Disaggregate probabilistic models to predict trip generation propensities and mode choice behaviour

by

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Abstract

Travel behaviour models serve as important tools to understand what factors affect trip generation and preferred mode of travel in different contexts. These models can be used to quantify the impacts and assess the consequences of development plans and policy actions. Growing populations and the increase in travel demand warrant investigation into determinants of travel behaviour that can guide policy changes and infrastructure investments. This thesis uses two cross-sectional datasets containing various socio-demographic and land-use attributes from 2015 and 2019. Trip-generation propensities for transit and automobile modes are predicted using a bivariate ordered probit approach which enables the determining of factors affecting the trip-generation propensity of each mode while establishing the correlation between their propensities. Further, a multinomial logit model is estimated to investigate the determinants of mode choice for home-based discretionary trips. The results show that improvement in areas with low transit accessibility can considerably increase the transit trip-making propensity and living in downtown Toronto increases the probability of choosing active modes of travel.

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Acronyms

ANOVA	Analysis of Variance
AV	Autonomous Vehicles
BE	Built Environment
BOP	Bivariate ordered probit
BSS	Bicycle Sharing Systems
GTHA	Greater Toronto and Hamilton Area
HBD	Home-based Discretionary
HM	Hausman-McFadden
IIA	Independence of Irrelevant Alternatives
IID	Independently and Identically Distributed
ITS	Intelligent Transportation Systems
LL	Log-likelihood
MNL	Multinomial Logit
MNP	Multinomial Probit
MaaS	Mobility as a Service
NHTS	National Household Travel Survey
PD	Planning District
PWSE	Probability Weighted Sample Enumeration
RUM	Random-Utility Maximization
SMTO	StudentMoveToronto
TAZ	Traffic Analysis Zone
TDM	Travel Demand Management

Chapter 1: Introduction

This chapter addresses the motivation for research and introduces the study area. After an overview of the data used, the accessibility metric and descriptive statistics are briefly discussed. Lastly, recent transit infrastructure improvements made in the Greater Toronto and Hamilton (GTHA) region will be discussed and the outline for this thesis will be presented.

1.1 Motivation for research

The GTHA's long-term vision and urban development plans are geared towards implementing transit-oriented development by building mixed land-use character and communities where all destinations are walkable or can be reached by transit (Ontario, 2020). Such communities enable people to walk or use transit to complete their discretionary or non-discretionary trips thereby reducing usage of personal automobiles and emissions. Encouraging transit usage in communities will help build sustainable transportation systems, reduce emissions, and undo the effects of pollution caused by greenhouse gases. Promoting transit usage requires a comprehensive understanding of the factors that affect trip-generation and mode choice behaviour in the current era.

Cities have seen an increase in population over the last few years. The trend of population increase in cities is expected to grow (Bouton et al., 2013), leading to the following issues (i) increased traffic congestion and the inadequacy of existing traffic infrastructure to handle this growth, (ii) clogged arterials and overflowing highways during peak hours, and (iii) public dissatisfaction with transit due to lower level-of-service (LOS) parameters which can lead to a decline in transit usage.

The problem of urban congestion is not new, is ever-increasing, and with 70% of the population expected to live in cities by 2050 (Bouton et al., 2013), this problem is anticipated to grow. Urban congestion will lead to an increase in travel demand whose supply cannot be met merely with an increase in the frequency of service or infrastructure expansion but tackling congestion needs a holistic approach to ensure efficient utilization of transit infrastructure. More than half of the world's population are settled in cities, a trend which is also true for Canada, with 81% of the people residing in urban areas (World Bank, 2021). The transit agencies continually collect and analyze data obtained through census, conventional household travel surveys, and workplace surveys (Madar et al., 2021). Transport planners aim to predict travel behaviour and guide the policymakers to base their policy changes and infrastructure investments. Knowing how trip generation is affected due to socio-demographics and land-use attributes enables policymakers to develop appropriate urban planning and policy decisions and effectively manage travel demand. In recent times, transportation researchers have been attention to the travel behavior of postsecondary students (Collins & Agarwal, 2015; Habib et al., 2018; Hasnine et al., 2017; Li et al., 2017; Xiong et al., 2019) for various reasons. First, post-secondary students are primarily underrepresented in conventional household travel surveys due to the survey methodology of traditional surveys which use home phones for collecting data. Students use personal smartphones and tend to be a mobile group who frequently change their living situation and location and are missed out on the sampling frame of household surveys. They also tend to ignore surveys that may not benefit them directly (Chen, 2012; Volosin, 2014). Second, post-secondary students maintain a continuous and constant demand for transit. Third, post-secondary students are human

resources of any country who will shape the future policies and development strategies as they mature and join the country's workforce and become frequent users of transit infrastructure. The habits formed during their post-secondary education will influence their travel behaviour and outlook through the rest of their lives (Balsas, 2003; Basmajian, 2015).

Although policymakers have tried to encourage public transport and discourage automobile usage through various policies, the demand for vehicles in Canada has increased from 2015 to 2020, as seen by the record of vehicle registrations in Figure 1.

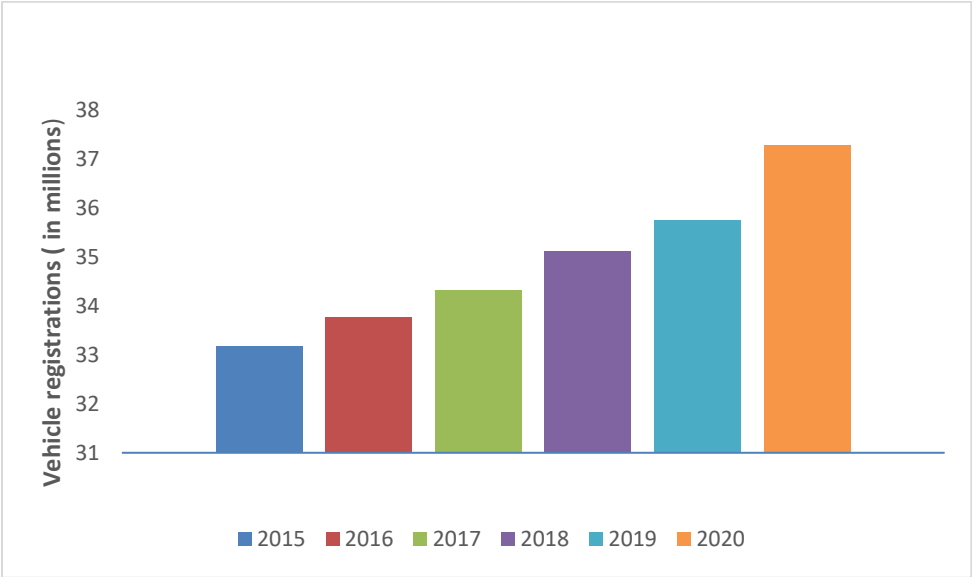


Figure 1: Total vehicle registrations in Canada by year (Statistics Canada, 2021a)

Urban passenger trips have also steadily increased at a lesser rate than automobiles since 2017, as seen in Figure 2. The urban passenger transit trips are lower for 2020 due to a slowdown of the economic activities in the year due to pandemic related restrictions.

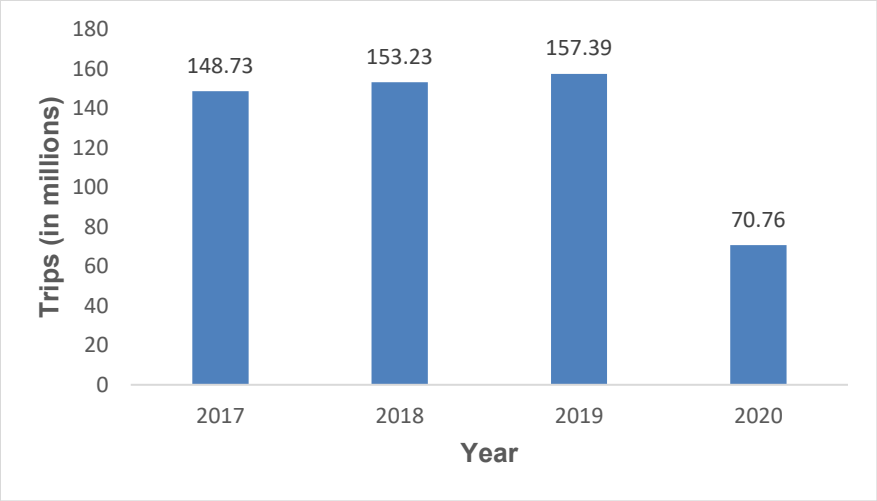


Figure 2: Graph showing urban transit trips by year (Statistics Canada, 2021b)

Having an efficient and reliable public transit system helps achieve sustainable transportation goals, reduces emissions, and can positively impact the habit formation of post-secondary students to choose public transit as a mode in the future. Although the coronavirus pandemic has required many to work and study remotely, there will be an increased demand for transit and infrastructure once institutional and economic activities are back to pre-pandemic levels. It is, therefore, necessary to understand what influences the trip-generation propensities and mode choice behaviour of one of the largest and the most constant transit demand generating cohort—the post-secondary students.

Extensive research has been conducted to understand factors affecting trip generation since increasing infrastructure capacity is not a sustainable approach for development and is not always feasible. Different techniques include travel demand management (TDM) strategies, travel behaviour modelling, micro-simulation of traffic networks in before and after scenarios and optimizing existing infrastructure through intelligent transportation systems (ITS). Metropolitan areas facing urban congestion experience air quality deterioration, frustration among commuters, and other disbenefits. Although motorized

modes such as automobile and transit have long been the topic of interest, there has been a lot of interest recently in modelling the active modes of travel such as cycling and walking (Delmelle & Delmelle, 2012; Ermagun & Samimi, 2015; Nash & Mitra, 2019; Scott & Ciuro, 2019).

Transportation and planning policy changes should be supported by a comprehensive understanding of associated advantages and disadvantages in a sound theoretical framework. Such a framework will include an inventory of existing travel trends and predicting what factors affect trip-generation patterns and influence mode choice behaviour.

This thesis makes use of two distinct modelling techniques. First, a bivariate ordered probit (BOP) approach, which is employed to predict trip-generation propensities of transit and automobile. The propensity change based on the explanatory variables helps reveal important behavioural trends. Second, a multinomial logit (MNL) model that will reveal the probability that a person chooses a particular mode based on their feasible choice set and explanatory variables included in the model. Mode choice is the most critical determinant affecting the number of automobiles on the transportation networks (Koppelman & Bhat, 2006).

Further, the results obtained by BOP and MNL modelling exercises are also analysed for marginal effects and elasticities, which helps quantify the effect of the explanatory variable on a particular mode. As an example, it is known from the results of the MNL model that living in downtown Toronto has a positive effect on choosing active modes of travel, but this effect is not quantified. A marginal effect analysis will quantify the

probability change in mode choice if a student lives downtown. Such analysis can be convenient for policy planners to evaluate and re-evaluate their policy decisions.

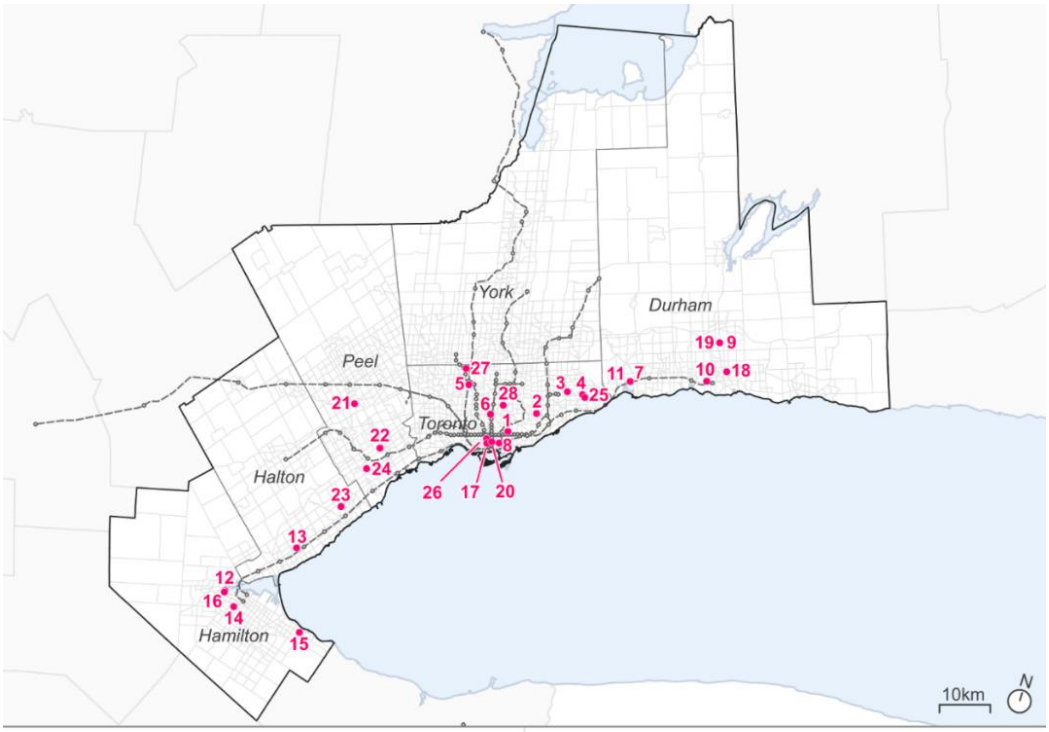
The primary objective of this thesis is to employ and calibrate the BOP and MNL modelling techniques to better understand the effect of personal and land-use attributes on the trip-generation propensities of transit and automobile and the determinants of mode choice for home-based discretionary (HBD) trips. These two different choice contexts are the integral components which define travel behaviour, and the model results will help deduce important behavioural insights which might be relevant in a policy context.

1.2 Study area

The study area of this thesis is the GTHA which has ten institutions with multiple campuses across the region. These institutions and their campuses are spread across the region, including downtown Toronto and the more suburban satellite municipalities. The City of Toronto, which has planning districts (PD) labelled from 1 to 16, will be closely studied for this thesis. PD 1 is the downtown Toronto area and consists of three post-secondary institutions: Ryerson University, Ontario College of Art and Design University, and the University of Toronto. PDs 2 to 16 are less dense than PD 1 but still fall under the City of Toronto limits and therefore of a higher density than other areas in the GTHA outside the City of Toronto limits (Rinner & Hussain, 2011). To meet the travel needs of the people of GTHA, various light rail transit extensions, bus rapid transit corridors, and GO Rail Services expansions are underway. In the future, Metrolinx, the agency responsible for overseeing the implementation of these transit projects, aims to double transit's share of travel, tripling ridership of trains, light rail lines, and bus rapid

transit systems. It also seeks to quadruple the ridership of GO Rail Services (Metrolinx, 2021). In May 2021, the province of Ontario in which the study area is situated has agreed to invest in projects totaling more than 26 billion dollars to improve the transit infrastructure in the GTHA region (Infrastructure Canada, 2021). These investments are in addition to current investments made in the transit infrastructure, thus reflecting the importance of public transit in the region.

The location of institutions and their different campuses relative to their host institution or the City of Toronto can be seen in Figure 3 (Allen, 2021).



	Institution	Campus		Institution	Campus
1	Centennial College	*Story Arts Centre*	15	Mohawk College	*Stoney Creek Campus*
2	Centennial College	*Ashtonbee Campus*	16	Mohawk College	*Institute for Applied Health Sciences*
3	Centennial College	*Progress Campus*	17	OCAD	*Only one campus*
4	Centennial College	*Morningside Campus*	18	Ontario Tech University	*Downtown Oshawa Campus*
5	Centennial College	*Downsview Campus*	19	Ontario Tech University	*North Oshawa Campus*
6	Centennial College	*Eglinton Learning Site*	20	Ryerson University	*Only one campus*
7	Centennial College	*Pickering Learning Site*	21	Sheridan College	*Davis Campus, Brampton*
8	Centennial College	*Performing Arts Commons*	22	Sheridan College	*Hazel McCallion Campus*
9	Durham College	*Oshawa Campus*	23	Sheridan College	*Trafalgar Road Campus*
10	Durham College	*Whitby Campus*	24	University of Toronto	*Mississauga Campus*
11	Durham College	*Pickering Learning Site*	25	University of Toronto	*Scarborough Campus*
12	McMaster University	*McMaster Campus*	26	University of Toronto	*St. George Campus*
13	McMaster University	*Burlington Campus/Ron Joyce Centre*	27	York University	*Keele Campus*
14	Mohawk College	*Fennell Campus (Main Campus)*	28	York University	*Glendon Campus*

Figure 3: Institutions and campuses located in the study area

A population increase of 6.2% was reported from 2011 to 2016 in the GTHA, and this trend is expected to continue (Statistics Canada, 2016). The GTHA has a diverse population, high influx of immigrants, international students, and educational institutions scattered across Toronto and suburban municipalities. Therefore, a comprehensive understanding of travel behaviour is needed to implement policy actions.

The post-secondary students primarily need to get to their schools, colleges, universities, or places of part-time work and help the province operate and maintain public transit infrastructure by maintaining constant ridership.

With the advent of new technologies such as connected and autonomous vehicles, hydrogen-powered buses, and cars, predicting the travel behavior of this cohort is essential for proper planning and revitalization of transit infrastructure.

1.3 Data sources

In this section, the StudentMoveToronto (SMTO) data used in this thesis have been briefly discussed. Using this data, the desired explanatory variables were extracted for the modelling contexts of this thesis. The calculation of the accessibility metric from the dataset used is discussed along with descriptive statistics of the dataset. Finally, descriptive statistics of the final combined dataset are presented.

1.3.1 SMTO survey

In 2015, researchers from four major universities located in the GTHA aimed to identify the student needs and options for transportation to predict their travel behaviour. This survey was timely as the province had promised to invest billions of dollars in improving the transit infrastructure and connectivity in the GTHA. A massive data collection effort was undertaken with the survey sent to the students of these institutions. In 2015, 15,226 students participated in the study. Their attributes such as age, gender, residence location, campus location, frequency of commute to campus, among other socio-demographics and attitudinal factors, were recorded. The collection of this data has resulted in various scholarly works and provided valuable insights to the policymakers (Butler & Sweet,

2020; Habib et al., 2018; Hasnine et al., 2018; Lin et al., 2019; Mitra, R., Habib, K. N., Siemiatycki, M., Keil, R. and Bowes, 2019).

In 2019, an improved survey was designed and recorded from 18,500 students. In the 2019 survey, other institutions, and colleges in the GTHA were also added to provide a comprehensive overview of travel behaviour and trends of the student population of the GTHA.

The chart below represents the proportion of students who took the survey belonging to different age groups. As seen in Figure 4, the cohort of people from 18-22 years constitutes about 51% of the total surveyed respondents.

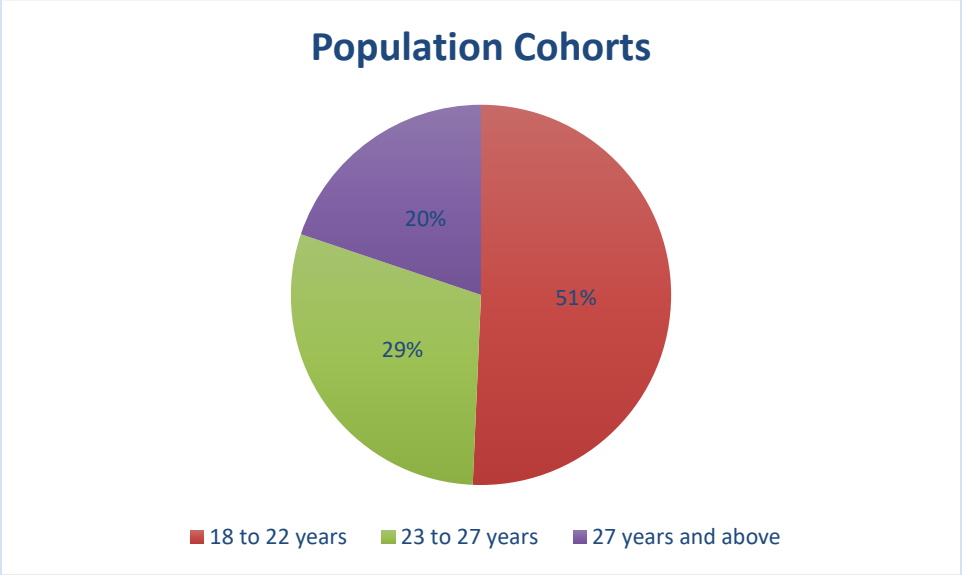


Figure 4: Population cohorts by age in the dataset

The 18-22 years cohort is a significant proportion compared to the other cohorts of the population. It is noted that the habits formed during this time of their lives determine their travel patterns and behaviour when they move over into the cohort of 23 years and older populations. This is the cohort where travel habits can be formed (Setiawan et al., 2015). From the data, it is found that at least 48% of the respondents made one trip per day using

transit as a mode. A key finding of the survey was that the average one-way commute to campus was 45 minutes, higher than other regions around the world (Páez & Whalen, 2010).

1.3.2 Inventory of data

This data is representative of Revealed Preference (RP) data, which is more advantageous than Stated Preference (SP) surveys whose observed choices are hypothetical and cannot reflect the change in personal attributes on the trip generation models (Hensher et al., 2000). In this thesis, two cross-sectional datasets from the SMTO data (Mitra, R., Habib, K. N., Siemiatycki, M., Keil, R. and Bowes, 2019) for the GTHA from 2015 and 2019 are used. Although the dataset used may not be a representative sample of the whole GTHA population, this rich dataset can be used to obtain considerable behavioural insight into the travel behaviour of students. Further, an accessibility metric for the transit mode is determined and is discussed in the next section.

1.3.3 Accessibility Metric

Accessibility can broadly be understood as the ease or difficulty of reaching opportunities. Place-based measures of employment accessibility are generated, the formulation of which is originally attributed to Hansen (1959).

$$A_i = \sum O_j \, f\left(t_{i,j}\right) \tag{5}$$

A_i is the accessibility measure for a zone i, and O_j is the number of job opportunities in a zone j, $t_{i,j}$ is the travel time from i to j by public transit. $f(t_{i,j})$ is a decay function that weights nearby locations more than those further away. For $f(t_{i,j})$, an inverse power function, which has been used in previous studies modelling the impacts of transit accessibility on activity participation and transit use in the Toronto region (Allen &

Farber, 2020; Yousefzadeh Barri et al., 2021)

$$f(t_{i,j}) = 180(90 - t_{i,j})^{-1} - 1 \quad (6)$$

Travel time in minutes using public transit, $t_{i,j}$, includes walking to and from stops, waiting for a transit vehicle, in-vehicle travel times, and any time spent transferring if required. Travel times were computed using input data for walking networks from OpenStreetMap, and data for transit networks is from historical transit schedules in General Transit Feed Specification format. A limitation of incorporating travel times using the described approach is that the in-vehicle travel times, waiting for a transit vehicle, time spent in transfers are weighed equally which is not an accurate representation of how users view the times spent during their commutes. Data on the locations of jobs, O_j, is from the 2016 Canadian census (Statistics Canada, 2016) and are spatially aggregated at the Dissemination Area (DA) level. (DAs typically consist of a few blocks and have 400-700 people) and is used for the data from 2015 as well as 2019. Once computed, accessibility measures were then linked to the students in the survey based on their home location and survey year. Opportunity-based metrics are commonly used for planning purposes as they provide a comprehensive measure of accessibility to the distribution of opportunities and give an accurate representation of the ability of the person to move from one place to another (Bliemer et al., 2016; Boisjoly & El-Geneidy, 2017; Ding et al., 2017). Areas with higher levels of employment are areas with higher levels of activity. Post-secondary institutions are usually located in areas with high activity and the inclusion of access to opportunities in the context of student travel behaviour acts as a proxy for transit accessibility to their campuses.

1.3.4 Descriptive statistics

The final dataset consisted of two cross-sectional datasets from 2015 and 2019. The survey contained questions on attitudinal factors, demographics, residence and campus locations, and a travel diary. In the data cleaning process, many entries that were found to have missing trip information in the travel diary were removed. Moreover, entries with conflicting responses such as making a car driving trip without owning a driving license which is not technically possible or having transit travel times greater than three hours which makes the transit mode unfeasible were removed from the data. After various stages of data cleaning, the total number of entries used in the final combined dataset for the BOP model was 17,539. There were 10,826 entries from 2015 and 6,713 entries from the 2019 dataset. These datasets were combined, and a host of explanatory variables appropriate to be in the model were chosen and derived from the dataset to use a final total of 14 explanatory variables for the BOP model. A key limitation of the data is that the survey data collected may have sampling errors as it may not be representative of the whole population which may bring about bias in the results produced by the model due to the associated sampling errors.

Table 1 shows the descriptive statistics of the data to understand the extent and gain an insight into the quality of the data used. Different regional transit services and options, such as light-rail transit (LRT), bus-rapid transit (BRT), GO Rail Services, etc., are counted as transit trips. Both car driving and car passenger trips are considered automobile trips in the context of this thesis.

Table 1: Descriptive Statistics

Variable	Value	Count	Percent (%)
Year of survey	2015	10827	62
	2019	6712	38

Gender	Male	9212	53
	Female	8069	46
	Other	258	1
University/Campus location	City of Toronto (PD 1)	10142	58
	Toronto area (PDs 2-16)	4559	26
	Outside Toronto Area	2838	16
Total trips made by mode	Transit	16025	57
	Automobile	12315	43
Age	Less than 22	10476	60
	Greater than 22	7063	40
Household living situation	Live with others	15697	89
	Live alone	1842	11
Transit-pass ownership	1, if owns a transit pass	9378	53
	0, otherwise	8161	47
Driving license ownership	1, if owns a driving license	8881	51
	0, otherwise	8658	49
Residence location	City of Toronto (PD 1)	3643	21
	Toronto area (PDs 2-16)	7347	42
	Outside Toronto Area	6549	37

Of the trips considered, the mode share for the automobile trips was 43%, and transit trips was 57% which is higher than expected for the GTHA.

Apart from the data extracted from the dataset, an accessibility metric as described in section 1.3.3 of this thesis was included as an explanatory variable in the model to capture the travel behaviour trends adequately.

1.4 Recent Transit Infrastructure Improvements in the GTHA

The province continually strives to improve the public transit infrastructure in the GTHA. It is estimated that by 2031, the population of GTHA will be 8.6 million, whose travel needs have to be accommodated (Metrolinx, 2013). In 2021 alone, the federal government pledged to fund five transit improvement projects in the GTHA. According to the regional transportation plan published in 2008, 62 rapid transit projects will be built by 2031. Most notably, the Ontario Line Subway, Scarborough Subway Extension,

Eglinton Crosstown West, Yonge North Subway Extension, Hamilton LRT, Finch West LRT, and Hurontario LRT are some of the most significant transit projects currently underway (Metrolinx, 2008). Planning is already underway for the extension of the Eglinton Crosstown West LRT project. Most recently, the Toronto-York Spadina Subway extension was opened along with opening various bus rapid transit (BRT) corridors across different regions in and surrounding the GTHA. The province also has increased sidewalks, bicycle storage facilities and increased accessibility to transit stations to promote active modes of travel and boost transit ridership (Metrolinx, 2013). These projects will provide essential infrastructure for the province, help accommodate the growing demand, and boost Ontario's economy.

1.5 Thesis outline

The conceptual framework adopted in this thesis for modelling the trip generation and mode choice behaviour can be seen in Figure 5. The rest of this thesis is organized as follows:

Chapter 2: provides a literature review of studies performed on travel behaviour among post-secondary students in general, followed by a review of behavioural modelling techniques and methods used in the context of transportation planning.

Chapter 3: discusses in detail the BOP modelling approach used in this thesis along with model background, empirical specification, and marginal effects analysis. After the presentation of results, a detailed discussion follows listing key findings, and deducing behavioural insights.

Chapter 4: discusses in detail the MNL model choice modelling technique with model background, empirical specification, and marginal effects analysis. A detailed discussion

of results which lists the key findings and policy implications derived from the MNL model follows.

Chapter 5: recommends future work directions, limitations in the modelling techniques used, a brief overview of how these limitations can be addressed and incorporated in future works to better understand the travel behaviours followed by conclusions and a References section.

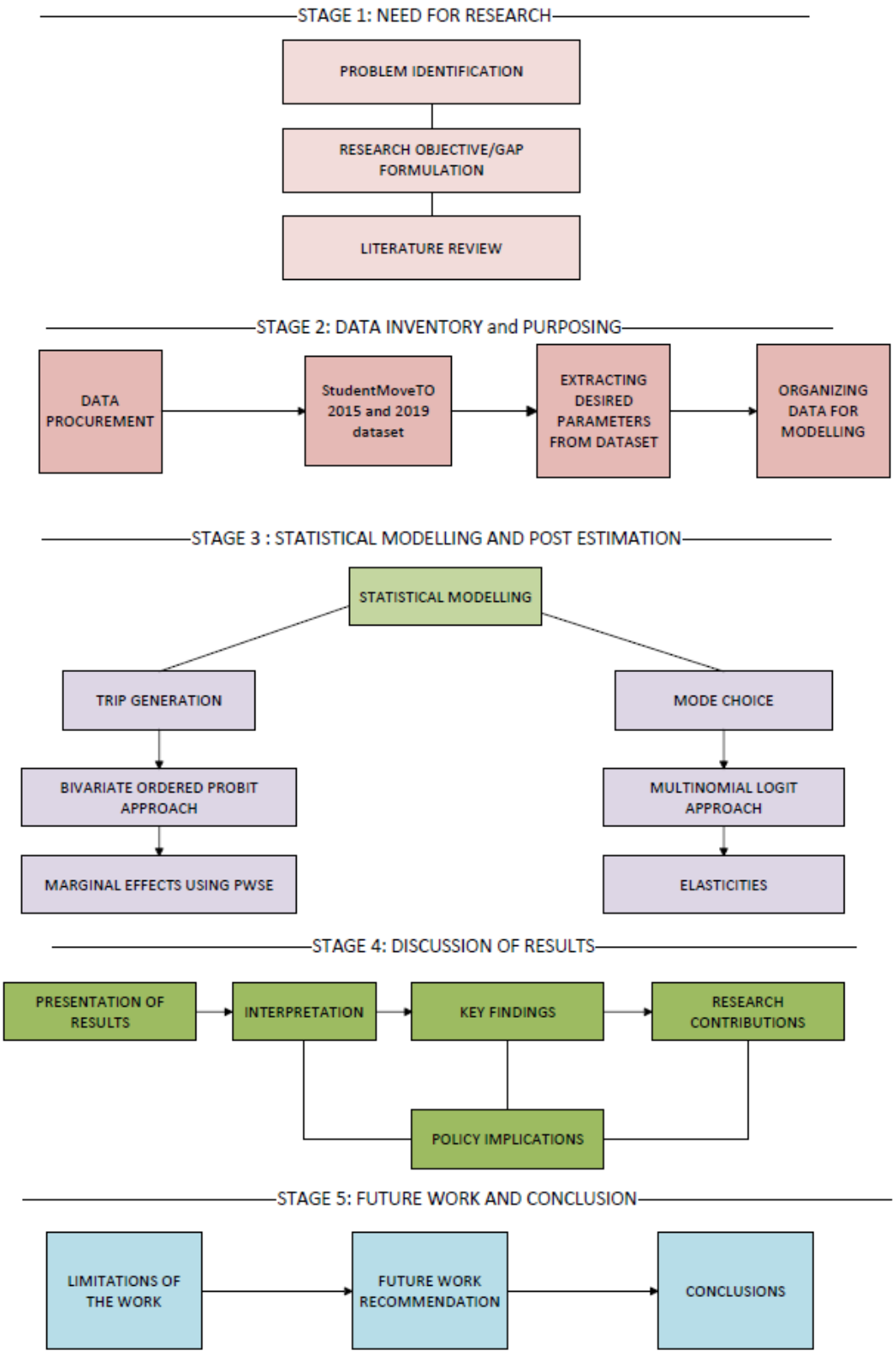


Figure 5: The adopted thesis framework

Chapter 2: Literature review

A detailed review of papers used for the formulation of this thesis has been performed in sections 2.1 to 2.3. Selected articles reviewed for this thesis have also been briefly summarized by the analysis method and key findings at the end of this chapter in Table 2 and Table 3.

2.1 Travel behaviour of post-secondary students

An understanding of the post-secondary students' travel behaviour can enable cities to implement sustainable travel practices as this young cohort of the population can be stimulated to develop travel habits and preferences for travel (Capasso & Astroza, 2019; Habib et al., 2018). The travel behaviour of post-secondary students and young adults has been the topic of interest of many transportation researchers. Different factors such as mobility tool ownership, gender, year standing, location of the institution, etc., affecting students' travel behaviour have been extensively researched.

An analysis of the travel behaviour of the university population of Iowa State University was investigated by Basmajian (2015). The purpose of the study was to analyze the effect of socio-demographics such as age, gender, year standing, residence location, etc., on the travel behaviour patterns of the university commuters. Using spatial data and data from the survey for Iowa University commuters, an MNL predicting students' mode choice behaviour was also developed. The study's key findings were that most of the university commuters were living far away from their campus due to lack of suitable housing options or accommodations that could promote active modes of travel such as walking and cycling. It also found that university transportation plans lacked knowledge of spatial data regarding students' off-campus housing. The study suggested the inclusion of

students in the transportation planning process of the universities, which would help identify the student residence areas off-campus for potential improvement of transit connectivity. The study also suggested awareness programs and incentives to promote public transit to their university, which might prove to be helpful in travel habit formation.

Mitra and Buliung (2015) explored the differences in mode choice behaviour between 11-year-old children and 14-15-year-old youths travelling to school in the Toronto region using the 2006 TTS data. They found that distance to school was the main factor discouraging youths from walking to school. They conclude that simply by designing and improving transport infrastructure, the youth's propensity to adopt active modes of travel may not increase, and encouragement through school programs and incentives must be introduced to shape the travel behaviour of these groups of students. Also, females aged 14-15 years are less likely to walk than males, which may suggests that females do not consider walking a safe mode of travel. It also found those dense neighbourhoods defined as having mixed land use and high retail density are neighbourhoods whose residents are more likely to choose walking as a mode of commute to schools.

In a city like Los Angeles (LA), which is highly automobile-oriented, Zhou (2012) aimed to find out whether students living in LA had a higher tendency to use automobiles for their commute compared to other regions. Zhou found that living in LA did not increase students' propensity to take cars, which is intuitive as one would expect students enrolled in college or university are often not financially independent and therefore incapable of owning and maintaining a personal automobile. One interesting finding is that almost 67% of students in LA travel during off-peak hours and therefore are not significant

contributors to peak hour congestion in LA. Students driving alone are most likely to live independently, treasure privacy more than others, and are willing to afford it in a city like LA.

Allen and Farber (2018) investigated factors that may prevent students from attending their campuses in the GTHA, such as constraints due to part-time work, transit accessibility, and their home location. They aimed to find out how their commute patterns affected their grades and participation in university activities using the 2015 SMTO data. They found that having longer commutes results in a low probability of students participating in on-campus activities. It also found that improving transit accessibility near low-income households will significantly increase the transit trip-making propensity. Interestingly, 35% of the respondents would have had faster commutes if they chose cycling as a mode from their origin rather than transit which means that cycling to campuses must be encouraged through awareness programs or by introducing bicycle-sharing-systems (BSS).

Chen (2012) performed Analysis of Variance (ANOVA) on an online version of the (NHTS) as the students are often not represented adequately in these household travel surveys administered by telephones. Chen found significant differences in students' travel behavior living on and off-campus in Virginia Central University and concludes that driving was a predominant mode of travel. Although it captured valuable behavioural insights, it is not extendable to other regions, especially GTHA, due to vast spatial and demographic differences. This study mainly focused on the differences between trips made by graduate or undergraduate and on and off-campus students.

Tuveri et al. (2020) used panel data from a survey administered through GPS applications installed on participating students' smartphones in Italy. Their aim was solely to gain insight into students' travel behavior as cars were the dominant mode of travel and to enable the transport policymakers to understand how a culture of public transit usage by students can be increased. Still, the dataset consisted of only 50 students which may have caused a bias in results. During the week-long survey, they sent a personalized travel plan (PTP) to each respondent based on their routes which suggested travel using public transit and walk or cycle and recorded if the suggested PTP was used. The authors found that students whose preferred mode of transport was a personal mode of transport (automobile, cycle, etc.) decreased by almost half after implementing the suggested PTP. Researchers have even tried to investigate the travel behaviour of the cohort of international students in Australia to explore any disparities in mobility options faced by this cohort in terms of implications on the tourism transportation industry (Gardiner et al., 2013). They found that people from China and India have a higher propensity to travel on day trips than North Americans and Europeans. The study also suggested that international students must not be considered as a homogenous cohort but consist of sub-groups so that the tourism industry can align with their travel behaviours. This insight on students' travel behavior may result in increased revenues for the tourism industry in Australia as 86% of the students in the dataset reported travelling for leisure.

Lin et al. (2019) investigated the effect of personal attributes and observed external variables on transport multimodality of post-secondary students using a Structured Equation Modelling (SEM) and a ordered probit approach using 2015 SMTO data. This study found that age and year of study significantly affect the multimodal behavior and

found that mobility tool ownership and land use variables are strongly related to the built environment (BE) variables such as street block size and access to transit. Having multiple mobility tools positively affects choosing multiple modes of travel, and higher transit accessibility results in higher transit usage.

Mitra and Nash (2019) investigated the cycling behaviour of students based on gender and the effect of BE variables. They found that females were less likely to use bicycles for commuting, especially in dense routes and roads with speed limits greater than 60 km/h. They discovered that cycling had a commute mode share of 7.6%, which is a significant mode share and is contrary to what one would expect for cycling. They also found that having a commute distance of 2-5 km is the most favoured cycling zone. Like the findings in this thesis, they found that the effect of having access to a vehicle is not statistically significant. Their study reinforces that the cycling infrastructure is not attractive to females as much as males and that the policymakers must strive to build infrastructure that can help promote females wanting to cycle than they currently do.

Using an internet-based survey for the students in Virginia, Khattak et al. (2011) aimed to model the differences between trip generation patterns of the general population and the student populations. This interest had risen because of the under-representation of students in household surveys and incomplete understanding of the travel behaviour of university students in Virginia. Using descriptive analyses, they categorized the heterogeneities present in students' travel behavior to be used in travel demand models. They looked at all commuter trips, did not focus on a subset of trips by purpose, and mentioned that trip-generation patterns vary based on trip type and must be included in future studies. The key takeaway of the study was that the location of the campus in an

urban or suburban area was the key factor in determining if a student's preferred choice was transit.

Moniruzzaman & Farber (2018) used 2015 SMTO data to identify what factors encouraged sustainable travel modes in students using an MNL approach. They found that students working part-time are less likely to use active modes of travel. Although the MNL model gave an idea of overall trends in changes in probability by mode, these changes were not quantified by analyzing the marginal effects. The paper suggested that the universities increase the availability of student housing near campuses. Lastly, they suggested that providing incentives for transit passes to students will encourage the usage of public transit and active modes of travel.

2.2 Trip Generation

Predicting trip generation has been a topic of interest for all cities as the regional highway networks and arterials face increasing congestion. Various tools are used to predict and forecast trip generation, such as computer software-based planning systems and trip generation manuals (Ben-Akiva & Lerman, 1985). These methods have historically been aggregate-based measures. They use aggregated zonal data rather than considering the disaggregate nature and presence of various personal and land-use attributes leading to a loss in the precision of the parameter estimates if the data is not homogenous. In the context of GTHA, where the immigrant population continues to grow, urban sprawl increases, different demographics, and personal attributes exist, the aggregated approach may not be suitable. Trip-generation manuals serve as a handy tool but may not suit all contexts and regions (Ben-Akiva & Lerman, 1985). Therefore, a disaggregate demand modelling technique is needed. Researchers have used various modelling techniques to

model trip generation based on data obtained from multiple surveys such as NHTSs, workplace commuting surveys, cell phone data, and travel planning mobile applications. Q. Zhang et al. (2019) aimed to explore the relationship between land-use density and household trip generation. They argue that although the BE plays an important role in the trip generation, the effect is different for discretionary and non-discretionary trips. They developed a transportation demand model using a negative binomial regression model for each type of mode based on a host of explanatory variables. A drawback of using this approach was that there was no correlation reported between any two predominant modes which limits the scope of policy actions for example. They found that increasing transit accessibility strongly influences discretionary trips. Their results showed that have an impact on trip generation patterns and thereby improve the model fit. A key finding of their study was that people living in densely populated neighbourhoods tend to make more trips than the population in suburban areas. In suburban areas with low densities, it is found that they exhibit a higher trip chaining behaviour as they bundle multiple trips into one, which is also indicative of the fact that there is a closer proximity to locations of interest in densely populated BEs.

Bwambale et al. (2019) has modelled the trip generation using location from call data records using an ordered response choice model. They proposed a hybrid framework that combined two discrete choice models. One model predicts the demographics, and the second model uses the results of the first model as input in the second model, which is an ordered-choice model. The modelling technique used in their study is similar to an ordered logit approach first proposed by McFadden (1973). The first model uses an MNL approach to predict the probability of belonging to a male group or a female group. These

propensities are then integrated into an ordered-logit model that predicts propensity of trip generation by mode based on these parameters. The results showed only an overall probability change trend in trip generation and these changes were not quantified through a marginal effects analysis.

2.2.1 Modelling techniques used for predicting trip-making propensities

Several techniques such as logit, ordered logit, probit, and ordered probit methods have been conventionally used to model trip generation. Since the increasing number of trips represents an increase in trip-generation levels, ordered techniques are suitable for this type of study. Researchers have used univariate ordered probit and ordered logit techniques to predict trip generation patterns as they are less computationally intensive. Using the 2015 Puget Sound Regional Travel Study data, which included hypothetical questions about the adoption of autonomous vehicles (AV) apart from the socio-demographics and location. Nair et al. (2018) used a univariate ordered probit approach and estimated the probability of AVs' adoption propensity based on the respondents' heterogeneities. They found that older travelers would be averse to adopting AVs. The younger populations are more willing to adopt AVs and use alternative mobility options such as mobility as a service (MaaS). These findings of the study were significant, but the effect of the adoption of AVs on other modes such as public transit, walking, or cycling could not be analysed due to the univariate approach.

de Palma and Picard (2005) used computer-based travel survey data from Paris and aimed to study the route choice behaviour when given a choice between choosing a known route with higher travel times or an unknown route with lower travel times. The respondents were asked what they would prefer, uncertainty in travel time on the known

route, or a likely less commute time with lesser information about the alternate route for their trip. Employing a univariate ordered probit approach to identify the risk aversion behaviour associated with route choice, the survey collected their risk aversion preferences and the model predicted that the risk aversion tendency is highest for transit users, blue collar workers and people going for business meetings. As with the univariate approach, the willingness to shift to an alternate route could not be modelled simultaneously.

The BOP approach can be employed to model two variables simultaneously. Although the univariate modelling techniques give us an idea of the influence of socio-demographic and land-use variables on the trip-generation of a particular mode, the effect on the propensities of generating trips using different modes is missing. The effect of an increase in the propensity of personal automobile usage trip generation of one mode on other modes such as transit is necessary as planners seek to decrease automobile trips through increased adoption of other sustainable modes. Therefore, a BOP analysis that simultaneously models the influence of the attributes on trip-generation and correlates the propensity of the two modes will help better understand and gain credible insight into the trip-generation patterns. Section 2.2.2 reviews the different studies that have used the BOP approach and the significance of their results.

2.2.2 BOP modelling

BOP models have been used in the past for exploring the relationship between two dependent variables based on a set of independent variables. The results obtained are significant when the correlation between the two variables is strong. Moreover, the ordered nature of BOP accounts for changes in the level of trip-generation associated

with the mode. The BOP technique is extensively used by researchers in travel behaviour modelling (Vignoli et al., 2013; Yamamoto & Shankar, 2004) and is also used by researchers across different fields such as accident analysis and voting research, etc. due to its' established accuracy (Abotalebi et al., 2019; Fujiwara et al., 2010; Greene & Hensher, 2010; L. Guo et al., 2017).

Anastasopoulos et al. (2012) have used the BOP approach to establish the relationship between household type and mobility tool ownership.

More recently, Xiong et al. (2019) have used the BOP approach to model the travel behaviour of students in Hong Kong. They found that bicycles were not considered safe by the children in the study area due to the absence of dedicated biking lanes. They also note that additional bus stops in the study area can promote the usage of both transit and bicycles due to lower distances of getting to a transit stop.

Dias et al. (2017) also used the BOP approach to estimate trip generation of ride-sourcing or car-sharing services. They concluded that having children reduces the likelihood of using rideshare and having lower income results in higher carsharing and complex travel patterns.

Although many have used the BOP modelling technique, none have calculated the marginal effects using the recommended probability weighted sample enumeration (PWSE) method which enables the quantification of the model results (Fujiwara et al., 2010; Vignoli et al., 2013) and provides disaggregate trends (Greene & Hensher, 2010). This thesis will perform a marginal effects analysis on the results from the BOP model in Chapter 3:.

2.3 Mode Choice Modelling

Discrete choice methods are generally used to analyze mode choice behaviour as making a travel mode choice from a given set of alternatives follows an unordered nature. Discrete choice modelling is an extensively used technique in transportation research. The usage of discrete choice modelling has been widely accepted in travel demand research, accident analysis, and predicting travel mode choice behaviour (Ben-Akiva & Bierlaire, 1999; Ben-Akiva & Lerman, 1985; Koppelman & Bhat, 2006; Train, 2003). Researchers have also used discrete choice modelling techniques in the field of economics, health sciences, behavioural modeling and political sciences (Dow & Endersby, 2004; Kropko, 2008; Mattisson et al., 2018; Nasruddin et al., 2020; Pinder, 1996). Section 2.3.1 of this thesis will review the use of discrete choice modelling in the context of transportation and section 2.3.2 will review the application of the MNL technique to analyze the travel behaviour of post-secondary students.

2.3.1 Mode Choice Modelling in the context of Transportation

Discrete choice modelling forms an integral part of transportation demand forecasting. In transportation planning, random utility maximization (RUM) models such as MNL, conditional logit, Mixed MNL (MMNL) etc. are used depending on research goals and nature of the data present. MNLs are commonly used for mode choice in transportation planning due to their computational tractability.

Guerra et al. (2018) used a relatively large dataset of more than 2.5 million trips across Mexico’s 100 largest urban areas from the 2015 Intercensus data for work trips. An MNL was estimated to determine the mode choice as a function of the people's personal and urban form attributes in the region. In the context of Mexico, they found that current

public policies have contributed to an increase in car ridership and associated congestion rather than decreasing it. The results obtained by Guerra et al. reinforce the findings reported by Day et al. (2010) that people with higher incomes have a higher probability of making automobile trips. Commuters living in low-density cities with a good roadway network favour cars as these have low transit supply due to a probable low transit demand. They employed a conventional MNL to gain significant insight into why the car ridership levels have not decreased even though substantial transit improvements have been made. As the results suggest, the current land use and urban form policies have increased car ridership due to the policies aimed at creating housing for moderate-to-low-income people away from the job clusters and therefore in areas with less transit supply. However, these probability changes were not quantified and only a general overall trend was reported.

Ben-Akiva & Lerman (1985) were one of the early researchers who comprehensively analysed the application of the MNL to the context of transportation mode choice. Recently, there has been a growing trend to design infrastructure which caters to pedestrians and cyclists to encourage choosing these active modes of travel. Cycling is an active mode of travel and is often encouraged by the municipalities and workplaces due to its positive environmental and health impacts. Several studies have found that younger populations tend to be more flexible in adopting new modes of travel such as shared bicycles, electric scooters, and MaaS options (Chakour & Eluru, 2014; Rashidi et al., 2012; Zolfaghari et al., 2013). To establish the feasibility of introducing such new modes of travel, Campbell et al. (2016) used data from an SP survey from Beijing where the bike-sharing concept was gaining popularity and estimated an MNL to model the factors

that influence switching from other modes of travel to cycling. They found that switching to bikeshare is very sensitive to activity levels and comfort perception. It found that motorized assistance in e-bikes and bikes lowers activity and makes people more willing to travel longer distances using these motorized cycling modes. Moreover, Campbell et al. find that women would be more inclined to switch to e-bikes in peak hours of congestion which implies that women tend to avoid crowded buses and congested public transit systems. Such modes are continually gaining significance among younger populations, including post secondary students. The increasing adoption of modes such as e-bikes and e-scooters among post-secondary students can alter their travel habits and preferences. The prediction of factors affecting choice of such new modes requires an understanding of the existing travel behaviour of post-secondary students. Institutions which are in downtown can benefit from motorized scooters and bicycles are convenient to get from one place to another without having to own or maintain and the flexibility to drop in any area of the downtown. As an example, the introduction of electric scooters in the downtown core of Ottawa where a large post-secondary institution is located has gained immense popularity among younger populations due to ease of access, flexibility to end the trip within a specified radius, and no cost of ownership in Ottawa (Bird, 2021). The implementation of such travel modes near main transit stations and around post-secondary institutions in the GTHA can increase the propensity of choosing transit as a mode of travel among students.

A key factor in determining the usage of transit is the ability to get to a transit stop. In transportation, the first or last mile travelled is studied to capture the effect of the distance to a transit stop on the transit usage. The first and last-mile trip is usually completed by

walking or cycling to nearby transit stops (Campbell et al., 2016). To determine how the distance to reach a transit stop can influence transit travel behaviours, Koh and Wong (2013) estimated an MNL for mode choice and noted that walking is usually the last/first part of a trip chain consisting of a transit trip. The propensity of taking transit increases if the bus stations are at a walkable distance (considered to be a mile) in the study. It also found that the probability of using a bicycle is low for near and far distances. The authors found that the highest usage of bicycles occurs at about a distance of 1.5 km to a bus stop which indicates that 1.5 km is probably a comfortable distance for cycling in the context of Singapore. At about 1.8 km, the propensity of walking decreases drastically, meaning that 1.8 km is the threshold up to which the people are most likely to walk. In the development of a feasible choice set for the MNL for this thesis, walking was excluded as a feasible mode for commute distances greater than 5 km and cycling was excluded for commute distances greater than 10 km. The study area in Koh & Wong's research is Singapore, however, the observed results of a comfortable threshold distance to use walking and cycling as a mode may be relevant in the context of the GTHA as well due to the similarity in transit infrastructure facilities in the two regions (Derrible & Kennedy, 2009).

Faghih-Imani & Eluru (2015) aimed to model the impacts of various personal, land use, and bicycle infrastructure attributes using data from Chicago's Divvy System on choosing a destination bicycle sharing system (BSS). They found that people prefer BSSs with longer bicycle paths nearby. It was also found that users choose stations that bring them closer to the CBD. This trend is higher in peak hours, which is likely due to users riding bicycles for their commutes to avoid peak-hour public transit. A possible reason

for this is because there is usually an increased number of passengers travelling in peak hours with congested waiting areas and seating situations on buses, a situation which also holds

for the City of Toronto where there are several post-secondary institutions and campuses. The specification of the MNL requires the model to have the Independence of Irrelevant Alternatives (IIA) property which implies that if a new alternative is introduced, the probability of choosing the new alternative will be equal to the probability decrease in other alternatives even if the new alternative is irrelevant to the some of the existing alternatives. Moreover, the error terms are independently and identically distributed (IID) which means that the unobserved or random variables are mutually independent and have the same probability distribution. Alternate modelling techniques such as a MMNL and the MNP in which the primary assumption is that random components follow a multivariate normal distribution which captures the correlation between the random components has not been used extensively for travel behaviour modelling. MNP is computationally challenging, and extensive simulation is required to maximize the model's log-likelihood function (Horowitz, 1980). Following the specification tests for the MNL proposed by Hausman & McFadden (1984), Cheng & Long (2007) found that in the context of transportation mode choice with model specifications like this thesis did not violate the IIA assumption. It is also noted that in cases where the random components are IID, and the IIA assumption is not violated, the MNL and MNP approaches both give similar results (Dow & Endersby, 2004).

2.3.2 MNL for mode choice modelling of post-secondary student travel behaviour

Given the advantages of the MNL, this modeling technique been used extensively to model transportation mode choice behaviour and changes in mode choice habits. Haggar et al. (2019) aimed to determine how travel mode choice habits change when students move out into different locations. Using a survey conducted using two questionnaires in the United Kingdom using responses from 250 individuals, they found that the new location of a house changed the travel mode choice and the old travel habits became obsolete. They also found that there is no direct link between the existing travel habits of students and the location of planned move to a new house. They note that if a student wanted to walk or cycle as a travel mode, they would choose new locations for their home which is within a walkable or biking distance. However, the scope of their study was limited due to the small sample size and that 73% of the respondents chose walking or cycling as a mode initially.

Ermagun & Samimi (2015) estimated an MNL and a nested logit (NL) model to determine factors that can promote active modes of travel such as walk and cycle for school trips in Tehran. They used a three-level NL and compared it with the MNL and found that the parameter estimates are not much different and both models represented similar overall trends and elasticities. As with all studies, increasing distance from home to school had a negative effect on choosing an active mode of travel due to increased amount of activity and time spent when using these modes of travel. An important factor in determining the mode choice of trips to school is the parent's perception towards a particular mode. They found that parents don't want their children to spend long times walking or cycling to school and would rather prefer they travel by school bus or personal car. There is also an indication of the notion that parents do not feel that the

existing walking paths to school are safe for children and improvements in the safety of sidewalks and segregation from main roads can increase the propensity of choosing walking as a mode to travel to school. Singh and Vasudevan (2018) aimed to investigate students' school trip mode choice behaviour in Kanpur, India, using a conventional MNL. Using a simple dataset, their model estimated about 15 parameters and had the mode choices as bicycle, cycle-taxi, school bus, taxi, family vehicle, and walking. One of the key findings is that children are most likely to go to far-off schools only if they have school bus service or family vehicle access. The probability of cycling as a mode decreases as the distance to school increases due to the absence of exclusive bicycle lanes in the study area. They also validated the model by performing the specification tests prescribed by Hausman & McFadden (1984) and found that the IIA assumption was not violated.

Although the studies by Ermagun & Samimi and Singh & Vasudevan focused on pre-secondary students, the trends observed in their study provide useful insights into the travel habit formation process of young post-secondary students who still live at home. Nguyen-Phuoc et al. (2018) aimed to examine the travel mode choice of university students in the context of Vietnam where the predominant mode of travel is motorcycles and there is an absence of an efficient public transit system. They found that the travel mode choice decision of students is based on their residence location, and LOS variables of public transport. In line with other studies (Collins & Agarwal, 2015; Nash & Mitra, 2019), they found that increasing distance from home to school has a strong negative effect on choosing walking as a mode of travel. It also found that existing public transport is inefficient and needs significant improvements in public transit LOS variables to

encourage the students to switch to public transport which the region's development plan wanted to achieve. Finally, they suggest that students using motorcycles will be willing to switch to public transport if the LOS variables such as travel time, and comfort are improved in the existing transit infrastructure.

Travel mode choices are also dependent on the time the trip is made, such as in peak hours or off-peak hours. Students in post-secondary institutions may have varying trip timings due to their class schedules. To capture the effect of trip timings on mode choice in the GTHA, Day et al. (2010) aimed to understand the relationship between modal and temporal decisions using an MNL. The study used cordon count data consisting of over 100,000 observations from the GTHA. It found that being employed full-time has a positive effect on choosing automobile as a mode. It also found that people with higher wages have higher Value of Time (VOT) and that free parking at workplaces encourages automobile usage. Also, as the trip distances increase, the probability of taking transit decreases. These are intuitive results and reinforce the strategic directions desired by the policymakers. The trends observed in their study are associated with employment status and work trip timings at peak hours. A similar trend can be expected among post-secondary students when the school trip timings are identical to the work trip timings in their study due to the same regional context being studied in this thesis. As an extension of this thesis, the factors affecting mode choice of students based on the time they make their trip can also be analysed.

Understanding mode choice behaviour is necessary to predict future travel demand as well as plan for infrastructure. To analyze what factors can promote the choice of sustainable travel modes among students in GTHA, Moniruzzaman & Farber (2018) used

the SMTO 2015 data similar to one used in this thesis to examine the factors affecting mode choice behaviour of commuter trips of students. They estimated an MNL model to predict mode choice behaviour and found that transit pass and bike ownership is important that can promote sustainable travel. Their study suggests that increasing transit pass ownership and improving cycling infrastructure can increase the adoption of sustainable travel modes. The choice set structure of the MNL estimated in their study was similar to the choice structure used in this thesis. The MNL was estimated using four alternatives car driving, car passenger, transit, and active modes. The active modes alternative included walking and cycling trips with no classification for walking and cycling. So, the parameters estimated by the model are assumed to effect walking and cycling by the same magnitude. Their study is in line with the research findings that having a high income increases the propensity of car driving as a mode (Lavieri & Bhat, 2019; Zhou, 2012). Moreover, the study also found that increasing the distance to campuses reduces the propensity of using active modes of travel. As seen in section 3.2 of this thesis, the propensity of walking or cycling increases if the distance to campus is within a 5 km distance. However, their study analysed all trips in general and not discretionary trips specifically, about which very less is known. Although the study provided overall trends in probability change, the effect of a change in an explanatory variable on the propensity of the mode choice of each alternative was not quantified.

To determine what factors can increase the propensity of walking to campuses, Ewing et al. (2004) examined the relationship between mode of travel to their campus and factors affecting their mode choice using an MNL for mode choice in Florida. Their study found that students living closer to schools are much more likely to walk or bike. Moreover, the

presence of sidewalks on main roads increased the propensity of walking to school. Interestingly, they found that land use variables such as density and mix do not have a direct effect on mode choices. However, as a limitation of their study, they note that BE influences the propensity of walking but could not be captured directly in their study. In line with other studies, having a higher income translated into an increased propensity of choosing automobile as a mode of travel.

Akar et al. (2012) used a web-based campus transportation survey similar to SMTO data used in this thesis. The survey was conducted in Ohio State University to understand the travel patterns among people commuting to campus. As the finding of this thesis which suggests residing in PD 1 where there is excellent transit connectivity increases the propensity of making transit trips, their study also found that proximity to bus stops increases the propensity of choosing transit as a mode of travel. Their study found that the car driving mode was the dominant mode of travel followed by walking, transit, and cycling. The study also notes that a large percentage of students reside within a couple of miles of campus and there is a potential for increasing the usage of cycling if the existing bicycle lanes are made safer and more bicycle storage facilities on campus are provided.

Hasnine et al. (2018) estimated MNL and NL models to gain behavioural insights on mode choice behaviour and found that female students travelling to downtown campuses are more likely to take transit than female students travelling to suburban campuses. This finding is representative of decreased transit usage and lower transit connectivity in areas outside the City of Toronto. A finding of this thesis also suggests that increasing transit connectivity areas outside the City of Toronto can increase the propensity of transit trip generation. Their study focused on commuter trips and is one of the few studies that

have comprehensively analysed the marginal effects and elasticities of socio-demographics and LOS variables. This thesis also performs a marginal effects analysis on the estimated MNL for HBD trips in section 4.2.3 of this thesis.

2.4 Gaps in literature and research contributions

Researchers have adopted several approaches to understand the travel behaviour of students for the GTHA. However, these studies focus either on trip generation patterns or mode choice behaviour. There is lack of a consecutive modelling exercise in the existing literature that calculates the trip-making propensities and the mode choice behaviour for the GTHA region like the approach used in this thesis. This thesis predicts the trip generation patterns of transit and automobiles with heavy inclusion of land-use variables such as residence location and transit accessibility. Since the existing literature is mainly focused on commuter trips, less is known about HBD trips. The MNL model for mode choice estimated in this thesis will help determine key factors influencing mode choice and the differences in trip-generation propensities for HBD trips.

This thesis aims to contribute to the literature in four ways:

- This thesis estimated a BOP model for predicting trip-generation and an MNL for analysing mode choice determinants. The BOP approach used in this thesis has not been used to investigate the travel behaviour using the SMTO data for the GTHA region.
- The marginal effects analysis for the BOP model performed in thesis using the recommended probability weighted sample enumeration (PWSE) approach has not been performed by anyone else to the best of my knowledge.

- This thesis will be able to explain the effect of socio-demographics and land-use variables on trip-making propensities for transit and automobile modes in the GTHA. The influence of the explanatory variables on the propensities has great potential in terms of validating policy actions and infrastructure investments in the GTHA.
- Lastly, this thesis specifically investigates the mode choice behaviour for HBD trips in the GTHA which has not been studied as closely compared to the literature on commuter mode choice behaviour.

As mentioned in the beginning of the chapter, **Table 2** and **Table 3** present a bibliometric overview of selected articles for literature review.

Table 2: A bibliometric overview of selected literature reviewed for trip-generation modeling

Authors and Year	Dataset	Investigated factors	Analysis method	Key findings
(Gardiner et al., 2013)	Two-phased leisure travel survey for international students	Leisure travel of international students	Descriptive statistical analyses	Nationality of students motivates different modes of travel for leisure
(Lin et al., 2019)	SMTO 2015	Multimodal behaviour of students	Ordered probit model	Land-use and mobility tool ownership has a strong effect on multimodality
(Gardiner et al., 2013)	Two-phased leisure travel survey for international students	Leisure travel of international students	Descriptive statistical analyses	Nationality of students motivates different modes of travel for leisure
(Yamamoto & Shankar, 2004)	4-year statewide accident data from Washington	Injury-severity in collisions with fixed-objects	BOP model	High vehicle speed and influence of alcohol increases the injury severity
(Vignoli et al., 2013)	Generations and Gender Survey	Relation between housing situation and fertility	BOP model	Increased housing security leads to earlier fertility
(Fujiwara et al., 2010)	Japan National Traffic Accident Database	Injury-severity and collision type	BOP model	Collision due to high vehicle speed increases injury severity

(Anastasopoulos et al., 2012)	Geocoded trip data from Greece	Relation between household and motorized mode ownership	BOP model	Longer work trips decreases motorcycle ownership
(Dias et al., 2017)	Puget Sound Regional Travel Study	Relation between age and car-sharing and ride-sourcing	BOP model	Users of ride-sharing and car-sourcing are young
(Chen, 2012)	University travel survey for commuters to campus in Virginia	Agent-based difference in trip generations	ANOVA and negative binomial model	Student group categories have little impact on travel activity
(Kroesen et al., 2017)	Two-phased mobility panel data	Alternative attitude-behaviour relationship in travel mode choice	SEM model	Attitudes define mode choice but the LOS attributes of the mode also define attitudes
(Rashidi et al., 2012)	Puget Sound Transportation Panel of Seattle area	Housing location choice	MNL model	Higher income leads to suburban housing choice
(Zolfaghari et al., 2013)	--	Housing location choice-set formation	Comparison of two-stage and single stage MNLs for choice-set formation	Two-stage MNLs outperform single-stage MNLs
(Bwambale et al., 2019)	Spatial data extracted from mobile phone data	Trip-generation model	MNL model	MNL developed using mobile phone data provided intuitive results
(Allen & Farber, 2018)	SMTO 2015	Student participation in on-campus activities	Multivariate logistic regression	Longer commutes leads to decreased participation in on-campus activities

Table 3: A bibliometric overview of selected literature reviewed for mode choice modeling

Authors and Year	**Dataset**	**Investigated factors**	**Analysis method**	**Key findings**
(Mitra & Buliung, 2015)	2006 Transportation Tomorrow Survey	Children's school travel behaviour	MNL model	Capital improvement of transport infrastructure may not be successful for altering mode choice
(Tuveri et al., 2020)	Panel survey conducted in two phases using a smartphone app	Tour-based student travel behaviour	Descriptive statistical analysis of before and after phases	Preferred mode of transport is the private mode
(Mitra & Nash, 2019)	SMTO 2015	Effect of BE and gender on cycling	Binomial logistic regression	Dedicated bicycle lanes will increase cycling in females

(Ben-Akiva & Lerman, 1985)	--	Travel Demand	Theory of discrete choice models for transportation	Established the credibility of using discrete choice models for transport planning
(Bouscasse et al., 2019)	--	Travel mode choice	Modifying the MNL by link functions replacing the existing logistic cumulative distribution functions	Developed new family of qualitative choice models for travel mode choice
(Haboucha et al., 2017)	Stated-preference survey	User adoption of autonomous vehicles	Logit Kernel model	Early adopters of AVs will be young, educated students
(Eluru et al., 2010)	San Francisco Bay Area Travel Survey	Activity-based travel	Joint multiple discrete continuous extreme and MNL	BE and travel times and costs significantly affect activity choice
(Mattisson et al., 2018)	Cross-sectional public health questionnaire for commuters in Sweden	Association between health indicators and mode choice	MNL model	Being obese reduces active travel mode choice probability
(McFadden, 1973)	--	Choice Behaviour	Theory for conditional logit choice models	Established theory of conditional logit and MNL
(Zhou, 2012)	Online travel survey for UCLA students	University student's mode choice behaviour	MNL model	Living in a community setting increases the odds of taking public transit
(Day et al., 2010)	Cordon count data from 1975 to 2004 for the GTA	Work trip timing and mode choice	MNL model	Transit is attractive for downtown destinations
(Guerra et al., 2018)	2015 Intercensus of Mexico	Relation between urban form, transit supply and travel behaviour	MNL model	Transit investments in low-income neighbourhoods will significantly increase the transit ridership as a whole
(Koh & Wong, 2013)	Face-to-face surveys conducted at chosen stations	Impact of land-use on pedestrians	MNL model	Better walking access to transit stations will also increase transit ridership
(Masoumi, 2019)	Interview data from Istanbul and Cairo	Mode choice causality and comparison with North American trends	MNL model	Mode choice decisions are context and region-sensitive

(Chakour & Eluru, 2014)	On-board travel survey for train commuters in Montreal	Influence of socio-demographics and land-use on train commuting	MNL models	Increasing public transportation service and accessibility increases transit use
(Rashidi et al., 2012)	Puget Sound Transportation Panel of Seattle area	Housing location choice	MNL model	Higher income leads to suburban housing choice
(Faghih-Imani & Eluru, 2015)	Chicago's Divvy system data from 2013	Bicycle-sharing system (BSS) user destination choice	MNL model	Dedicated bicycle lanes surrounding the BSSs increase the usage of a BSS

Chapter 3: Trip generation

3.1 Model Background and Empirical Framework

This thesis uses a BOP approach to estimate the effects of socio-demographics and land-use attributes on the trip generation propensities for transit and automobile. The results are then further analysed to obtain the marginal effects and deduce essential policy implications. The explanatory variables used for developing the model have been described in the following subsections.

3.1.1 Methodology

The data used for developing the BOP model in this thesis includes only statistically significant variables. The inclusion of only statistically significant variables in the model will ensure that the post-estimation analysis of marginal effects quantifies valuable behavioural insights.

3.1.2 Empirical Framework

The empirical framework used for estimating the BOP model is as follows (J. Y. Guo et al., 2007):

$$f_q^* = \alpha' x_q + u_q \qquad f_q = m \qquad if\, \delta_{m-1} < f_q^* < \delta_m \tag{1}$$

$$g_q^* = \beta' y_q + v_q \qquad g_q = n \qquad if\, \theta_{n-1} < g_q^* < \theta_n \tag{2}$$

Where,

f_q^* and g_q^* = Trip-making propensity functions associated with transit and automobile modes respectively

x_q and y_q = The explanatory variables

α' and β' = The coefficient parameter estimates vector which will be estimated

u_q and v_q = jointly normal distribution of error terms with a mean vector of zeros and correlation parameter, ρ

f_q and g_q = Observed trips made with transit (m) and automobile modes (n) respectively

δ_m and θ_n = Threshold bounds for the model, which will be estimated in the model

Using the maximized log likelihood function as defined below, the parameter estimates are calculated.

$$LL = \sum_{q=1}^{Q} \sum_{m=0}^{M} \sum_{n=0}^{N} I_q(m,n) \,.\ln\,(P_q(m,n)) \tag{3}$$

Where $I_q(m,n)$ = 1, if an individual q made m transit trips and n automobile trips and $P_q(m,n)$ is the probability of an individual q making m transit trips and n automobile trips and is calculated as:

$P_q(m,n) = prob(\ \delta_{m-1} < f_q^* < \delta_m\ and\ \theta_{n-1} < g_q^* < \theta_n\ )$

$= prob(\delta_{m-1} - \alpha' x_q < u_q < \delta_m - \alpha' x_q$ and $\theta_{n-1} - \beta' y_q < v_q < \theta_n - \beta' y_q)$

In simple terms, it is an algebraic operation of the bivariate normal cumulative distribution function as

$$\begin{aligned} P_q(m,n) = {} & \Phi_2(\delta_m - \alpha' x_q, \theta_n - \beta' y_q\ ; \rho) \\ & - \Phi_2(\delta_{m-1} - \alpha' x_q, \theta_n - \beta' y_q\ ; \rho) \\ & - \Phi_2(\delta_m - \alpha' x_q, \theta_{n-1} - \beta' y_q\ ; \rho) \\ & + \Phi_2(\delta_{m-1} - \alpha' x_q, \theta_{n-1} - \beta' y_q ; \rho) \end{aligned} \tag{4}$$

Where Φ_2, is the bivariate cumulative normal distribution function.

The ordinal nature of the number of trips by transit or automobile enables the usage of an ordered approach over unordered approaches. This is advantageous as the analysis of the marginal effects can quantify the difference in usage levels associated with a mode. For example, being under the age of 22 increases the propensity to make 1,2,3+ transit trips but decreases the propensity to make 0 transit trips. Surely, being under 22 increases the probability of taking transit but it is also associated with high levels of transit usage compared to automobiles and has been discussed in detail in section 3.2 of this thesis.

3.1.3 Definition of explanatory variables

The final BOP model included 14 explanatory variables, with the dependent variables being transit and automobile trips each having a possible value of 0, 1, 2, 3+ trips representing an increasing level of usage by each mode. The independent explanatory variables are defined as follows:

1. Year dummy: A dummy variable that returns 1 if the year of survey is 2019 and 0 if the survey is from 2015.
2. Age dummy: A dummy variable which returns 1 if the respondent is below 22 and 0 otherwise.
3. Distance to campus less than 5 km: A dummy variable which returns 1 if the distance to campus from the home location of the respondent is less than 5 km and 0 otherwise.
4. Distance to campus greater than five and less than 20 km: A dummy variable which returns 1, if the distance to campus lies between 5 and 20 km and 0 otherwise

5. Frequency commute dummy: A dummy variable which returns 1, if the frequency of commute per week is greater than 3, and 0 otherwise
6. Household owner dummy: A dummy variable which returns 1 if the respondent is a homeowner and 0 otherwise
7. Living with others dummy: A dummy variable which returns 1, if the respondent lives with roommates, family, or friends, etc., and 0 otherwise.
8. Transit accessibility: This is the natural log of the accessibility metric calculated based on the respondent's location.
9. Residence location (within PDs 2-16): A dummy variable which returns 1 if the respondent lives within PDs 2-16(non-downtown but still within City of Toronto limits) and 0 otherwise.
10. Residence location (outside City of Toronto): A dummy variable which returns 1, if the respondent lives outside the City of Toronto limits and 0 otherwise
11. Transit pass ownership: A dummy variable which returns 1 if the respondent reported owning a transit pass and 0 otherwise.
12. Driving license ownership: A dummy variable which returns 1 if the respondent reported owns a driving license and 0 otherwise.
13. Location of Campus (within PD 1): A dummy variable which returns 1 if the respondent's primary institution lies in PD1 and 0 otherwise
14. Location of Campus (within PDs 2 to 16): A dummy variable which returns 1 if the respondent's primary institution lies in PDs 2 to 16 and 0 otherwise.

After the model is estimated, a correlation parameter that reveals how closely the dependent variables are related is obtained. In the model, since the transit and

automobile trips are considered substitutes of each other, a strong correlation is expected.

3.2 Results and discussion

The prediction power of the BOP model is determined through an analysis of model goodness-of-fit. The parameter estimates calculated by the BOP model are discussed in detail and a marginal effects analysis is performed in sections 3.2.2 and 3.2.3 of this thesis.

3.2.1 Model goodness-of-fit

The McFadden R^2 which represents how good a model has fit over the null model is calculated using the equation below:

$$R^2 = 1 - \left(\frac{maximized\ Log\ Likelihood}{null\ Log\ Likelihood}\right) \tag{5}$$

The log-likelihood (LL) of the null model is the log-likelihood of an equiprobable model with no constraints is calculated using the equation:

$$LL\ (null) = \ln\left(\frac{1}{i}\right) * n \tag{6}$$

Where,

n = number of observations

i = number of possible outcomes.

The R^2 was calculated to be 0.30, suggesting that the estimated model performs 30% better than the null model specification. The prediction power of the model can be considered as satisfactory as a McFadden R^2 of 0.2-0.4 is indicative of very good model fit (D. Hensher et al., 2000; Ortúzar & Willumsen, 2011). However, McFadden's R^2 does not account for the number of observations and the number of independent or explanatory

variables used in the model. An adjusted R^2 which accounts for the number of independent variables and number of observations is calculated as follows (Ben-Akiva & Lerman, 1985) :

$$R^2_{adj} = 1 - \left(\frac{(1 - R^2) * (N - 1)}{N - p - 1}\right) \quad (7)$$

Where, N is the number of observations in the model and p is the number of independent variables. The adjusted R^2 for the BOP model is 0.29, which is also representative of a good model fit.

3.2.2 Sociodemographic and land-use parameter estimates

The variables included in the model are all statistically significant except the year dummy variable for the automobile trip-making propensity.

In estimating the transit trip-making propensity, only living within 5 km of campus hurt its propensity. For the automobile trip-making propensity, being under the age of 22, living within 20 km of campus, commuting to campus more than three times a week, and having a campus in the City of Toronto, all had a negative effect. The results yielded by the BOP model are seen in Table 4.

Table 4: Parameter estimates from the BOP model

Parameter	Description	TRANSIT		AUTOMOBILE	
		estimate	*t-stat*	*estimate*	*t-stat*
Year dummy variable	1, if survey is from 2019, 0, if survey is from 2015	-0.107	5.655	-0.0335	1.636
Age dummy	1, if under 22, 0 otherwise	0.119	6.0764	-0.0764	3.802
Distance to campus <5 km	1, if true, 0, otherwise	-0.0973	3.160	-0.390	12.853

Distance to campus >5 and <= 20 km)	1, if true, 0, otherwise	0.186	6.750	-0.06257	2.33913
Frequency commute dummy	1, if greater than 3, 0 otherwise	0.285	9.827	-0.380	13.312
Household owner dummy	1, if true, 0, otherwise	-	-	0.0702	4.0436
Living with others dummy	1, if true, 0, otherwise	-	-	0.209	6.240
Transit accessibility	Accessibility score	0.0710	6.761	-	-
Residence location (within PDs 2-16)	1, if true, 0 otherwise	0.595	20.335	0.290	8.444
Residence location (outside Toronto Area)	1, if true, 0 otherwise	0.235	5.882	0.725	18.844
Transit pass ownership	1, if owns, 0 otherwise	-	-	0.172	9.537
Driving license ownership	1, if owns, 0 otherwise	0.343	20.677	-	-
Location of Campus (PD1)	1, if true, 0, otherwise	0.173	5.801	-0.244	11.641
Location of Campus (PDs 2 to 16)	1, if true, 0, otherwise	0.122	4.131	-	-
Threshold bounds	Threshold 1 Threshold 2 Threshold 3	1.711 2.109 3.205	12.225 15.0280 22.683	0.439 0.802 1.363	7.449 13.561 22.898
Correlation Parameter, ρ	Represents correlation of both modes	-0.613			

The year dummy variable is negative for both automobile and transit but is not statistically significant for the automobile trips. This suggests that the propensity of automobile trip-making from 2015 to 2019 has decreased or remained constant, whereas the transit trip-making propensity is lower in 2019 relative to 2015. Since the data represents only post-secondary students, the declining trend in transit propensity cannot be extended to the whole GTHA population. Also, gender was of no statistical significance for the propensities of both transit and automobile trips. This finding shows

that post-secondary students' transit and automobile trip-making behaviour does not vary based on gender. However, gender may have an impact on trip-making propensities of walking or cycling. Although the model provides excellent overall feedback, it is important to briefly discuss the practicality of the trend predicted by each variable separately.

Age

Being under 22 increases the probability of making transit trips and decreases the probability of making automobile trips. This can be explained by low-income levels, less interest in driving relative to earlier generations (Delbosc & Currie, 2014), and generally financially discouraging parking provisions at their campuses.

Distance to Campus

If the distance to campus is less than 5 km, it decreases the probability of both transit and automobile trip-making. This result suggests the existence of using other active modes of travel such as bike, walk, or a combination given the proximity to campus. However, living within 5 to 20 km of a campus increases the transit trip-making propensity. It also decreases the automobile trip-making propensity which tells us that if the distance to campus is within a 20 km range, using transit is more feasible than using automobiles. Usually, there is a higher density in and around institutions and campuses. As the distance from these areas increases, it is observed that the land use density decreases and therefore the transit options.

Frequency of Commute

It is also noted that students who commuted to campus more than three times a week tend to use transit more than automobiles for their commutes. It shows that students are

discouraged from using automobiles as a mode of transport for going to campus more than three times a week, revealing that using transit is more attractive than automobiles for a regular commute to campus. This can also be attributed to the generally high cost of parking at campuses. Further, this finding suggests transit is a more viable daily commute option though the automobile trips may be made to access more discretionary or household maintenance-type activities.

Transit Accessibility

This parameter was only included in the transit-trip-making propensity as the automobile trips are considered independent of transit accessibility. The transit accessibility scores were highly significant and show that increasing transit accessibility increases transit trip-making propensities. This finding reinforces the expectation of the municipalities that encourage transit-oriented development where most of the necessities are walkable or reachable by nearby transit options, which reduces the need for personal driving and reduces energy consumption. As the GTHA encourages transit-oriented development, this can be achieved by increasing transit accessibility and promoting mixed land-use and walkable neighbourhoods.

Residence Location

The City of Toronto, consisting of 16 PDs, is high-density and a significant trip attraction hub with the highest level of transit connectivity and options in the GTHA and has been closely analysed in this thesis. PD 1, the downtown Toronto area, is of the highest density in the City of Toronto. The PDs 2-16, also located in the City of Toronto limits, are higher density than other areas outside the City of Toronto but still less than PD 1. Living outside PD 1 increases the probability of making either a transit or automobile trip,

whereas residing in PD 1 decreases trip generation propensity by either mode. One explanation for this is that many students living in PD1 may choose active modes such as walking and cycling for their commutes as PD1 is high-density and has excellent mixed land-use character.

Household Ownership

For the transit trips, household ownership or living situation has no statistical significance and was not included in the model. However, for the automobile trip-making propensity, owning a house and living with others positively impacts automobile trip-making. A possible rationale for this finding is that owning a home generates trips such as grocery and home-related maintenance trips. People not owning a home also generate maintenance trips. However, tenants usually live in high-density and mixed land-use neighbourhoods where the destination for maintenance trips can be reached by walking or cycling, significantly reducing the probability of using either transit or automobile trips. Interestingly, if a student is living with their family or roommates, it still increases the automobile trip making propensity, indicative of a household where chores are evenly distributed. This trend is also suggestive of the presence of students existing as a separate unit within a shared household.

Transit-pass and driving-license ownership

The effect of owning a driving license is not significant for the automobile trip-making propensity and was only included in the transit trips. Similarly, owning a transit pass was not significant for the transit trip-making propensity. The parameter for transit-pass ownership was included in the analysis of automobile trips and driving license ownership was included in the analysis of transit trips. The results tell us that having a transit pass

increases the propensity for automobile trips and having a driving license increases the transit trip-making propensity. These results are counterintuitive as an opposite trend is expected. However, similar results have also been observed in Habib et al. (2018). One possible explanation is that owning mobility tools like drivers' licenses and transit passes increase trip-making propensity more generally. Trip chaining behaviour on the way to or from transit stations before returning home may also explain the significance of transit pass ownership on automobile trip making. This may be because there are no transit subsidies for students in the GTHA (Butler & Sweet, 2020) similar to Ottawa, and so many students may prefer to pay per trip rather than owning transit passes. From September 2021, the City of Hamilton has introduced subsidized transit passes for the students of the institutions located in the City of Hamilton which is also a part of the study area considered in this thesis (Government of Ontario, 2021). This pass only works in the City of Hamilton as there is no subsidy for using services from other transit agencies such as GO Rail, the Toronto subway, the ZUM bus service in Mississauga, etc. However, students reside in different areas of the GTHA, and further research related to the feasibility of introducing universal transit subsidies for students in the GTHA to encourage transit usage is needed.

Location of Campus

For transit trips, having a campus in the City of Toronto increases the transit propensity but decreases for automobile trips which implies that the current policies that discourage automobile trips in the City of Toronto are beneficial. Also, congestion during their commute decreases the propensity to make automobile trips by post-secondary students coming into their campus located in the City of Toronto.

Correlation Parameter

The correlation parameter of -0.613 suggests a strong and negative correlation between the transit and automobile trips which implies that as the number of transit trips increases, the number of automobile trips decreases and vice-versa, which is as expected as they are considered substitutes of each other in the model. This finding is significant as it implies that increasing the usage of transit will reduce the number of automobile trips and subsequently help achieve sustainability goals.

3.2.3 Marginal effects and policy implications

Although the parameter estimates give an idea about the effects on the probability of choosing transit or automobile, these must be quantified to realize the significance and sensitivity of the explanatory variables on trip-making propensities. It is noted that there is no literature where a marginal effects analysis post-estimation of a BOP model has been done (Abotalebi et al., 2019; Fujiwara et al., 2010; Vignoli et al., 2013; Yamamoto & Shankar, 2004).

Adapting a PWSE approach as briefly described in (Greene & Hensher, 2010), this thesis determines the marginal effect of each parameter by calculating the contribution of each individual on the marginal effect. The individual marginal effects are weighted by their associated univariate or marginal choice probability of making 0, 1, 2, 3+ transit or automobile trips by an individual, therefore avoiding highly aggregated results. The marginal probability of making 0, 1, 2, 3+ trips by a mode is calculated using the equation for joint probability defined in section 3.1.2 of this thesis:

$$P_q(m,n) = \Phi_2(\delta_m - \alpha' x_q, \theta_n - \beta' y_q\,;\rho) - \Phi_2(\delta_{m-1} - \alpha' x_q, \theta_n - \beta' y_q\,;\rho)$$

$$- \Phi_2(\delta_m - \alpha' x_q, \theta_{n-1} - \beta' y_q \,; \rho)$$

$$+ \Phi_2(\delta_{m-1} - \alpha' x_q, \theta_{n-1} - \beta' y_q; \rho)$$

Where, *m* can take the value 0, 1, 2, or 3+ transit trips and *n* can take the value 0, 1, 2, or 3+ automobile trips and other variables are as defined in section 3.1.2 of this thesis. For example, the univariate probability for having 1 transit trip is determined as:

$$P_q(1, n) = P_q(1,0) + P_q(1,1) + P_q(1,2) + P_q(1,3) \quad (8)$$

Further, the joint probabilities are calculated at the two possible values of each dummy variable in the BOP model as defined in section 3.1.2 of this thesis. The difference between these joint probabilities is the marginal effect for each individual. These marginal effects are then multiplied with the associated univariate probability of the outcome for everyone to get the individual contributions on the marginal effect. Finally, the sum of these individual contributions is divided by the sum of the associated univariate probability of the outcome being analysed. This is repeated for all possible outcomes and summed to get the required marginal effect associated with each parameter.

For example, for calculating the marginal effect on the probability of generating 1 transit trip for the parameter representing being under 22, the univariate probability for generating 1 transit trip is calculated. Then, the joint probability of making 1 transit trip and *m* automobile trips by considering that age of all individuals is under 22 is calculated to get 4 joint probabilities for each individual. The joint probabilities are calculated again by considering that the age of all individuals is above 22. These two joint probabilities are then subtracted to get the marginal effect for each individual. This difference is then multiplied by the univariate probability of making 1 transit trip to get the required

marginal effect at the individual level. The summation of these individual marginal effects is then divided by the sum of univariate probability of making 1 transit trip. This is repeated for each outcome *m,* resulting in 4 contributions to the marginal effect for having 1 transit trip. Finally, the summation of these contributions is the required value of the marginal effect on the probability of making 1 transit trip for being under 22. This is then repeated for all estimated parameters whose results are presented in Table 5.

Table 5: Marginal effects for the parameter estimates

Parameter	**P (transit trips = i)**				**P (auto trips = j)**			
	0	1	2	3	0	1	2	3
Year dummy	0.0395	-0.00289	-0.0210	-0.0207	0.0104	-0.00153	-0.00357	-0.00813
Age under 22	-0.0411	0.00301	0.02176	0.0217	0.0239	-0.00341	-0.00810	-0.0187
Distance to campus <5 km	0.0359	-0.00265	-0.0192	-0.0186	0.123	-0.0218	-0.0445	-0.0836
Distance to campus >5 and <= 20 km)	-0.0697	0.00445	0.03733	0.0356	0.0194	-0.00285	-0.00668	-0.0151
Frequency commute dummy	-0.102	0.0108	0.05772	0.0489	0.126	-0.0126	-0.0373	-0.101
Residence location (within PDs 2-16)	-0.227	0.0136	0.126	0.0997	-0.089	0.0115	0.0275	0.0740
Residence location (outside Toronto Area)	-0.0849	0.00490	0.0414	0.0502	-0.248	0.0354	0.0820	0.156
Transit pass ownership	--	--	--	--	-0.0538	0.00808	0.0186	0.0411
Driving license ownership	-0.128	0.00912	0.0692	0.0625	--	--	--	--

Location of Campus (within PD 1)	-0.0187	0.00131	0.00983	0.00993	0.0783	-0.0116	-0.0267	-0.0579
Location of Campus (within PDs 2 to 16)	-0.0448	0.00373	0.0243	0.0228	--	--	--	--

The above results can be interpreted to predict response to changes in personal or land-use attributes due to policy action and are summarized graphically in Figure 6 to Figure 13 for ease of interpretation.

A finding from this model is that overall ridership has decreased from 2015 to 2019 as seen in Figure 6. This is an unexpected finding as the province has opened several BRT corridors and improved transit connectivity such as the subway extension from downtown Toronto directly to York University. However, this trend is not extendable to the whole population of the GTHA as the data used in this thesis focuses only on students and may not be representative of the whole population in the GTHA. The existence of this trend can be studied in future works by analysing the survey data from other household or workplace travel surveys. Moreover, this can also be attributed to the finding that millennials tend to make lower trips than other middle-aged groups (Enam & Konduri, 2018; Grimsrud & El-Geneidy, 2014).

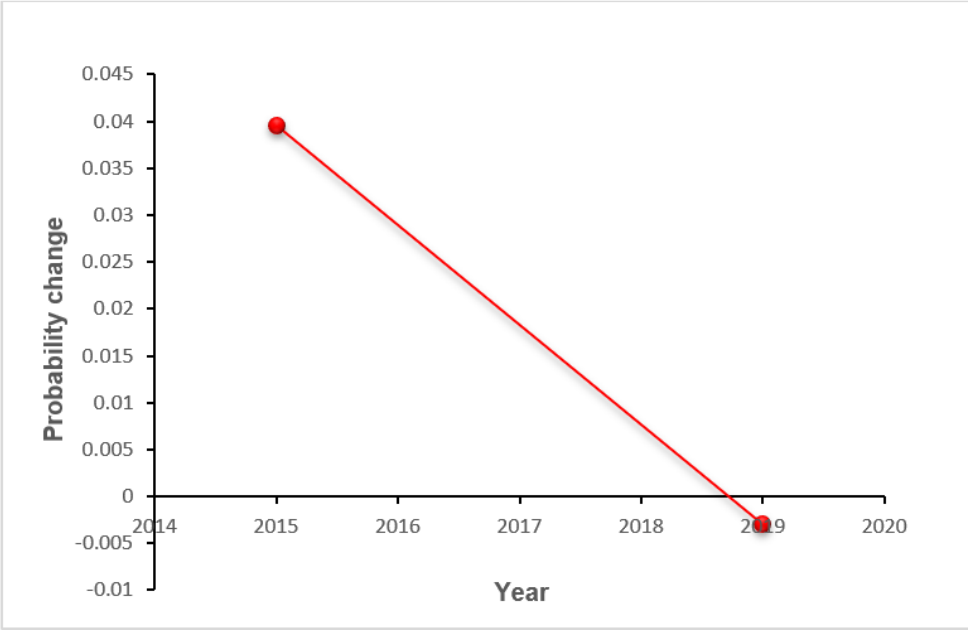


Figure 6: Decreasing trip-generation propensity in Ridership from 2015 to 2019

Further, the probability of using transit trips increases by at least 0.02 if the student is under 22. However, the probability of making automobile trips decreases by at least 0.02, as seen in Figure 7. It reinforces the expectation that being under 22 is associated with a high level of transit usage. If the commute distance to campus is less than 5 km, the trip-making propensity by either mode decreases by 0.05 as can observed in Figure 8. This decrease in the propensity represents the presence of active travel modes such as walking and cycling to their campuses for students living within 5 km of a campus. The mode choice model estimated in this thesis reinforces this expectation, as seen in section 4.2 of this thesis. The policymakers must invest in affordable housing options for students within a 5 km radius of campus to promote active travel and reduce peak congestion effects. Furthermore, having a commute distance between 5 and 20 km of a campus decreases the propensity of automobile trips while increasing the propensity of transit

trips, as seen in Figure 9. This represents the potential of a mixed land-use with good transit connectivity within a 20 km distance to campus.

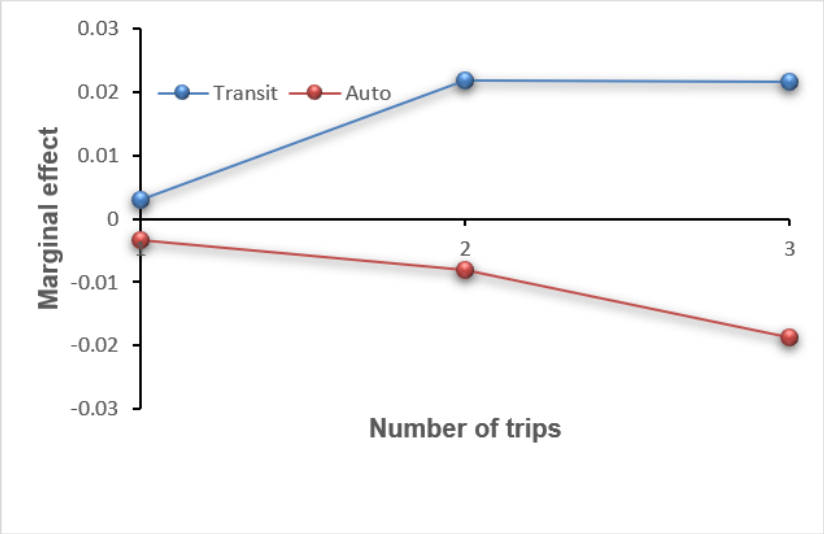


Figure 7: Marginal effect for being under 22

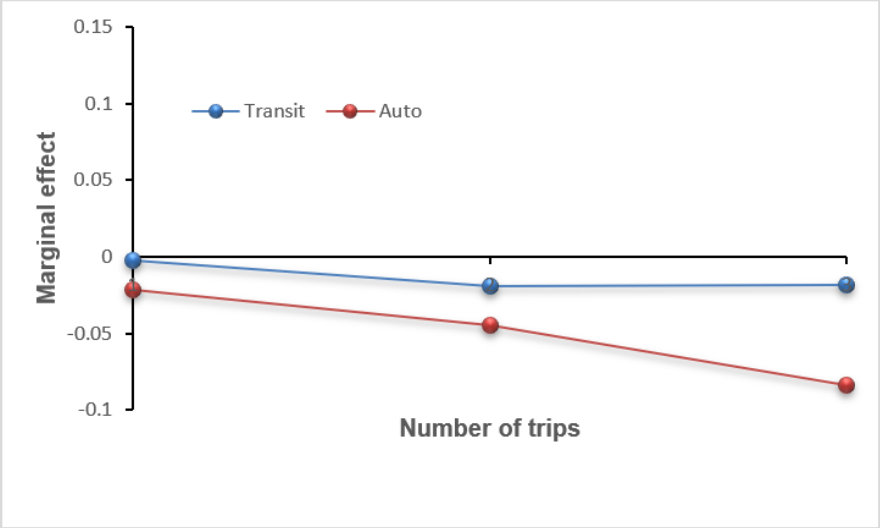


Figure 8: Marginal effects for having a commute distance to campus less than 5 km

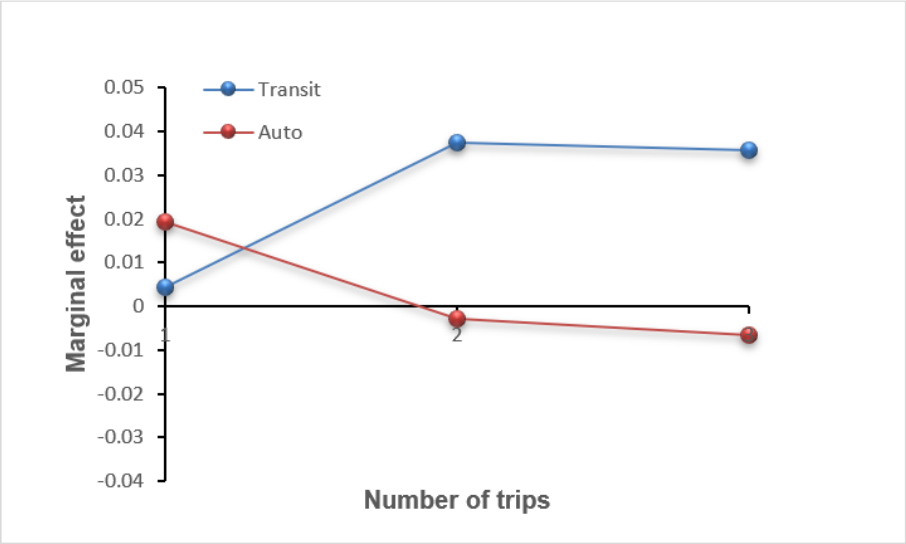


Figure 9: Marginal effects for commute distance between 5 and 20 km

As seen in Figure 10, if the commute frequency is greater than three times per week, this decreases the automobile trip-making propensity and increases the transit-trip-making propensity as previously discussed.

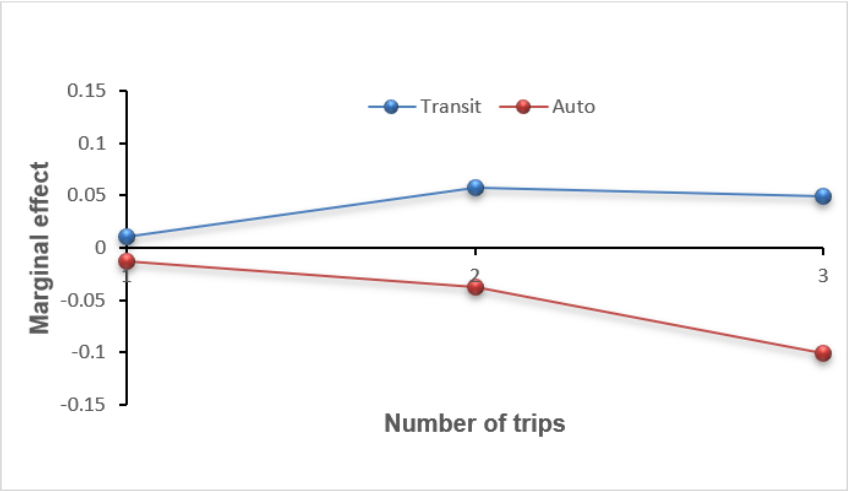


Figure 10: Marginal effects if commuting more than 3 times a week

Living outside PD1 increases both the transit and automobile trip-making propensity by 0.1 as seen in Figure 11 and Figure 12, meaning that there is a tendency to generate transit and automobile trips more than other active modes of travel. This may also be due

to the unfeasibility of adopting other active modes of travel due to distance to locations of choice or infrastructure constraints and warrants closer investigation.

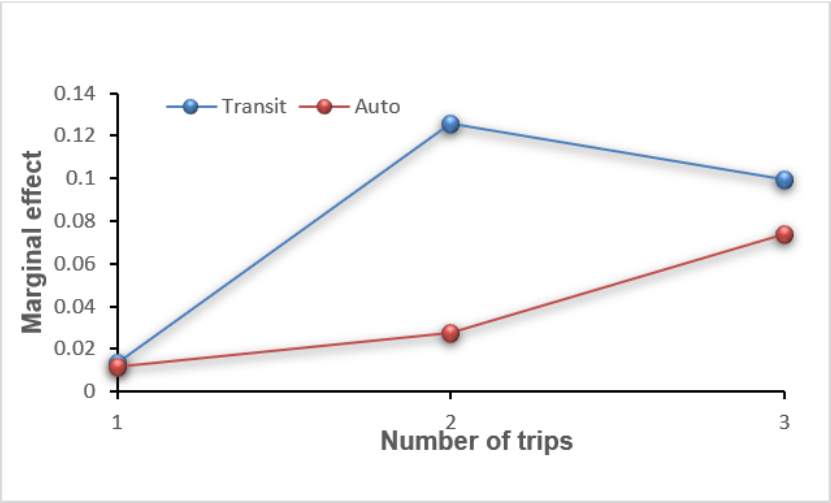


Figure 11: Marginal effects for living within PDs 2 to 16

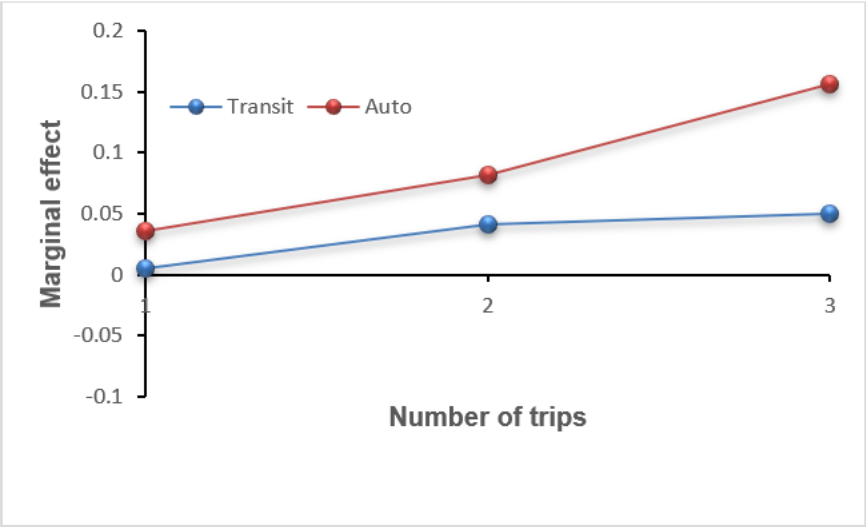


Figure 12: Marginal effects for living outside City of Toronto

Having a campus in the downtown core (PD 1) increases transit trip-making propensity and decreases automobile trip-making propensity. This can be attributed to the fact that

the downtown core has less availability of affordable parking and the existing transit connectivity of GTHA to the downtown core promotes transit usage while significantly decreasing the automobile trip-making propensity, as seen in Figure 13.

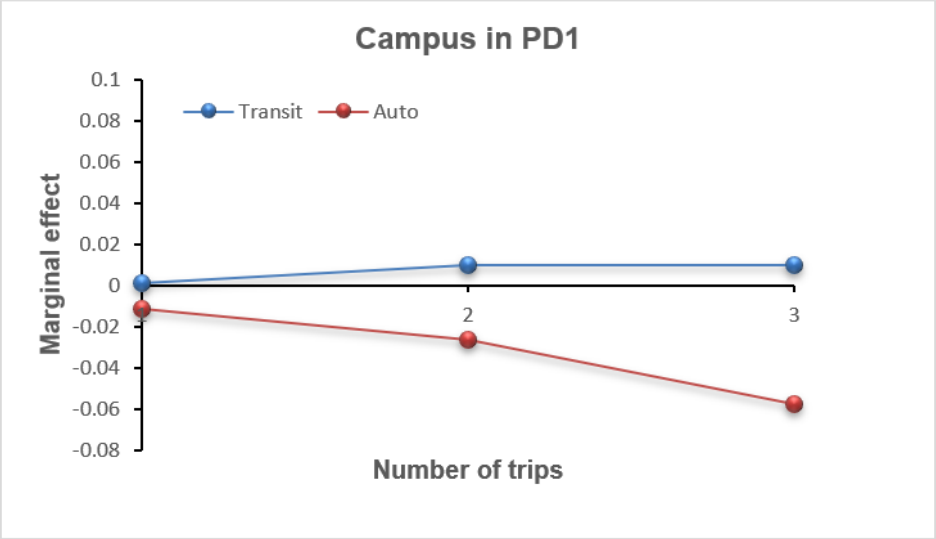


Figure 13: Marginal effect of having a campus in PD1

Overall, trip-generation propensities of both modes show a decline but is not statistically significant for the automobile trip-making propensity. This finding is in line with what has been reported for other regions (Diab, Deweese, et al., 2020; Diab, Kasraian, et al., 2020; Miller et al., 2018). There is a decreasing trend in transit usage among the younger populations as it is found that they are more reluctant to generate trips if they can fulfil their activities without physically leaving their place of residence (Alemi et al., 2019; Circella et al., 2016; Enam & Konduri, 2018; Olsson et al., 2020). With the increasing adoption of technologies such as remote learning, virtual meetings, and online shopping, younger people are more connected and tech-savvy, leading to decreased trip generation. From a policy perspective, affordable student housing options must be made available within a 5 km distance of a campus as this will reduce the need to make a trip by transit

or automobile and promote active modes of travel. Moreover, an integrated transit pass subsidy that works across different regional transits, subways, GO Rail services, streetcars etc. must be introduced which will encourage students to get transit passes and increase the trip-making propensity. With the evidence shown for the decline in transit trip-generation by students, the institutions and campuses must introduce educational awareness and incentivization programs for encouraging transit usage among this cohort.

Chapter 4: Mode Choice

4.1 Model background and Empirical Framework

This thesis estimates an MNL which determines mode choice behaviour for HBD trips as there is lesser known about HBD trips than conventional commuter trips (Ao et al., 2020; Cervero & Kockelman, 1997; Tuveri et al., 2020). Conventionally, the researchers have focused on commuter trips without separately analyzing the HBD and non-HBD trips (Daisy et al., 2018; Ermagun & Samimi, 2015; Hasnine et al., 2018; Tuveri et al., 2020). The main reason is that commuter trips are assumed to be the trips that significantly contribute to the peak hour congestion. However, as the volume of discretionary trips grows, they also contribute to congestion on the traffic networks during off-peak hours (Eluru et al., 2010; Leite Mariante et al., 2018). Thus, a comprehensive understanding of the determinants of mode choice for HBD trips is required. Non-discretionary trips to work or school are being made in a routine from a habit formed due to various attributes of the person and alternatives' themselves. Whereas discretionary trips are more flexible and vary from person to person, and the respondent is not typically constrained by a penalty such as being late to work or school. For example, in a work trip, the respondent might be forced to take transit because there is no parking at work and parking at a different location and walking may not be time-efficient and feasible. However, depending on the destination, the respondent may be willing to choose an automobile and pay for parking for a discretionary trip. There is a lot of versatility in the determinants of HBD trips and varies significantly from person to person. A general commuter mode choice model cannot predict these variations.

For the MNL modelling in this thesis, the data was thoroughly cleaned to include only relevant and statistically significant parameters to ensure credible prediction. Moreover, to account for the impact of mobility tool ownership and possible mode choices based on location, unbalanced choice sets were created based on a set of rules, as discussed in detail in section 4.1.1 of this thesis.

The explanatory variables used in estimating the MNL are as defined in section 3.1.3 of this thesis.

4.1.1 Methodology

The utility of choosing a mode for travel can be thought of as a function of attributes of the alternative and characteristics of the respondent along with an unobserved component.

In an MNL, an alternative is chosen as the base outcome which is the car passenger mode for this thesis as it was found to be most widely used by the respondents for discretionary trips in the dataset. The choice of the base outcome is arbitrary and does not alter the model results (Bernasco & Block, 2020).

Following the discrete choice modelling framework proposed by McFadden in 1973 and subsequently adapted for the context of transportation choices of travel route, mode, and destination choice decisions (Ben-Akiva & Bierlaire, 1999; Ben-Akiva & Lerman, 1985; Train, 2003), this thesis builds on these concepts to estimate an MNL model.

The MNL model estimated in this thesis is made up of four components which are described below (Bernasco & Block, 2020):

1. Decision-maker: The person or agent that makes a choice given a feasible choice set.

2. Alternatives: Different travel modes available to the decision-maker. The decision-maker can choose only one alternative from the choice set. The multi-modality is not considered in the MNL estimated for this thesis, and the alternatives are considered mutually exclusive.
3. Attributes: These are of two types. Each alternative has specific attributes such as travel time and cost and are known as alternative-specific variables. Moreover, there are also personal attributes such as gender, age, etc. that influence the choice of travel mode. Since these vary from person to person, they are known as case-specific variables
4. Random Utility Maximization (RUM) Theory: The decision-maker chooses the alternative that maximizes their utility of selecting a mode (which provides them with the highest attractiveness given the attributes).

The possible travel mode choices in the estimated MNL are as shown in Figure 14.

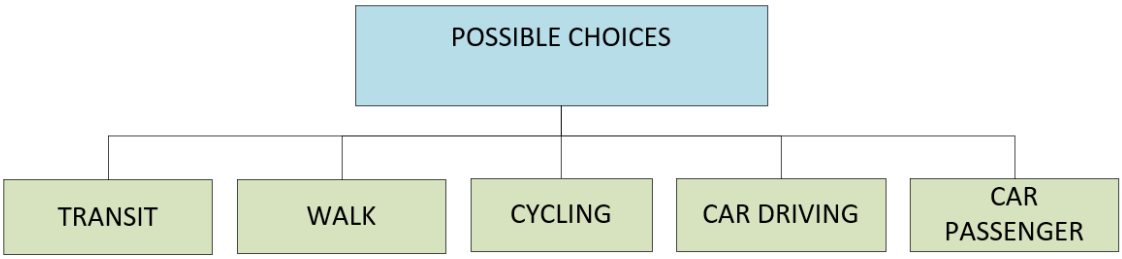


Figure 14: Possible Choices for the MNL

Given that the mobility tools and location may make a specific mode unfeasible as a choice, the choice sets were designed to vary from person to person. Therefore, every respondent had a different feasible choice set. For example, people who do not have a driving license will not have car driving as a possible mode choice. The creation of

feasible choice sets ensures that the results are unbiased and represent a plausible substitution pattern essential for the IIA assumption of the MNL to be valid. The availability of mode choices in a respondent's feasible choice set is based on the following set of rules:

1. Car driving: This mode is available to each respondent with a driving license and owning a vehicle
2. Car passenger: This mode is available to all respondents
3. Transit: This mode is available to all respondents
4. Walk: This mode is available to all respondents where the commuting distance is less than 5 km
5. Cycling: This mode is available to all respondents where the commuting distance is less than 10 km

4.1.2 Empirical framework

Every choice has an observable utility and a random utility component often described as an unobserved utility or error term in the MNL framework.

The unobserved utility is the difference between the utility gained by an individual and the estimated utility of the model. The magnitude of this utility is also representative of the behavioural components not captured by the model.

The RUM model used in this study can be expressed as (Koppelman & Bhat, 2006):

$$u_i = X_i\beta + (z_i A)' + \varepsilon_i \qquad (1)$$

Where,

$u_i =$ is the utility for case i

X_i = a data matrix of size $J \times p$ where J is the number of available alternatives and p is the number of alternative-specific variables

β = a $p \times 1$ vector of alternative-specific regression coefficients

z_i = a $q \times 1$ vector of case-specific regression coefficients, where q is the number of case-specific variables

$A = (\alpha_1, \dots \dots \dots, \alpha_j)$ is a data matrix of size $q \times J$

ε_i = a $J \times 1$ vector which is IID type 1 extreme-value random variables with mean γ (The Euler- Mascheroni constant) ~0.577 and variance $= \frac{\pi^2}{6}$ or commonly known as the unobservable or unobserved/random part of the utility function.

The coefficient matrix of the model needs to be normalized by fixing one of the coefficient matrix of an alternative α_j to be the zero vector as the base alternative. This is because the u_i vector quantifies the gained utility from the J-1 alternatives over the chosen base alternative to produce only (J-1) sets of coefficients.

Given the nature of the dataset of unbalanced choice sets, if an alternative j, is unavailable to i^{th} individual, the jth row is omitted in u_i. The alternative which is chosen is therefore the one that maximizes the u_i function.

The choice probability for an individual n choosing alternative i from a set of J alternatives is calculated according to (McFadden, 1973),

$$P_{ni} = \frac{e^{V_{ni}}}{\sum_1^j \left(e^{V_{nj}}\right)} \qquad (2)$$

Where,

$$j = 1, \dots, J$$

$$n = 1, \dots, N$$

The parameter estimates found using MNL are calculated by maximizing the log-likelihood function as described below:

$$LL(\alpha_j, \beta) = \sum_1^n \sum_1^j y_{nj} \ \ln (P_{nj}) \tag{3}$$

Where,

$y_{nj} = 1$, if individual n chooses alternative j and 0 otherwise

The values of (α_j, β) which results in the maximum log-likelihood function are the parameter estimates (α_j, β) yielded by the model.

4.2 Results and discussion

The driving cost for an automobile is 50 cents per kilometre (CAA, 2021). The driving costs associated with a car also include wear and tear of vehicle, insurance costs, and parking costs, among other costs which are not present in the car passenger mode. In the model, the travel cost for car passenger as a mode is included as half the cost of driving an automobile.

The cost of travel for walk and cycle modes was zero as there are no out-of-pocket costs for making a walking or cycling trip.

The travel cost associated with transit is based on the origin and destination of the trip which is calculated based on the 2011 Transportation Tomorrow Survey (TTS) transit cost data by O/D pairs as described in section 1.3.3 of this thesis.

4.2.1 Model goodness-of-fit

To assess the performance of the predictions made by the model, a goodness-of-fit measure or McFadden's R^2 is calculated. This is a widely accepted method for calculating the goodness-of-fit of a model (Brus et al., 2016; Chiou et al., 2013; Hasnine et al., 2018). The equation to calculate the McFadden R^2 is as described in section 3.2.1

of this thesis. The maximized LL of the MNL model is -751.35 and the null LL was calculated to be -1681.86 resulting in a R^2 of 0.45. This is representative of a good fit and tells us that the estimated model performs 45% better than the null model specification and is representative of a very good model fit (D. Hensher et al., 2000; Ortúzar & Willumsen, 2011). However, as discussed in section 3.2.1 of this thesis, McFadden's R^2 doesn't account for the number of observations or the number of independent or explanatory variables used in the model resulting in over-estimating the model goodness-of-fit and can be adjusted to account for the effect of the number of observations and independent variables used. The adjusted R^2 for the MNL model is 0.43, which is also representative of a good model fit.

4.2.2 Sociodemographic and land-use parameter estimates

The results of the parameter estimates can be seen in Table 6 and the mode of car passenger is chosen a base outcome due to its highest frequency of occurrence in the dataset for HBD trips and universal availability.

Table 6:Parameter estimates from MNL

	Mode				
Parameter*	**Car Driving**	**Transit**	**Walk**	**Cycle**	**Car Passenger****
Travel Cost	-0.0837(-2.63)	-0.0837(-2.63)	--	--	-0.0837(-2.63)
Travel time	-0.109 (-5.07)	-0.0404 (-4.91)	-0.103(-10.91)	-0.103(-3.37)	-0.109 (-5.07)
Age under 22	-0.502(-1.87)	-0.351(-1.83)	-0.717(-2.34)	-1.014(-2.18)	--
Being a female	-0.613(-2.05)	-0.576(-2.03)	--	-1.75(-3.63)	--
Residence in PD1	--	1.33(3.48)	1.43(3.58)	1.415(2.64)	--
Residence outside City of Toronto	0.895(2.90)	-0.974(-2.89)	-0.798(-1.97)	--	--
Transit pass ownership	-0.536(-1.90)	1.154(4.44)	--	-2.25(-2.12)	--
Constants	2.39(7.04)	0.928(2.19)	3.51(7.33)	0.945(1.30)	--

*Parameter estimate values reported as estimate(t-stat)
**Base outcome

The parameters included in the model are not a result of *a priori* knowledge. Rather the data was carefully analysed and purposed to ensure that only relevant and statistically significant variables were included in the model. The values for t-statistics seen in Table 6 are significant indicating that the parameters estimated by the model are significantly different than zero.

The overall trends relating to the probability change of choosing a particular mode revealed by the MNL are summarized in Table 7. The overall trends are a representation of the probability change that occurs for a respondent's utility of choosing that mode. Knowing the overall trends that determine mode choice is helpful, but policymakers and transport planners want to quantify these changes in the form of sensitivities or elasticities. A marginal effects analysis will be performed for the parameters estimated by the MNL in section 4.2.3 of this thesis to quantify these trends.

Table 7: Probability change trends from MNL

	Mode				
Parameter	**Car Driving**	**Transit**	**Walk**	**Cycle**	**Car Passenger**
Travel Cost	↓	↓	--	--	↓
Travel time	↓	↓	↓	↓	↓
Age under 22	↓	↓	↓	↓	--
Being a female	↓	↓	--	↓	--
Residence in PD1	--	↑	↑	↑	--
Residence outside City of Toronto	↑	↓	↓	--	--

Transit pass ownership	↓	↑	--	↓	--

4.2.3 Marginal effects and policy implications

The effect of a change in one variable on another variable is known as the marginal effect (ME) (Koppelman & Bhat, 2006; Train, 2003). In the context of the MNL estimated in this thesis, the ME is the change in the probability of choosing a mode with respect to a change in an attribute or the explanatory variable being analysed. A marginal effects analysis can help identify potential areas of improvement and derive essential policy implications. This metric quantifies the change in the probability of selecting a mode based on a change in the explanatory variable.

The equation by which the MEs for the MNL model are calculated as (Koppelman & Bhat, 2006):

$$ME = \beta_k \times P_i \times (1 - P_i) \quad (4)$$

For continuous variables such as travel time and cost, calculating the rate of change in an explanatory variable on the probability of mode choice is recommended (Ewing et al., 2004; Koppelman & Bhat, 2006). The formula used to calculate the required elasticities is (Koppelman & Bhat, 2006):

$$Elasticity = \beta_k \times X_{ik} \times (1 - P_i) \quad (5)$$

The elasticity is calculated for each attribute X_i and parameter k in the MNL model.

It is also noted that the marginal effects and elasticities must be negative if the parameter estimate of that attribute is negative. The results obtained in Table 8 and Table 9 are consistent with this expectation.

Table 8: Marginal effects for socio-demographics from MNL

Parameter	Mode			
	Car Driving	**Transit**	**Walk**	**Cycle**
Age under 22	-0.01321	0.00645	-0.0202	-0.01212
Being a female	-0.0201	-0.0178	--	-0.0377
Residence in PD1	--	0.138	0.0801	0.0135
Residence outside City of Toronto	0.196	-0.136	-0.0602	--
Transit pass ownership	-0.103	0.193	--	-0.0333

Table 9: Elasticities for travel time and cost from MNL

Parameter	Mode				
	Car Driving	**Car Passenger**	**Transit**	**Walk**	**Cycle**
Travel Cost	-0.0304	-0.0645	-0.0345	--	--
Travel Time	-0.0445	-0.0445	-0.0170	-0.0429	-0.0437

There are no travel cost elasticities for the walk and cycle modes as there is no travel cost associated with these modes. To further illustrate the findings of the marginal effects analysis, the results are presented in graphical format from Figure 15 to Figure 21. The effect of each explanatory variable on the mode choice probabilities are also discussed in detail in sections 4.2.3.1 to 4.2.3.7 of this thesis.

4.2.3.1 Effect of gender on mode choice

The probability of choosing car passenger as a mode for HBD trips increases by 4% if the student is female, as seen in Figure 15. Moreover, the probability of selecting car driving, transit, and cycling as a mode for HBD trips decreases for females by 2 to 4%. The decrease in probability of choosing cycling as a mode can be attributed to the cautious

nature of females in using cycling as a mode in the existing BE (Mitra & Nash, 2019). Investing in making the cycling infrastructure safer can increase the probability of choosing cycling as a mode of travel for females. This finding of the thesis supports the suggestions made by various researchers that propose designing safer cycling infrastructure and meeting the needs of the females more closely (Nash & Mitra, 2019). Interestingly, for HBD trips, the probability of choosing car driving as a mode decreases, while the probability of choosing car passenger increases, suggesting a strong presence of travelling with companions or usage of ride-hailing services for HBD trips by females. Gender can be assumed to have no effect on the probability of choosing walking as a mode as the variable was not statistically significant in the MNL estimated in this thesis. The decrease in probability of choosing transit as a mode is a trend observed in the MEs for all explanatory variables which implies that the probability of choosing transit as a mode decreases for HBD trips. The decreasing trend in the probability of choosing transit for HBD trips is concerning and policymakers must focus on improving LOS variables of transit such as travel time using transit to increase the probability of choosing transit as a mode for HBD trips.

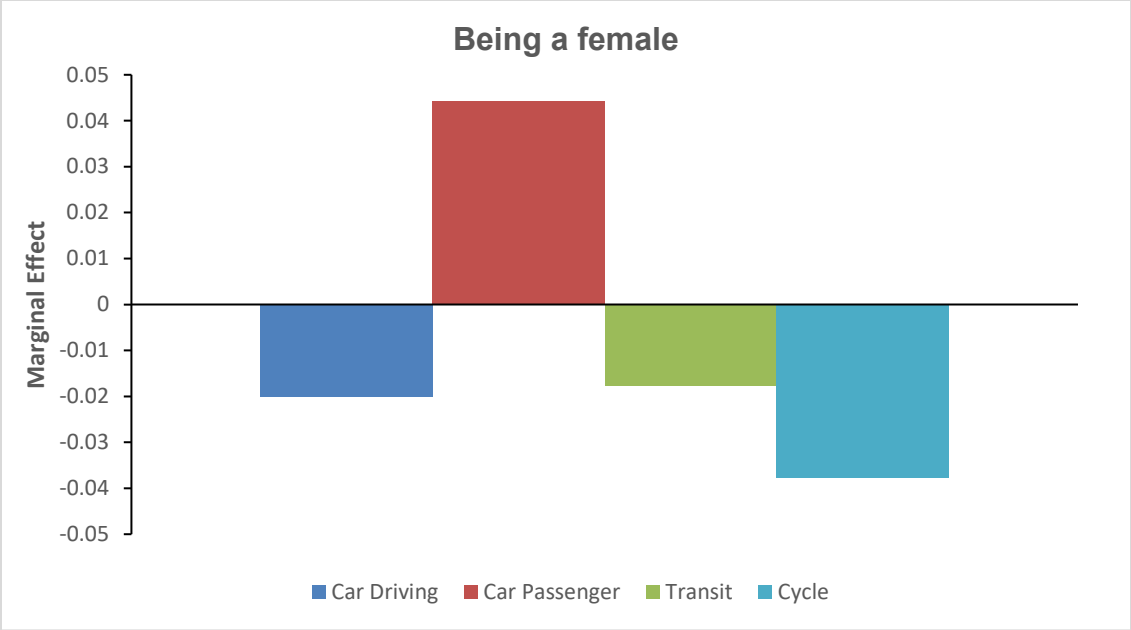


Figure 15: Marginal Effect for being a female

4.2.3.2 Effect of being under the age of 22 on mode choice

The trip-generation model estimated in section 3.2.2 of this thesis showed that the propensity of generating transit trips increases for students under the age of 22. This finding also holds in the mode choice context as the students under 22 are more likely to choose transit or car passenger as a mode rather than car driving, walking, or cycling for HBD trips. Being under 22 is also associated with an increase in probability of choosing car passenger as a mode for HBD trips. The increase in probability of the car passenger mode and the finding of section 4.2.3.1 that the probability of the car passenger mode increases for HBD trips suggests that the probability of choosing car passenger as a mode increases for HBD trips in general. The probability of choosing car driving as a mode decreases as students under 22 are unlikely to afford the ownership and maintenance costs associated with the car driving mode. There is a decrease in probability of choosing walking or cycling as a mode for HBD trips. Younger populations can be associated with

increased physical activity (Shannon et al., 2006), however, given the discretionary nature of the trips, the decreasing trend for walking and cycling modes is understandable. The probability of walking and cycling modes follows a decreasing trend for all explanatory variables except for residing in PD 1 indicates that discretionary activity locations are usually outside of a feasible walkable or bikeable distance from a student's home location.

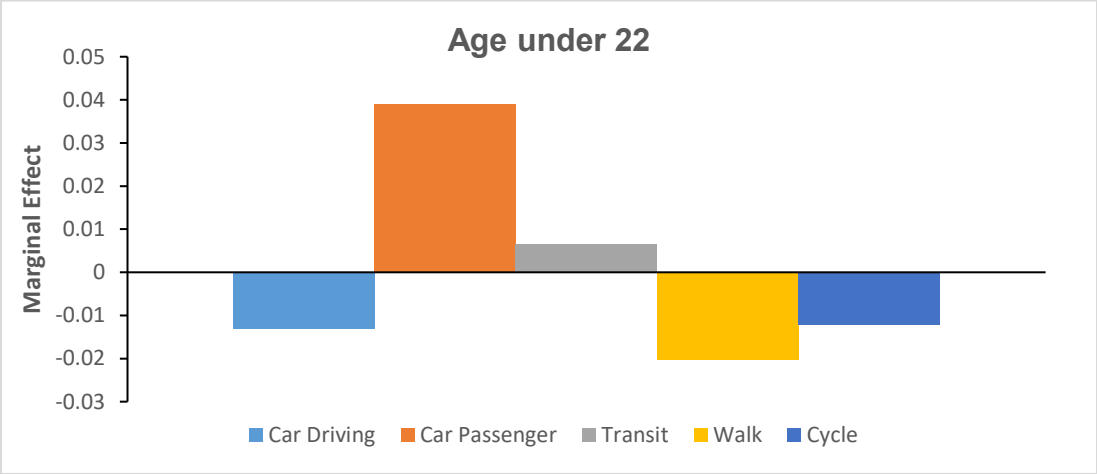


Figure 16: Marginal effects for being under the age of 22

4.2.3.3 Effect of residing outside City of Toronto on mode choice

The probability of choosing car driving or car passenger as a mode increases if a student lives outside the city of Toronto. These findings suggest that students prefer to use car driving or car passenger as a mode if they live outside the City of Toronto due to lower transit connectivity and options. Moreover, the probability of taking transit or walking decreases for HBD trips if a student resides outside the City of Toronto. Regions outside the city of Toronto have a lesser density and lower land-use mix than the City of Toronto as seen in Rinner & Hussain (2011) and therefore lesser transit options. Section 4.2.3.4 of this thesis finds that residing in PD 1 where there is excellent transit connectivity

(Alshalalfah & Shalaby, 2007), the probability of choosing walking, cycling, and transit as a mode increases while decreasing the probability of car passenger mode whereas the effect on car driving mode is statistically insignificant. Therefore, the policymakers must focus on increasing transit connectivity and encouraging diverse land-use mix outside the City of Toronto to increase the propensity of choosing transit for HBD trips.

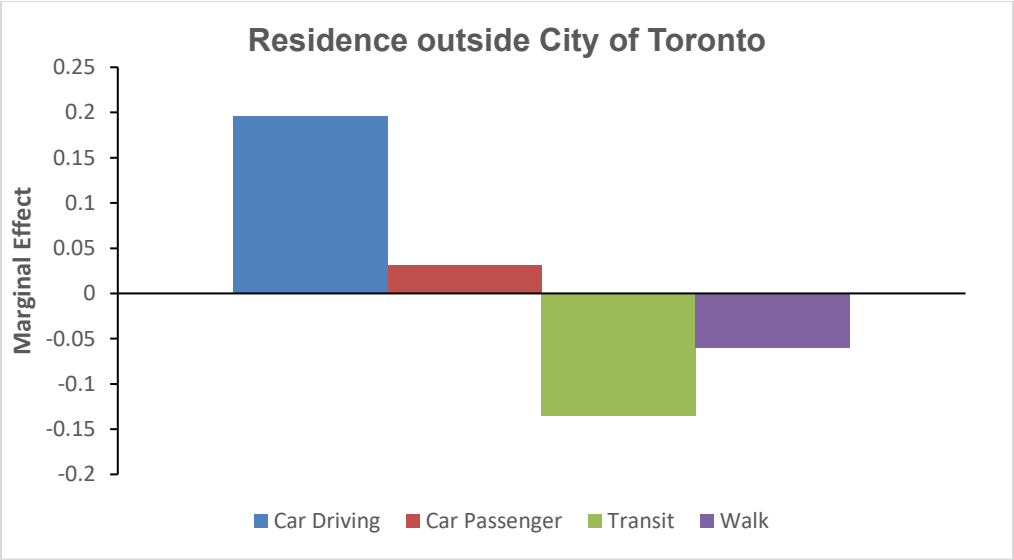


Figure 17: Marginal effects for living outside City of Toronto limits

4.2.3.4 Effect of residing in PD 1 on mode choice

Residing in PD 1 or the downtown core of Toronto is associated with a decrease in the probability of choosing the car passenger mode for HBD trips, as seen in Figure 18. This can be attributed to having excellent transit connectivity and convenience to reach discretionary activities from PD 1 (Alshalalfah & Shalaby, 2007).

Moreover, the probability of choosing transit, walking, and cycling as a mode increases if a student resides in PD 1. This is consistent with the findings of the BOP model estimated in section 3.2.3 of this thesis where the trip-generation propensity of transit, walking and cycling increased if a student resided in PD 1 due to the presence of a BE that encourages

walking and cycling (Nash & Mitra, 2019). Another possible reason for this trend is that walking and cycling modes are feasible to reach the discretionary activities in PD 1 which has a high land-use mix.

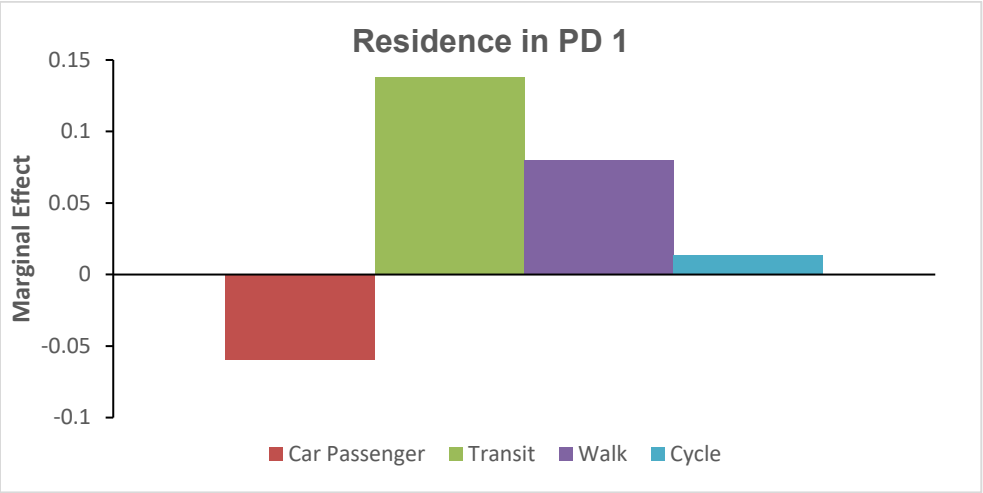


Figure 18: Marginal effects for living inside PD1

4.2.3.5 Effect of transit pass ownership on mode choice

In the trip-generation model estimated in section 3.2 of this thesis, transit pass ownership was not included in the BOP model as it was not statistically significant. However, the transit pass ownership is found to be highly significant in the MNL model for choosing transit as a mode due to the discretionary nature of the trips. It is revealed that owning a transit pass considerably increases the probability of choosing transit for HBD trips as seen in Figure 19. This is consistent with previous findings (Moniruzzaman & Farber, 2018), who reported that owning a transit pass increased the probability of choosing transit as a mode by 24%. As a key policy implication of this finding, encouraging transit pass ownership by introducing transit subsidies for students in the GTHA can promote public transit usage (Zhou, 2016). Since there are various regional transport agencies

operating in the GTHA, an integrated fare system based on travel distance can also be beneficial in increasing the propensity of taking transit for HBD trips (Metrolinx, 2008).

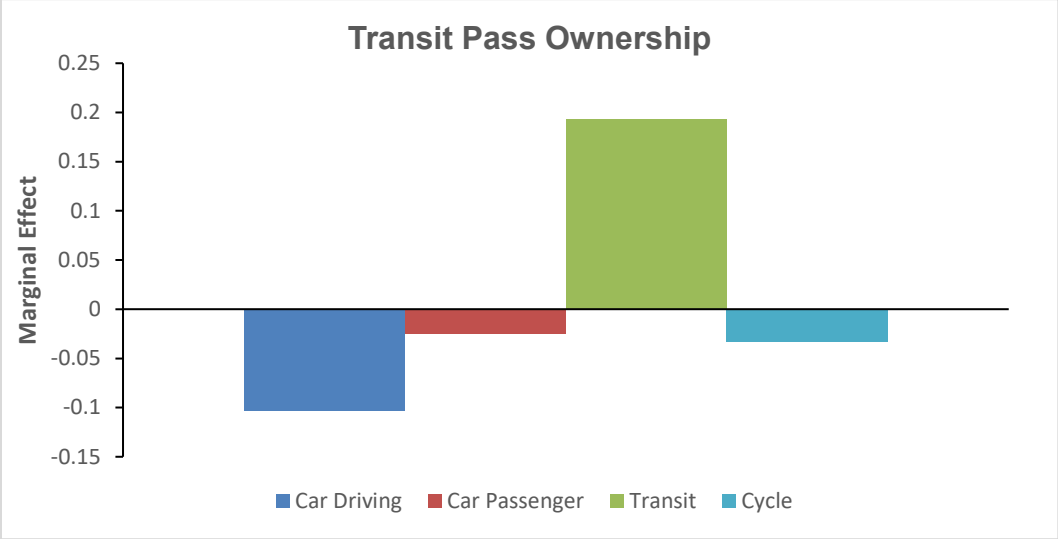


Figure 19: Marginal effect for transit pass ownership

4.2.3.6 Effect of travel cost on mode choice

Travel times and costs are important LOS metrics influencing travel mode choice (Eluru et al., 2010). The elasticities calculated for HBD trips in this section are comparatively lower than similar studies who analysed the elasticities of travel costs and times on commuter trips (Ermagun & Samimi, 2015; Ewing et al., 2004; Hasnine et al., 2017). However, the sensitivity of travel cost is different for each mode as seen in Figure 20: Elasticity of travel costs by mode.

The decrease in probability of choosing the car driving mode is understandable for the GTHA region as the automobile ownership and maintenance costs are higher in the GTHA than in other regions in Canada (CAA, 2021). The higher sensitivity of travel cost for the car passenger mode indicates that the existing cost of choosing car passenger as a

mode is already high and students may shift to alternate modes such as transit if the travel costs for car passenger increase.

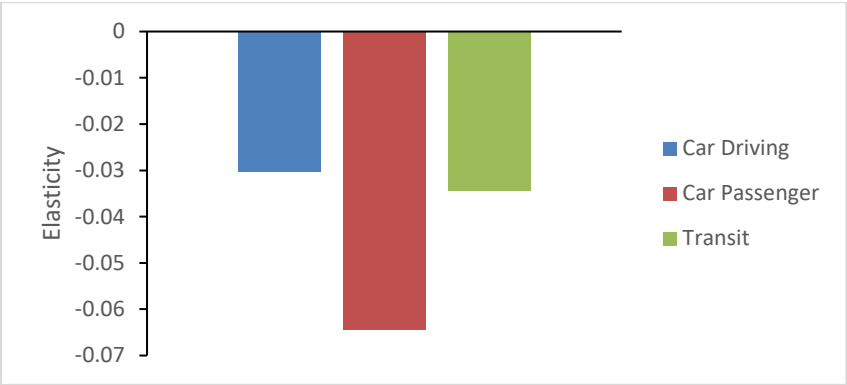


Figure 20: Elasticity of travel costs by mode

4.2.3.7 Effect of travel time on mode choice

Infrastructure improvements directly impact the travel times associated with each mode and the probability of choosing a particular mode also changes. As seen in Figure 21, the probability of choosing car driving, and car passenger modes is the most sensitive to an increase in travel time. The higher sensitivity of the car driving, and car passenger modes is because these modes are chosen over transit due to usually lower travel times. If the travel times for car driving and car passenger modes increase, the probability of choosing car driving or car passenger can decrease considerably. The elasticities for walking and cycling due to travel time are similar. The results show that the probability of choosing walking or cycling as a mode decreases for HBD trips. This maybe because given the nature of walking and cycling modes, increased travel times are also associated with increased physical effort. The elasticities for travel time are lower than the trends observed for commuter trips (Cervero & Kockelman, 1997; Hasnine et al., 2018). Overall, the negative elasticities for travel times are because the students have hectic

schedules due to academic responsibilities and are not willing to spend long times in commuting to their discretionary activities. Also, a decrease in any LOS variable is always associated with a negative effect on the probability of choosing that mode (Chakour & Eluru, 2014; Chang & Lu, 2013).

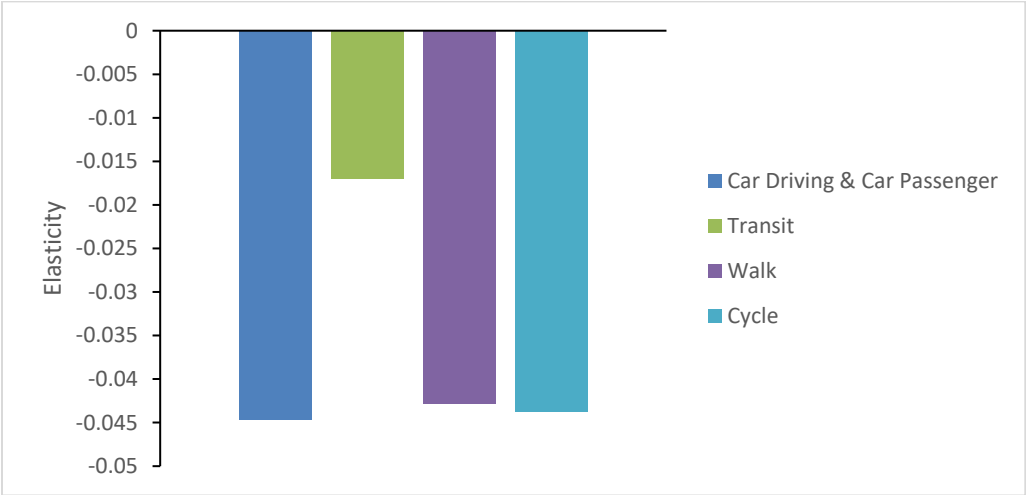


Figure 21:Elasticities of travel time by mode

4.3 Testing the validity of the IIA assumption

The IIA property of the MNL estimated in the thesis needs to be tested for its validity using statistical tests. Otherwise, the model produces erroneous results due to model misspecification. The MNL is powerful and computationally efficient and has been used in several studies on travel behavior (McFadden, 1973). However, the IIA assumption and IID property of the errors/random components which means that unobservable characteristics are identical across observations undermine the credibility of the model. Since the MNL model is sometimes assumed to produce erroneous results if the IIA assumption is violated, a specification test as described in (Hausman & McFadden, 1984) to verify that IIA assumption has not been violated is performed. Researchers have widely used the HM specification test to verify the validity of the IIA assumption in

MNL models (Abrari Vajari et al., 2020; Cheng & Long, 2007; Horowitz, 1981; H. Zhang et al., 2021). The HM test used in this thesis requires estimating a separate NL and an MNL instead of an unrestricted MNL and a restricted MNL for justifying the inclusion of explanatory variables as in the classical LR test.

In a study comparing the MNL with the MNP, Horowitz, (1980) suggests that if an MNL is used, diagnostic testing for model specification such as validating the IIA assumption by a LR test between restricted and unrestricted MNL models must be performed. Due to the nature of the unbalanced choice sets in the thesis, the HM test used in this thesis requires the estimation of a NL model whose empirical framework allows a violation of the IIA within alternatives which can significantly increase the prediction capabilities of the model and compete against the MNL (Hausman & McFadden, 1984; McFadden, 1987). For this, a NL is estimated with the same parameters as estimated in the MNL, but the number of alternatives is varied due to nesting multiple modes into one mode. A total of 6 nested logit models with different choice structures were estimated. The chosen NL outperformed other possible choice set specifications of the NL model in terms of maximized LLs and the significance of estimated parameters. The possible choice set for the chosen NL can be seen in Figure 22.

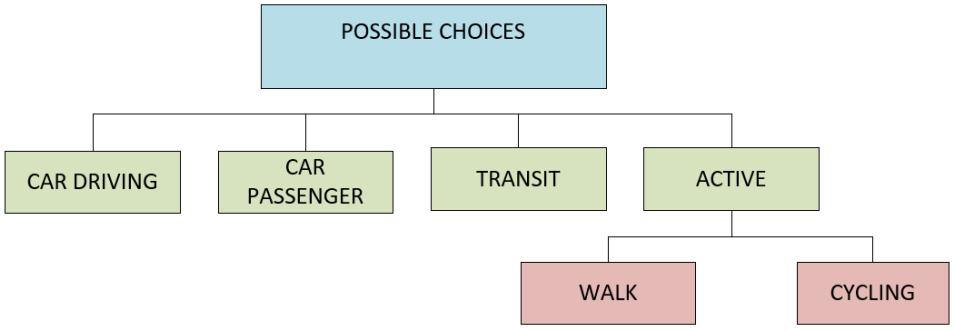


Figure 22: Possible choices for the chosen NL

The empirical form of the test is taken from (Hausman & McFadden, 1984) and follows an asymptotic χ^2 distribution:

$$LLR\ test\ statistic = 2\big(LL(\alpha, \lambda) - LL(\beta)\big) \tag{6}$$

Where,

$LL(\alpha, \lambda) =$ log-likelihood of the NL model, -751.0155 for the chosen NL

$LL(\beta) =$ log-likelihood of the MNL model, -751.346 for the estimated MNL in this thesis

α = Matrix containing parameter estimates from the nested logit

$\lambda =$ dissimilarity parameter representing added utility of choosing a mode, usually between 0 and 1

$\beta =$ Matrix containing parameter estimates from the MNL

This test-statistic obtained from the LR test is then compared to the critical χ^2 value corresponding to the difference in degrees of freedom between the MNL and the nested logit to accept or reject the hypotheses defined as follows:

H_0 = IIA assumption is valid

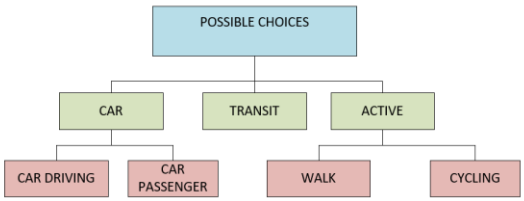
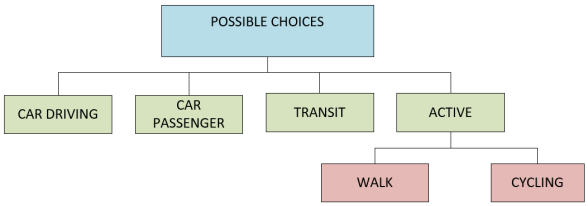
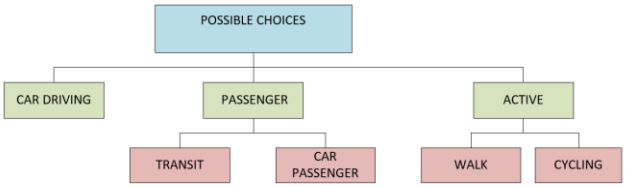
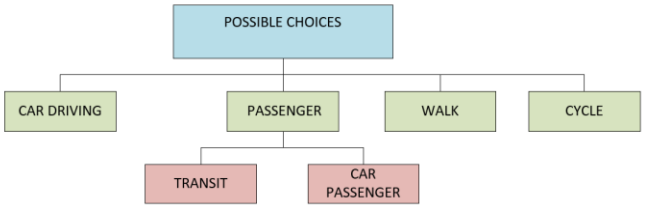
H_a = IIA assumption is not valid

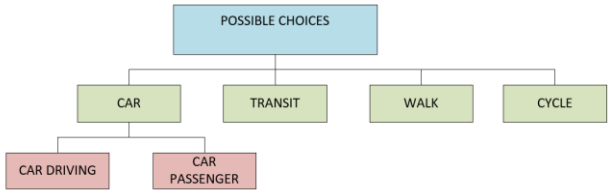
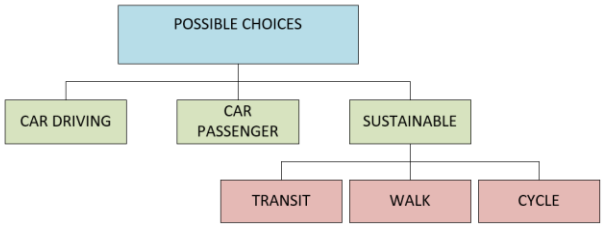
In the context of mode choice analysis with unbalanced choice sets, this hypothesis setting is appropriately specified (Brus et al., 2016; Çelik & Oktay, 2014).

The LR test statistic is 1.505, which is lesser than the critical χ^2 value at both 95% confidence (5.991) and 99% confidence (9.210) intervals (NIST & SEMATECH, 2021). Based on this result, the null hypothesis that the IIA assumption holds in the MNL can not be rejected. Therefore, the results of the HM test suggest that the IIA assumption holds for the MNL estimated in the thesis. This finding also supports the study of

McFadden (1987) who finds that for IIA to hold logically, each alternative must have the ability to be weighted independently by the respondent. The MNL estimated in this thesis has unbalanced choice sets for each respondent which represents a plausible substitution pattern. Table 10 shows the nesting structures and LLR test statistics of the 6 different nested logit models estimated.

Table 10: 6 Different nesting structures and LLs at convergence

Nesting structure	LL at convergence	χ^2 value for LLR test
	-750.544	1.604
	-750.5934	1.505
	-750.351	1.99
	-750.734	1.224

	-750.908	0.876
	-750.843	1.006

Chapter 5: Future work and conclusions

This chapter will identify the limitations associated with the BOP and MNL models estimated in this thesis and make recommendations for future work which can increase the prediction scope of the model and help derive important behavioural insights which maybe relevant in a policy context.

5.1 Limitations of the models estimated in this thesis

The techniques used for gaining behavioural insights in this thesis are based on widely accepted statistical principles. However, as with all modelling exercises, certain limitations can decrease the model's predicting power. These limitations arise mainly due to two reasons—data restrictions and model capability constraints. The survey data used may contain sampling errors and result in biased outcomes from the model. Moreover, the accessibility metric used for analysis quantifies the in-vehicle travel time and time spent waiting at a transit stop in the same manner which may not be true for some respondents. These limitations have varying effects on the modelling techniques used in this thesis and are discussed in sections 5.1.1 and 5.1.2.

5.1.1 Limitations of the BOP model

BOP approach is an accurate and advanced modelling technique suitable for meeting the objectives of thesis. However, in the context of trip-generation, this thesis considered the correlation between transit and automobile trips only and the influence of personal and land use attributes on these propensities. For a comprehensive analysis of the trip-generation propensities of each mode, a multivariate ordered probit approach can prove to be fruitful. This approach will incorporate the influence of all heterogeneities in the data while also establishing correlations between the trip-generation propensities between

different alternatives. This would give significant insight and a candid look into how the usage of one mode decreases or increases the propensity of another mode. Knowing the correlation of a mode with other modes can also help identify spatial variations and quantify how sensitive the trip generation is to a particular policy action, which can be beneficial for policymakers and transportation planners. Moreover, alternative techniques such as Poisson or Negative Binomial regression models which require count data can be used to model the effect of personal and land-use attributes on the number of trips by a particular mode. This can enable the analysis of varying levels of the trip-generation patterns across different zones.

5.1.2 Limitations of the MNL

MNL is one of the most computationally tractable and less intensive yet a powerful modelling technique. In this thesis, the IIA assumption was assumed to hold in the estimated MNL based on the HM test. However, the independence of the utility of the unobserved components among alternatives in the MNL can be overcome by using different modelling techniques such as nested logit (NL), cross-nested logit, and mixed multinomial logit (MMNL). The NL is different from the MNL as the alternatives similar to each other are put in a nest. This allows for a correlation among alternatives in the nest but not across nests. As an example, modes such as cycling, and walking can be nested in an active travel mode nest. This means that the utility of choosing either walking or cycling depends on choosing active travel as a mode. A CNL model is a direct adaptation of the NL model where an alternative may belong to more than one nest and therefore, the correlation among nests can be estimated. MMNL is more computationally challenging to use than a cross-nested logit as the integrals representing choice

probabilities do not have a closed-form expression like the probability functions seen in sections 3.1.2 and 4.1.2 of this thesis and require extensive simulation for approximation (McFadden & Train, 2000). The MNL estimated in this thesis included aspects such as age, sex, and residence location but unobserved components due to preference heterogeneity always exist in the MNL technique (Bhat, 2000). Using the MMNL technique, unobserved components such as the respondent's lifestyle, culture, and the impact of travel habits formed during their life can be captured as interaction between the unobserved variables is allowed. Although the results of the HM test in section 4.3 of this thesis suggest that IIA assumption holds, a MMNL approach which doesn't require the IIA assumption can provide highly credible insights.

Moreover, for the development of a feasible choice set for each respondent in the MNL, certain assumptions as described in section 4.1.2 of this thesis were made which might not hold for all individuals. As an example, some people might walk for distances greater than 5 km or cycle for distances greater than 10 km whereas in the current choice set specification, they do not have the walking as a choice if the commute distance is greater than 5 km and they do not have cycling as a choice if the commute distance is greater than 10 km. Since the travel costs and times are highly significant in the MNL estimated in this thesis, individuals quantify the utility of choosing a mode based on travel cost and time similar to commuter trips.

Finally, the transit travel times used for the study were from the 2011 TTS data, which is old and may have changed for the chosen study area due to constant transit improvements being carried out by municipalities. The inclusion of more recent travel times can help increase the relevance of the effect of travel times on choosing transit as a mode.

5.2 Future work Recommendations

This thesis may not have captured all latent modal attributes to the fullest due to the multimodal behaviour of trip chains and variations in activity choice destinations for discretionary trips. In the MNL, a feasible choice set was determined, but the determination of a consideration choice set which more closely identifies the modes that a respondent may consider choosing may increase the prediction power of the model. In this study, heavy emphasis was placed on personal and land-use attributes or the "demand-side" characteristics, and it would be interesting to see the effect of the attributes of the transport "supply-side" other than accessibility such as level of comfort and ease of access on the travel preferences for the students. It is apparent that introducing transit subsidy will increase the transit mode share, but the degree to which such subsidies can work remains to be seen in future work. Moreover, a multi-level MNL for analysing all trips in a trip chain or tour-based mode choice modelling can quantify the trip-chaining behaviour present among the post-secondary students. Challenging the conventional notion that the characteristics of an individual determine mode choice greater than the characteristics of the mode itself, Kroesen et al. (2017) aimed to study the popular notion that although behaviours affect mode choice, the characteristics of a mode itself influence travel behaviours. They studied this causality using a structural equation model and found that the characteristics of a mode such as comfort and ease of access affect the travel habits of people greater than the socio-demographics as assumed in this thesis and future works can incorporate a greater number of LOS variables and their effect on travel habits.

Supplementary economic analyses, which will exclusively look at the mode share increases rather than travel behaviour can direct strategic planning decisions. Similarly, sustainability in transportation is an extensively researched field whose aim is to look at how car-ownership can be reduced, and transit-ridership increased. As an expansion of this work, a microscopic analysis of the car ownership levels, automobile sales, introduction of transit subsidies, and BE variables that factor into the ownership of these modes can be determined. Thus, adopting sustainable travel practices, encouraging transit usage, and shaping sustainable travel behaviour through incentivization and educational programs at schools and colleges may prove to be fruitful.

5.3 Conclusions

The post-secondary students of the GTHA are part of a niche population due to the multi-cultural population, extremities in socio-demographics, and varying income levels. Travel behaviour is of interest to researchers and policymakers as the population continues to grow, personal automobile infrastructure becomes more congested, and transit investments increase. There will be an increase in students, employees, and all activities that depend on students. An increase in the number of commuters to post-secondary institutions can only be expected. This thesis presents a BOP model for predicting trip generation and a MNL model for predicting mode choice behaviour. The BOP model gave significant insights into factors affecting the trip generation of transit and automobile. The strong negative correlation between trip-generation propensities of transit and automobile implies that as the trip-making propensity increases, the automobile trip propensity decreases. This is an important finding and essential policy implications related to discouraging automobile usage and encouraging transit usage can

be derived from this. Furthermore, having a commute distance of less than 5 km decreases the transit and automobile trip-making propensities, which implies a high level of usage of active modes of travel such as walking and cycling in PD 1. Policymakers must plan communities and areas around campus to be of mixed land-use character containing medium to high-density housing options which can accommodate students so that peak hour congestion is avoided, and sustainable travel practices are encouraged.

The MNL results show that having a residence in PD1 decreased the propensities of using automobile modes while increasing the propensity of transit, walking, and cycling modes. This indicates that PD 1 has excellent transit connectivity and options to reach discretionary activities. However, living outside the City of Toronto increases the propensity of trip-making by automobiles and decreases the propensity of using transit, walking, or cycling for travel. This points to a huge potential in increasing propensity of taking transit in areas outside the City of Toronto if transit options and connectivity is brought to service levels in PD 1 and the City of Toronto in general. Moreover, there are no subsidies for transit usage by postsecondary students in the GTHA. Students are willing to reduce their commute frequency to campus per week or find it cheaper to pay per trip during daily travel rather than having a non-subsidized monthly transit pass. Given the vital link between transit accessibility and transit trip-making propensity, transit investments must focus on areas with lower transit accessibility.

The MNL results also show that the car driving, and car passenger modes are the most susceptible to a decrease in the probability of choosing them as a mode if the travel times increase. This indicates that the primary reason people use automobiles over other modes is due to time savings. It can be concluded that existing travel times for transit are high

and improvements in transit connectivity aimed at reducing transit commute times is necessary to make people shift to transit for their travel. Using a personal automobile for commuting is also the most sensitive to travel costs, suggesting that existing ownership and maintenance costs are already very high for personal cars. Increasing automobile costs further will surely decrease the choosing personal automobile as a mode of transport but may introduce social equity issues.

This thesis builds on the modelling techniques used for predicting trip-generation and determining mode choice using existing literature. The marginal effect analysis for the results obtained by both the BOP and MNL models helped quantify the effect of personal and land-use attributes on trip-generation and mode choice behaviour of the post-secondary students in GTHA. The creation of feasible choice sets in the MNL is an improvement over commonly used unconstrained choice sets in MNL modelling. The model specification test used in the study contribute to literature on mode choice behaviour using MNL models in the transportation context. Finally, this thesis suggests an improved approach of using two separate models for predicting trip-generation and mode choice behaviour to gain behavioural insights into the travel behaviour of students. These findings are highly relevant in a policy context and can be of great benefit to policymakers and urban planners. The estimated models represent the trends in the GTHA but can be replicated for use in different regions around the world.

References

Abotalebi, E., Scott, D. M., & Ferguson, M. R. (2019). Can Canadian households benefit economically from purchasing battery electric vehicles? *Transportation Research Part D: Transport and Environment*, *77*(November), 292–302. https://doi.org/10.1016/j.trd.2019.10.014

Abrari Vajari, M., Aghabayk, K., Sadeghian, M., & Shiwakoti, N. (2020). A multinomial logit model of motorcycle crash severity at Australian intersections. *Journal of Safety Research*, *73*, 17–24. https://doi.org/10.1016/j.jsr.2020.02.008

Akar, G., Flynn, C., & Namgung, M. (2012). Travel choices and links to transportation demand management. *Transportation Research Record*, *2319*, 77–85. https://doi.org/10.3141/2319-09

Alemi, F., Circella, G., Mokhtarian, P., & Handy, S. (2019). What drives the use of ridehailing in California? Ordered probit models of the usage frequency of Uber and Lyft. *Transportation Research Part C: Emerging Technologies*, *102*(May 2018), 233–248. https://doi.org/10.1016/j.trc.2018.12.016

Allen, J. (2021). *SMTO Institutions Map*.

Allen, J., & Farber, S. (2018). How time-use and transportation barriers limit on-campus participation of university students. *Travel Behaviour and Society*, *13*(February), 174–182. https://doi.org/10.1016/j.tbs.2018.08.003

Allen, J., & Farber, S. (2020). Planning transport for social inclusion: An accessibility-activity participation approach. *Transportation Research Part D: Transport and Environment*, *78*(January), 102212. https://doi.org/10.1016/j.trd.2019.102212

Alshalalfah, B. W., & Shalaby, A. S. (2007). Case Study: Relationship of Walk Access

Distance to Transit with Service, Travel, and Personal Characteristics. *Journal of Urban Planning and Development*, *133*(2), 114–118. https://doi.org/10.1061/(asce)0733-9488(2007)133:2(114)

Anastasopoulos, P., Karlaftis, M., Haddock, J., & Mannering, F. (2012). Household automobile and motorcycle ownership analysed with random parameters bivariate ordered probit model. *Transportation Research Record*, *2*(2279), 12–20. https://doi.org/10.3141/2279-02

Ao, Y., Zhang, Y., Wang, Y., Chen, Y., & Yang, L. (2020). Influences of rural built environment on travel mode choice of rural residents: The case of rural Sichuan. *Journal of Transport Geography*, *85*(April), 102708. https://doi.org/10.1016/j.jtrangeo.2020.102708

Balsas, C. J. L. (2003). Sustainable transportation planning on college campuses. *Transport Policy*, *10*(1), 35–49. https://doi.org/10.1016/S0967-070X(02)00028-8

Basmajian, C. (2015). *An analysis of travel behavior of university population consisting of students , faculty and staff at Iowa State University Major : Community and Regional Planning Program of Study Committee :*

Ben-Akiva, M., & Bierlaire, M. (1999). *Discrete choice methods and their application to short term travel decisions* (Issue 1985).

Ben-Akiva, M., & Lerman, S. (1985). *Discrete Choice Analysis:Theory and Application to Travel Demand*.

Bernasco, W., & Block, R. (2020). *Discrete Choice Modeling* (pp. 1–37). VU University Amsterdam, Netherlands.

Bhat, C. R. (2000). Incorporating Observed and Unobserved Heterogeneity in Urban

Work Travel Mode Choice Modelling. *Transportation Science*, *34*(2).

Bliemer, M. C. J., Mulley, C., & Moutou, C. J. (2016). Handbook on transport and urban planning in the developed world. In *Handbook on Transport and Urban Planning in the Developed World*. https://doi.org/10.4337/9781783471393

Boisjoly, G., & El-Geneidy, A. M. (2017). The insider: A planners' perspective on accessibility. *Journal of Transport Geography*, *64*, 33–43. https://doi.org/10.1016/j.jtrangeo.2017.08.006

Bouscasse, H., Joly, I., & Peyhardi, J. (2019). A new family of qualitative choice models: An application of reference models to travel mode choice. *Transportation Research Part B: Methodological*, *121*, 74–91. https://doi.org/10.1016/j.trb.2018.12.010

Bouton, S., Cis, D., Mendonca, L., Pohl, H., Remes, J., Ritchie, H., & Woetzel, J. (2013). How to make a city great. *McKinsey Cities Special Initiative*, *September*, 35.

Brus, D. J., Slim, P. A., Gort, G., Heidema, A. H., & Van Dobben, H. (2016). Monitoring habitat types by the mixed multinomial logit model using panel data. *Ecological Indicators*, *67*, 108–116. https://doi.org/10.1016/j.ecolind.2016.02.043

Butler, A., & Sweet, M. (2020). No free rides: Winners and losers of the proposed Toronto Transit Commission U-Pass program. *Transport Policy*, *96*(October 2019), 15–28. https://doi.org/10.1016/j.tranpol.2020.05.019

Bwambale, A., Choudhury, C. F., & Hess, S. (2019). Modelling trip generation using mobile phone data: A latent demographics approach. *Journal of Transport Geography*, *76*(February), 276–286. https://doi.org/10.1016/j.jtrangeo.2017.08.020

CAA. (2021). *Driving Costs*. https://carcosts.caa.ca/

Campbell, A. A., Cherry, C. R., Ryerson, M. S., & Yang, X. (2016). Factors influencing

the choice of shared bicycles and shared electric bikes in Beijing. *Transportation Research Part C: Emerging Technologies*, *67*, 399–414. https://doi.org/10.1016/j.trc.2016.03.004

Capasso, D., & Astroza, S. (2019). *Are Millennials Really All That Different Than Generation X? An Analysis of Factors Contributing to Differences in Vehicle Miles of Travel*. *August*.

Çelik, A. K., & Oktay, E. (2014). A multinomial logit analysis of risk factors influencing road traffic injury severities in the Erzurum and Kars Provinces of Turkey. *Accident Analysis and Prevention*, *72*, 66–77. https://doi.org/10.1016/j.aap.2014.06.010

Cervero, R., & Kockelman, K. (1997). Travel demand and the 3Ds: Density, diversity, and design. *Transportation Research Part D: Transport and Environment*, *2*(3), 199–219. https://doi.org/10.1016/S1361-9209(97)00009-6

Chakour, V., & Eluru, N. (2014). Analyzing commuter train user behavior: A decision framework for access mode and station choice. *Transportation*, *41*(1), 211–228. https://doi.org/10.1007/s11116-013-9509-y

Chang, M.-S., & Lu, P.-R. (2013). A Multinomial Logit Model of Mode and Arrival Time Choices for Planned Special Events. *Journal of the Eastern Asia Society for Transportation Studies*, *10*, 710–727. https://doi.org/10.11175/easts.10.710

Chen, X. (2012). Statistical and activity-based modeling of university student travel behavior. *Transportation Planning and Technology*, *35*(5), 591–610. https://doi.org/10.1080/03081060.2012.701818

Cheng, S., & Long, J. S. (2007). Testing for IIA in the multinomial logit model. *Sociological Methods and Research*, *35*(4), 583–600.

https://doi.org/10.1177/0049124106292361

Chiou, Y. C., Hwang, C. C., Chang, C. C., & Fu, C. (2013). Reprint of "modeling two-vehicle crash severity by a bivariate generalized ordered probit approach." *Accident Analysis and Prevention*, *61*, 97–106. https://doi.org/10.1016/j.aap.2013.07.005

Circella, G., Fulton, L., Alemi, F., Tiedeman, K., Mokhtarian, P. L., & Handy, S. (2016). *What Affects Millennials ' Mobility ? PART I : Investigating the Environmental Concerns , Lifestyles , Mobility-Related Attitudes and Adoption of Technology of Young Adults in California*.

Collins, P. A., & Agarwal, A. (2015). Impacts of public transit improvements on ridership, and implications for physical activity, in a low-density Canadian city. *Preventive Medicine Reports*, *2*, 874–879. https://doi.org/10.1016/j.pmedr.2015.10.001

Daisy, N. S., Millward, H., & Liu, L. (2018). Trip chaining and tour mode choice of non-workers grouped by daily activity patterns. *Journal of Transport Geography*, *69*(April), 150–162. https://doi.org/10.1016/j.jtrangeo.2018.04.016

Day, N., Habib, K. N., & Miller, E. J. (2010). Analysis of work trip timing and mode choice in the Greater Toronto Area. *Canadian Journal of Civil Engineering*.

de Palma, A., & Picard, N. (2005). Route choice decision under travel time uncertainty. *Transportation Research Part A: Policy and Practice*, *39*(4 SPEC. ISSS.), 295–324. https://doi.org/10.1016/j.tra.2004.10.001

Delmelle, E. M., & Delmelle, E. C. (2012). Exploring spatio-temporal commuting patterns in a university environment. *Transport Policy*, *21*, 1–9. https://doi.org/10.1016/j.tranpol.2011.12.007

Derrible, S., & Kennedy, C. (2009). Network analysis of world subway systems using updated graph theory. *Transportation Research Record*, *2112*, 17–25. https://doi.org/10.3141/2112-03

Diab, E., Deweese, J., Chaloux, N., & El, A. (2020). Adjusting the service ? Understanding the factors affecting bus ridership over time at the route level in Montréal , Canada. *Transportation*, *0123456789*. https://doi.org/10.1007/s11116-020-10147-3

Diab, E., Kasraian, D., Miller, E. J., & Shalaby, A. (2020). The rise and fall of transit ridership across Canada : Understanding the determinants. *Transport Policy*, *96*(October 2019), 101–112. https://doi.org/10.1016/j.tranpol.2020.07.002

Dias, F. F., Lavieri, P. S., Garikapati, V. M., Astroza, S., Pendyala, R. M., & Bhat, C. R. (2017). A behavioral choice model of the use of car-sharing and ride-sourcing services. *Transportation*, *44*(6), 1307–1323. https://doi.org/10.1007/s11116-017-9797-8

Ding, C., Wang, D., Liu, C., Zhang, Y., & Yang, J. (2017). Exploring the influence of built environment on travel mode choice considering the mediating effects of car ownership and travel distance. *Transportation Research Part A: Policy and Practice*, *100*, 65–80. https://doi.org/10.1016/j.tra.2017.04.008

Dow, J. K., & Endersby, J. W. (2004). Multinomial probit and multinomial logit: A comparison of choice models for voting research. *Electoral Studies*, *23*(1), 107–122. https://doi.org/10.1016/S0261-3794(03)00040-4

Eluru, N., Pinjari, A. R., Pendyala, R. M., & Bhat, C. R. (2010). An econometric multi-dimensional choice model of activity-travel behavior. *Transportation Letters*, *2*(4),

217–230. https://doi.org/10.3328/TL.2010.02.04.217-230

Enam, A., & Konduri, K. C. (2018). Time Allocation Behavior of Twentieth-Century American Generations: GI Generation, Silent Generation, Baby Boomers, Generation X, and Millennials. *Transportation Research Record*, *2672*(49), 69–80. https://doi.org/10.1177/0361198118794710

Ermagun, A., & Samimi, A. (2015). Promoting active transportation modes in school trips. *Transport Policy*, *37*, 203–211. https://doi.org/10.1016/j.tranpol.2014.10.013

Ewing, R., Schroeer, W., & Greene, W. (2004). School location and Student Travel. *Journal of the Transportation Research Board*, 55–63.

Faghih-Imani, A., & Eluru, N. (2015). Analysing bicycle-sharing system user destination choice preferences: Chicago's Divvy system. *Journal of Transport Geography*, *44*, 53–64. https://doi.org/10.1016/j.jtrangeo.2015.03.005

Fujiwara, A., Zhang, J., & Mohammad, A. (2010). A Joint Modeling of Injury Severity and Collision Type for Examining Influential Factors of Traffic Accidents Occurring at Intersections of National Highways in Japan. *Journal of the Eastern Asia Society for Transportation Studies*, *8*, 1838–1853.

Gardiner, S., King, B., & Wilkins, H. (2013). The travel behaviours of international students: Nationality-based constraints and opportunities. *Journal of Vacation Marketing*, *19*(4), 287–299. https://doi.org/10.1177/1356766712471233

Government of Ontario. (2021). *Ontario Builds*. 2021. https://www.ontario.ca/page/building-ontario-transit

Greene, W. H., & Hensher, D. A. (2010). Modeling ordered choices: A primer. *Modeling Ordered Choices: A Primer*, 1–365. https://doi.org/10.1017/CBO9780511845062

Grimsrud, M., & El-Geneidy, A. (2014). Transit to eternal youth: Lifecycle and generational trends in Greater Montreal public transport mode share. *Transportation*, *41*(1), 1–19. https://doi.org/10.1007/s11116-013-9454-9

Guerra, E., Caudillo, C., Monkkonen, P., & Montejano, J. (2018). Urban form, transit supply, and travel behavior in Latin America: Evidence from Mexico's 100 largest urban areas. *Transport Policy*, *69*(August 2017), 98–105. https://doi.org/10.1016/j.tranpol.2018.06.001

Guo, J. Y., Bhat, C. R., & Copperman, R. B. (2007). Effect of the built environment on motorized and nonmotorized trip making: Substitutive, complementary, or synergistic? *Transportation Research Record*, *2010*, 1–11. https://doi.org/10.3141/2010-01

Guo, L., Zhao, X., Yu, S., Li, X., & Shi, Z. (2017). An improved car-following model with multiple preceding cars' velocity fluctuation feedback. *Physica A: Statistical Mechanics and Its Applications*, *471*, 436–444. https://doi.org/10.1016/j.physa.2016.12.071

Habib, K. N., Weiss, A., & Hasnine, S. (2018). On the heterogeneity and substitution patterns in mobility tool ownership choices of post-secondary students: The case of Toronto. *Transportation Research Part A: Policy and Practice*, *116*(August), 650–665. https://doi.org/10.1016/j.tra.2018.06.002

Haboucha, C. J., Ishaq, R., & Shiftan, Y. (2017). User preferences regarding autonomous vehicles. *Transportation Research Part C: Emerging Technologies*, *78*, 37–49. https://doi.org/10.1016/j.trc.2017.01.010

Haggar, P., Whitmarsh, L., & Skippon, S. M. (2019). Habit discontinuity and student

travel mode choice. *Transportation Research Part F: Traffic Psychology and Behaviour*, *64*, 1–13. https://doi.org/10.1016/j.trf.2019.04.022

Hansen, W. G. (1959). How Accessibility Shapes Land Use. *Journal of the American Planning Association*, *25*(2), 73–76. https://doi.org/10.1080/01944365908978307

Hasnine, M. S., Lin, T., Weiss, A., Habib, K. N., & Board, T. R. (2017). *Is It the Person or the Urban Context? The Role of Urban Travel Context in Defining Mode Choices for School Trips of Post-Secondary Students in Toronto*. 18p. https://trid.trb.org/view/1439049

Hasnine, M. S., Lin, T. Y., Weiss, A., & Habib, K. N. (2018). Determinants of travel mode choices of post-secondary students in a large metropolitan area: The case of the city of Toronto. *Journal of Transport Geography*, *70*(April 2017), 161–171. https://doi.org/10.1016/j.jtrangeo.2018.06.003

Hausman, J., & McFadden, D. (1984). Specification Tests for the Multinomial Logit Model. *Econometrica*, *52*(5), 1219–1240.

Hensher, D., Louviere, J., & Swait, J. (2000). Stated choice methods:analysis and application. *Journal of Econometrics*, *89*(1–2), 197–221.

Horowitz, J. (1980). The accuracy of the multinomial logit model as an approximation to the multinomial probit model of travel demand. *Transportation Research Part B: Methodological*, *14*(4), 331–341. https://doi.org/10.1016/0191-2615(80)90013-2

Horowitz, J. (1981). Identification and diagnosis of specification errors in the multinomial logit model. *Transportation Research Part B*, *15*(5), 345–360. https://doi.org/10.1016/0191-2615(81)90019-9

Infrastructure Canada. (2021). *Largest public transit investment in GTA history will*

create jobs and kickstart the economy. https://www.canada.ca/en/office-infrastructure/news/2021/05/largest-public-transit-investment-in-gta-history-will-create-jobs-and-kickstart-the-economy.html

Khattak, A., Wang, X., Son, S., & Agnello, P. (2011). Travel by university students in Virginia: Is this travel different from travel by the general population? *Transportation Research Record*, *2255*, 137–145. https://doi.org/10.3141/2255-15

Koh, P. P., & Wong, Y. D. (2013). Comparing pedestrians' needs and behaviours in different land use environments. *Journal of Transport Geography*, *26*, 43–50. https://doi.org/10.1016/j.jtrangeo.2012.08.012

Koppelman, F. S., & Bhat, C. (2006). *A self-instructing course on choice modeling: Multinomial and nested logit models* (Issue 1). U.S. Department of Transportation.

Kroesen, M., Handy, S., & Chorus, C. (2017). Do attitudes cause behavior or vice versa? An alternative conceptualization of the attitude-behavior relationship in travel behavior modeling. *Transportation Research Part A: Policy and Practice*, *101*, 190–202. https://doi.org/10.1016/j.tra.2017.05.013

Kropko, J. (2008). *Choosing Between Multinomial Logit and Multinomial Probit Models for Analysis of Unordered Choice Data*.

Lavieri, P. S., & Bhat, C. R. (2019). Modeling individuals' willingness to share trips with strangers in an autonomous vehicle future. *Transportation Research Part A: Policy and Practice*, *124*(March), 242–261. https://doi.org/10.1016/j.tra.2019.03.009

Leite Mariante, G., Ma, T. Y., & Van Acker, V. (2018). Modeling discretionary activity location choice using detour factors and sampling of alternatives for mixed logit models. *Journal of Transport Geography*, *72*(August 2017), 151–165.

https://doi.org/10.1016/j.jtrangeo.2018.09.003

Li, L., Hasnine, M. S., Nurul Habib, K. M., Persaud, B., & Shalaby, A. (2017). Investigating the interplay between the attributes of at-fault and not-at-fault drivers and the associated impacts on crash injury occurrence and severity level. *Journal of Transportation Safety and Security*, *9*(4), 439–456. https://doi.org/10.1080/19439962.2016.1237602

Lin, T., Hasnine, S., & Habib, K. M. N. (2019). Influence of latent attitudinal factors on the multimodality of post-secondary students in toronto. *Canadian Journal of Civil Engineering*, *46*(6), 251–260. https://doi.org/10.1139/cjce-2017-0333

Madar, G., Maoh, H., & Gingerich, K. (2021). Modeling commercial vehicle trip generation at the business-establishment level. *Canadian Journal of Civil Engineering*, *48*(6), 669–680. https://doi.org/10.1139/cjce-2019-0599

Masoumi, H. E. (2019). A discrete choice analysis of transport mode choice causality and perceived barriers of sustainable mobility in the MENA region. *Transport Policy*, *79*(April), 37–53. https://doi.org/10.1016/j.tranpol.2019.04.005

Mattisson, K., Idris, A. O., Cromley, E., Håkansson, C., Östergren, P. O., & Jakobsson, K. (2018). Modelling the association between health indicators and commute mode choice: a cross-sectional study in southern Sweden. *Journal of Transport and Health*, *11*(October), 110–121. https://doi.org/10.1016/j.jth.2018.10.012

McFadden, D. (1973). Conditional logit analysis of qualitative choice behavior. In *Frontiers in Econometrics*. Academic Press, New York. https://doi.org/10.1080/07373937.2014.997882

McFadden, D. (1987). Regression-based specification tests for the multinomial logit

model. *Journal of Econometrics*, *34*(1–2), 63–82. https://doi.org/10.1016/0304-4076(87)90067-4

McFadden, D., & Train, K. (2000). Mixed MNL models for discrete response. *Journal of Applied Econometrics*, *15*(5), 447–470. https://doi.org/10.1002/1099-1255(200009/10)15:5<447::aid-jae570>3.0.co;2-1

Metrolinx. (2008). The Big Move. In *Government of Ontario*.

Metrolinx. (2013). *Approved changes to the big move*. https://www.metrolinx.com/en/regionalplanning/bigmove/The_Big_Move_Approved_Changes_EN.pdf

Metrolinx. (2021). *Metrolinx Projects*. http://www.metrolinx.com/en/greaterregion/projects/default.aspx

Miller, E. J., Shalaby, A., Diab, E., & Kasraian, D. (2018). *Canadian Transit Ridership Trends Study Final Report* (Issue October).

Mitra, R., Habib, K. N., Siemiatycki, M., Keil, R. and Bowes, J. (2019). *StudentMoveTOFrom Insight to Action on Transportation for Post-Secondary Students in the GTHA: 2019 Transportation Survey Findings.* Www.StudentMoveTO.ca

Mitra, R., & Buliung, R. N. (2015). Exploring differences in school travel mode choice behaviour between children and youth. *Transport Policy*, *42*, 4–11. https://doi.org/10.1016/j.tranpol.2015.04.005

Mitra, R., & Nash, S. (2019). Can the built environment explain gender gap in cycling? An exploration of university students' travel behavior in Toronto, Canada. *International Journal of Sustainable Transportation*, *13*(2), 138–147.

https://doi.org/10.1080/15568318.2018.1449919

Moniruzzaman, M., & Farber, S. (2018). What drives sustainable student travel? Mode choice determinants in the Greater Toronto Area. *International Journal of Sustainable Transportation*, *12*(5), 367–379. https://doi.org/10.1080/15568318.2017.1377326

Nair, G. S., Astroza, S., Bhat, C. R., Khoeini, S., & Pendyala, R. M. (2018). An application of a rank ordered probit modeling approach to understanding level of interest in autonomous vehicles. *Transportation*, *45*(6), 1623–1637. https://doi.org/10.1007/s11116-018-9945-9

Nash, S., & Mitra, R. (2019). University students' transportation patterns, and the role of neighbourhood types and attitudes. *Journal of Transport Geography*, *76*(March), 200–211. https://doi.org/10.1016/j.jtrangeo.2019.03.013

Nasruddin, H. N., Baharudin, M. R., Abdul Rahman, A., Mahadi, M. R., Mohd Noor, S. B., & Mahmood, M. R. (2020). Relationship of travel distances on total evacuation time among secondary students in Malaysia. *Policy and Practice in Health and Safety*, *18*(1), 1–8. https://doi.org/10.1080/14773996.2019.1708636

Nguyen-Phuoc, D. Q., Amoh-Gyimah, R., Tran, A. T. P., & Phan, C. T. (2018). Mode choice among university students to school in Danang, Vietnam. *Travel Behaviour and Society*, *13*(May), 1–10. https://doi.org/10.1016/j.tbs.2018.05.003

NIST, & SEMATECH. (2021). *Engineering Statistics Handbook*. U.S. Department of Commerce. https://doi.org/https://doi.org/10.18434/M32189

Olsson, L. E., Friman, M., Lättman, K., & Fujii, S. (2020). Travel and life satisfaction - From Gen Z to the silent generation. *Journal of Transport and Health*, *18*(November

2019). https://doi.org/10.1016/j.jth.2020.100894

Ontario. (2020). *Transit Oriented Development in Ontario*. https://www.ontario.ca/page/transit-oriented-communities

Páez, A., & Whalen, K. (2010). Enjoyment of commute : A comparison of different transportation modes. *Transportation Research Part A*, *44*(7), 537–549. https://doi.org/10.1016/j.tra.2010.04.003

Pinder, J. P. (1996). Decision analysis using multinomial logit models: Mortgage portfolio valuation. *Journal of Economics and Business*, *48*(1), 67–77. https://doi.org/10.1016/0148-6195(95)00046-1

Rashidi, T. H., Auld, J., & Mohammadian, A. K. (2012). A behavioral housing search model: Two-stage hazard-based and multinomial logit approach to choice-set formation and location selection. *Transportation Research Part A: Policy and Practice*, *46*(7), 1097–1107. https://doi.org/10.1016/j.tra.2012.01.007

Rinner, C., & Hussain, M. (2011). Toronto's urban heat island-exploring the relationship between land use and surface temperature. *Remote Sensing*, *3*(6), 1251–1265. https://doi.org/10.3390/rs3061251

Scott, D. M., & Ciuro, C. (2019). What factors influence bike share ridership? An investigation of Hamilton, Ontario's bike share hubs. *Travel Behaviour and Society*, *16*(February 2018), 50–58. https://doi.org/10.1016/j.tbs.2019.04.003

Setiawan, R., Santosa, W., & Sjafruddin, A. (2015). Effect of habit and car access on student behavior using cars for traveling to campus. *Procedia Engineering*, *125*, 571–578. https://doi.org/10.1016/j.proeng.2015.11.063

Shannon, T., Giles-Corti, B., Pikora, T., Bulsara, M., Shilton, T., & Bull, F. (2006).

Active commuting in a university setting: Assessing commuting habits and potential for modal change. *Transport Policy*, *13*(3), 240–253. https://doi.org/10.1016/j.tranpol.2005.11.002

Singh, N., & Vasudevan, V. (2018). Understanding school trip mode choice – The case of Kanpur (India). *Journal of Transport Geography*, *66*(January), 283–290. https://doi.org/10.1016/j.jtrangeo.2017.12.007

Statistics Canada. (2016). *2016 Census of Population*. https://www12.statcan.gc.ca/census-recensement/2016/dp-pd/index-eng.cfm

Statistics Canada. (2021a). *Table 23-10-0067-01 Vehicle registrations, by type of vehicle*.

Statistics Canada. (2021b). *Table 23-10-0251-01 Passenger bus and urban transit statistics, by the North American Industry Classification System (NAICS)*.

Train, K. E. (2003). Discrete choice methods with simulation. In *Discrete Choice Methods with Simulation* (Vol. 9780521816). https://doi.org/10.1017/CBO9780511753930

Tuveri, G., Sottile, E., Piras, F., & Meloni, I. (2020). A panel data analysis of tour-based university students' travel behaviour. *Case Studies on Transport Policy*, *8*(2), 440–452. https://doi.org/10.1016/j.cstp.2020.03.005

Vignoli, D., Rinesi, F., & Mussino, E. (2013). Intentions and Housing Conditions in Italy. *Population, Space and Place*, *19*(2013), 60–71.

Volosin, S. E. (2014). A Study of University Student Travel Behavior. *Igarss 2014*, *1*, 1–5.

World Bank. (2021). *Urban population of Canada*. 2021. https://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS?locations=CA

Xiong, H., Ma, L., Wei, C., Yan, X., Srinivasan, S., & Chen, J. (2019). Exploring Behavioral Heterogeneities of Elementary School Students' Commute Mode Choices Through the Urban Travel Big Data of Beijing, China. *IEEE Access*, *7*, 22235–22245. https://doi.org/10.1109/ACCESS.2019.2897890

Yamamoto, T., & Shankar, V. N. (2004). Bivariate ordered-response probit model of driver's and passenger's injury severities in collisions with fixed objects. *Accident Analysis and Prevention*, *36*(5), 869–876. https://doi.org/10.1016/j.aap.2003.09.002

Yousefzadeh Barri, E., Farber, S., Kramer, A., Jahanshahi, H., Allen, J., & Beyazit, E. (2021). Can transit investments in low-income neighbourhoods increase transit use? Exploring the nexus of income, car-ownership, and transit accessibility in Toronto. *Transportation Research Part D: Transport and Environment*, *95*(April), 102849. https://doi.org/10.1016/j.trd.2021.102849

Zhang, H., Wang, L., Yu, S., Zhao, J., & Shi, Z. (2021). Identifying government's and farmers' roles in soil erosion management in a rural area of southern China with social network analysis. *Journal of Cleaner Production*, *278*, 123499. https://doi.org/10.1016/j.jclepro.2020.123499

Zhang, Q., Clifton, K. J., Moeckel, R., & Orrego-Oñate, J. (2019). Household Trip Generation and the Built Environment: Does More Density Mean More Trips? *Transportation Research Record*, *2673*(5), 596–606. https://doi.org/10.1177/0361198119841854

Zhou, J. (2012). Sustainable commute in a car-dominant city: Factors affecting alternative mode choices among university students. *Transportation Research Part A: Policy and Practice*, *46*(7), 1013–1029. https://doi.org/10.1016/j.tra.2012.04.001

Zhou, J. (2016). Proactive sustainable university transportation: Marginal effects, intrinsic values, and university students' mode choice. *International Journal of Sustainable Transportation*, *10*(9), 815–824. https://doi.org/10.1080/15568318.2016.1159357

Zolfaghari, A., Sivakumar, A., & Polak, J. (2013). Simplified probabilistic choice set formation models in a residential location choice context. *Journal of Choice Modelling*, *9*(1), 3–13. https://doi.org/10.1016/j.jocm.2013.12.004