captive transit users would pay more for reducing walking time, service headway, and on-board real-time information provision.
- Car captives would pay more for reducing journey time and number of transfers, and real-time information provision. At the same time, car choice users are willing to pay more for reducing walking time and service headway, which is similar to the behaviour of the choice transit users.

7.2.4 Conclusions and contributions from Chapter 5

The research utilized a sequential analytical approach to investigate and quantify the influence of subjective psychological aspects on shaping non-transit customers' perceptions towards utilitarian public transit service attributes. To the best of the authors' knowledge, this research is the first in the transit quality literature to quantify how subjective psychological factors influence preferences towards service attributes in a choice experiment context (i.e., Objective 6)and examine the association between non-transit customers' socioeconomic characteristics and subjective psychological attributes (i.e., Objective 7). The research simultaneously examines the influence of Car Reliance, Transit Stigma, Perceived Behavioural Control, Social Norm, and Environmental Consciousness psychological aspects in shaping transit service desired quality while accounting for customers' socioeconomic characteristics.

- The analysis confirmed that the inclusion of subjective psychological factors is a statistically significant improvement in explaining customers' preferences compared to considering only their socioeconomic characteristics. The results concluded that the significant effects of customers' subjective psychological factors on service attributes are as follows:
  - Non-transit users with high car reliance psychological orientation are less sensitive to trip fare and service headway than others with a lower degree of car reliance.
  - Non-transit users with high perceived behavioural control (PBC) are less sensitive to the number of transfers while more sensitive to trip fare than others with low PBC towards transit.

- Non-transit users with high environmental consciousness are less sensitive to walking time to/from bus stops and have higher preferences to at-stop real-time information provision than others with low environmental consciousness.
- Non-transit users with high social norm attitudes towards transit are less sensitive towards the number of transfers than others with low social norm attitudes.
- Transit-stigma psychological aspect does not prove significant in explaining non-transit users' preferences towards the considered service attributes.

- The multivariate analysis of variance (MANOVA) confirmed statistically significant differences in the considered subjective psychological latent variables across three socioeconomic characteristics, namely: vehicle ownership, age and education level. Those differences are as follows:
- The five considered subjective psychological factors are highly sensitive to vehicle ownership. Zero vehicle ownership is associated with the highest social norm and perceived behavioural control towards transit, as well as high environmental consciousness. In contrast, two-vehicle ownership is associated with the highest car reliance and transit stigma attitudes. It is worth mentioning that zero vehicle ownership is associated with higher transit stigma than in the case of one vehicle ownership.
- Age is a significant clustering variable for transit stigma, social norm towards transit, and environmental consciousness latent variables. Young respondents (Gen-Z) have the highest social norm towards transit and, interestingly, the highest transit

stigma. They also have the highest environmental consciousness attitudes, while middle-aged respondents (Millennials and Gen-X) have the lowest. It is worth mentioning that car reliance attitude and perceived behavioural control towards transit are not sensitive to age.

- Education level is significantly associated with car reliance, transit stigma and perceived behavioural control towards transit. Potential transit users with university/college degrees have lower car reliance, transit stigma, and perceived behavioural control towards transit than others. It is worth pointing out that social norms towards transit and environmental consciousness are not associated with the education level.
- The significant differences in car reliance, social norm and environmental consciousness across potential transit users' age are dependent on their educational level. In contrast, differences in transit stigma latent variable across age are not dependent on education levels. Also, differences in perceived behavioural control across educational levels are not dependent on age.

7.2.5 Conclusions and contributions from Chapter 6

The research investigates the influence of socioeconomic characteristics and built environment attributes on travel behaviour in the City of Hamilton (i.e., Objective 8). This research employed a Nested Logit (NL) model along with a quadratic polynomial trend surface to investigate the contextual (spatial) effects of built environment attributes across the City of Hamilton (i.e., Objective 9). This research, as far as is known, is the first to investigate the role of the built environment and its spatial effects on Hamiltonians' travel behaviour considering five main transportation modes, namely: walk, bike, public transit, car as a driver, and car as a passenger.

- The results show that Socioeconomic demographics play a pivotal role in explaining Hamiltonians' mode choice behaviour. For instance:
    - Middle-aged respondents are more likely to choose the car as a driver travel mode and less likely to walk or use transit than other age groups. Young respondents have a higher tendency to consider public transit or car as a passenger as their main travel mode more than others.
    - Students and part-time employees are less likely to drive than other employment groups. Unemployed respondents and students have a higher tendency to walk. Housemaker, unemployed and retired categories are the most likely to be car passengers. Retirees and self-employed respondents are the least likely to choose public transit as their mode of travel. Moreover, retirees are less likely to consider biking as their main travel mode than other employment groups.
    - Males are more likely to bike more than females and gender self-identified respondents. Self-identified and male respondents are more likely to choose walking or public transit as their main travel modes more than females. Additionally, male respondents are less likely to choose car-passenger compared to others.
    - Respondents without access to a private vehicle are more likely to use transit, and respondents with one vehicle have a higher tendency to use HSR than respondents with two or more vehicles. Respondents with two or more vehicles

per household are more likely to drive than respondents with only one vehicle. Respondents with a driving license are less likely to consider HSR, car-passenger, walking, and biking as their main travel modes than respondents without a driving license.

- Journey time is a statistically significant explanatory variable for walking, public transit, and car as a driver travel modes. Car as a driver and HSR are less likely to be used for trips less than 15 minutes, while walking is more likely to be chosen for such trips.
- The results affirmed the significant role that built environment attributes play in explaining travel behaviour. Also, it is worth noting that the built environment's influence is not equally efficacious across the city.
- The results indicate a positive association between sidewalk density and the use of public transit and walk as primary travel modes. Additionally, it is also noted that the influence of sidewalk density on walking and public transit travel modes decreases when the distance from the CBD increases.
- The results show a positive correlation between bike lanes density and biking while a negative correlation between bike lanes density and public transit. The effect of bike lane density is not equally efficacious across the city.
- Land use entropy (mix) is negatively associated with the use of the car as a passenger travel mode. The effect of land use entropy on biking decreases when the distance from the CBD increases. While the influence of land use entropy on walking and car as a passenger increases when the distance to the CBD increases.

- The contextual variations in mode choice behaviour were mapped based on eight Hamiltonians' profiles. The profiles represent most of the working class (i.e., full-time and part-time employees) as well as students with no access to a private vehicle and retirees. The results show that:
  - The probability of choosing walking as the main travel mode is higher in the areas where built environment attributes are relatively high. In comparison, the probability of biking is slightly higher in the western suburbs (i.e., Ancaster, Dundas and Waterdown).
  - The probability of using public transit use is relatively low across the city for all profiles except for students with no access to a private vehicle, for whom this probability is higher in the east part of the city, near the edge of urban boundaries and near places where built environment attributes are high.
  - The probability of considering car-driver is high across the city; however, it is slightly lower in the downtown and near places where the built environment attributes are high. For the car as a passenger travel mode, the probability is marginally higher in areas where built environment attributes are relatively low.
- A significant improvement to the built environment attributes across the City of Hamilton were imposed to examine the influence of such improvement on the mode choice behaviour:
  - The results suggest that improving the built environment can substantially increase the probability of walking and biking as primary travel modes while

decreasing the likelihood of choosing the car as a passenger, HSR, and car as a driver.

- For public transit, improving the built environment decreases the likelihood of using transit in the peripheral neighbourhoods than in the core areas (e.g., downtown).
- Improving the built environment negatively influences the likelihood of choosing the car as a driver in the east and west ends of the city than the rest of the city. While for the car as a passenger, the negative effect is spatially consistent all over the city.
- From a geographical perspective, improving the built environment increases the likelihood of walking in the east and west parts of the city more than in other areas. While improving the built environment increases the likelihood of biking in the southwest part of the city.

- The results indicated that improving built environment attributes, albeit significant, will not drastically change travel behaviour in the City of Hamilton. However, the results also pinpoint locations for maximizing the impact of improving built environment attributes.

7.3 Limitations and future work

The research presented in this dissertation contributes to the current transit quality literature by providing a better understanding of the heterogeneity associated with transit customers' preferences and travel behaviour at various levels.

It is worthwhile to recognize that there are some limitations associated with this research. First, the data were collected through an online survey. Despite its various advantages (e.g., flexibility, short completion time, lower satisficing, and socially desirable responding biases), it has a major disadvantage, which is sample bias, as not all people have access to the internet. Further, the second wave of the data collection (in April 2019) was administered by a public transit provider (i.e., Hamilton Street Railway), and the sample over-represents public transit users. Finally, although a sample weighting technique was used to correct the nonproportional sampling, the actual (population) shares of some travel modes, such as biking, are vastly lower than the shares of car and transit travel modes.

In the light of this contribution, various possible extensions and research questions could be raised.

- A customer-oriented multi-objective optimization framework for public transit service reconfiguration is essential for transit agencies to satisfy transit customers and attract new riders. The findings of this dissertation could be used as inputs to guide the reconfiguration process based on customers' expectations. The proposed optimization framework will incorporate various parameters such as, among others, customers' preferences, willingness to pay for service improvements, differences between customer groups, travel demand, road network and financial constraints. Given the level of complexity in this optimization problem, machine learning techniques are proved to be a promising alternative for modelling travel behaviour and could be utilized to represent complex relationships in a data-driven manner

(Chen et al., 2018). Of all machine learning algorithms, genetic algorithms exhibit outstanding capability in solving complex real-life problems (Katoch et al., 2021).

- The findings of this dissertation could also be incorporated into an agent-based model to develop a customer-oriented planning tool while accounting for the interactions between public transit, built environment, other travel modes and customers. The agent-based modelling approach simulates the actions and interactions of autonomous individuals and assesses their effects on the system as a whole (Zheng et al., 2013). The advancement in computational power and database technologies allow for processing large-scale microsimulation models (Macal and North, 2013). The agent-based approach could be employed to explore various hypotheses about system dynamics, support decision-making in a risk-free virtual environment, presents a detailed description of a system, and capture emergent behaviour (Bonabeau, 2002). The agent-based approach is well-suited for systems consisting of existing dynamic and heterogeneous agents with a heterogeneous topology of interactions and exhibiting complex behaviour.

7.4 References

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