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Influence of Latent Attitudinal Factors on the Multimodality of Post-Secondary Students in Toronto

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Abstract

The study explores the causal relationships between latent factors and various observed external variables along with their ability to explain multimodal behaviours of post-secondary students in Toronto. Multimodality was measured by the number of unique modes used by any individual for their daily travels. As opposed to using a single mode of transportation, use of multiple modes for different trips indicates the degree and the nature of multimodality. For the empirical investigation, the study uses structural equation modelling (SEM) and ordered probability modelling for a dataset collected through a large-scale travel diary survey among four major universities in Toronto representing over 180,000 post-secondary students in the region. The results of the empirical investigation reveal that latent attitudes are influential factors in determining the multimodal behaviour of post-secondary students in Toronto. The results also found that mobility tool ownership and land use characteristics have a significant influence on those latent attitudes, and are direct determinants of the degree of multimodality. In particular, the results indicate that smart fare payment cards have a considerable effect on latent attitudes for post-secondary students. These findings could have policy implication from the planning perspective and should warrant further investigations.

Keywords: multimodality, travel behaviour, students, latent variables, latent factors, SEM, structural equation model, bivariate ordered probit model

1. Introduction

Post-secondary students represent a very unique and dynamic group of travellers within the urban context. They have been shown to be consistently more multimodal. They are more frequent users of public transit and active transportation and has increasingly avoided the use of automobiles (Kuhnimhof et al. 2012; Grimsrud & El-Geneidy 2014; Zhou 2012). Habits formed during this period can have a strong influence on their travel behaviour later in life, when they become active in the workforce, their family and the wider society (Grimsrud & El-Geneidy 2014). Thus, travel habit that post-secondary students adopt in their early life is expected to have wide-ranging consequences for future transportation planning as this demographic slowly displace the aging baby boomers. It is then important to understand the driving force behind the travel behaviours of students in higher education institutions, especially how their inherent attitudes shape their travel behaviour and how those same latent attitudes are shaped by various external variables (observed through travel surveys). Such understanding will better inform planners and policy makers to develop effective policies that anticipate the future.

Despite the immense policy implications, post-secondary students have been under-represented in travel behaviour research until recently. It has been gaining attention in very recent years, but many questions within this area of research remain unexplored. Much effort has been expended to explore predominant trends in travel behaviours of students, young adults, and late adolescents, but our understanding of the causes of these trends are still far from complete. In particular, existing research has revealed that attitudinal information is valuable in explaining the degree of multimodality among post-secondary students, but the nature of these attitudes and their precise relationship with multimodality behaviour and other observable variables have yet to be fully explored (Lavery et al. 2013).

Drawing from existing research into latent factors and their effect on travel behaviour among the general population, this study explores the effect of latent attitudes on the multimodality of university students in

Toronto. The study uses data from a web-based travel survey conducted in fall 2015 among the students of four major universities in the Greater Toronto region. The survey collected a sample of around 8 percent of the region's 180,000 university students. The remainder of this paper is organized as following: Section 2 presents a brief on the current state of travel behaviour research into post-secondary students; Section 3 presents a discussion on the dataset used for the current investigation; Section 4 outlines the statistical models that are used for the empirical investigation; Section 5 presents a discussion on the results of the empirical investigation; Finally, the paper concludes with summary of key findings and recommendations for further research.

2. Literature Review

The body of research into travel behaviour of students and young adults is still limited but has been gaining increasing attention in more recent years. Students and young adults represent the coming generation of the workforce. Thus, the increasing attention on this particular demographic is a logical progression of existing research as a wider range of analysis tools become more readily available to researchers.

Existing literature on the subject of student and young adult travel behaviour have covered a range of methods. Earlier studies have relied on descriptive statistics to explore broad trends in the group's travel behaviour. Studies of this nature have identified a decreasing trend in the ownership and use of automobiles among university/post-secondary students and young adults, with a corresponding increase in the use of other modes and increasing levels of multimodality (Kuhnimhof et al. 2012; Grimsrud & El-Geneidy 2014).

Other studies examined student and young adult travel behaviour using discrete choice models, in most cases logistic regression analysis, which has identified income, household type and location as influential factors defining travel behaviour level of multimodality (Kuhnimhof et al. 2015; Grimsrud & El-Geneidy

2013). In particular, home location, along with built environment characteristics were found to be the most influential factors affecting travel behaviour both in the distribution of distance travelled and the multitude of travel destinations (Kuhnimhof et al. 2015; Whalen et al. 2013). Studies from both Zhou and Grimsrud and El-Geneidy carried out in Los Angeles and Montreal, respectively, revealed strong correlations between mobility tool ownership and mode choice behaviour (Zhou 2012; Grimsrud & El-Geneidy 2013). In addition, Grimsrud and El-Geneidy presented empirical evidence supporting the notion of long-term retention of student mode choice habits in the later life stages. The disparity in the larger transportation culture of the two cities under study and the similar findings by the authors suggests some level of universality in the travel behaviour of post-secondary students regardless of local cultural and environmental differences.

A facet of travel behaviour that has seen limited attention in the existing literature is the degree of multimodality among university students. Using data collected from students of McMaster University in Hamilton, Lavery et al. explicitly modeled student multimodality using an ordered probit model with the inclusion of attitudinal variables (Lavery et al. 2013). Lavery characterized multimodality as the number of modes available to the individual students as a feasible option (stated by individual respondents) and modelled the stated modality as an ordered response in their model. They found that demographics, location, and land-use characteristics influence students' level of multimodality. Their study also investigated effects of attitudinal information and found them to be influential factors of multimodality along with other observable external variables. However, their treatment of the attitudinal information as direct exogenous inputs in their model implies that attitudes are directly measurable. This may be counter-intuitive as attitudes are inherently unobservable and can only be indirectly measured through proxies.

By comparison, Heath and Gifford's study on a university student population was presented with more theoretical rigor in their inclusion of attitudinal information (Heath & Gifford, 2002). The authors presented

a study of student public transportation use before and after the implementation of a universal bus pass program. They adopted Ajzen's theory of planned behaviour (TPB) as the theoretical basis for their analysis of latent attitudinal information. In their study, latent factors representing TPB constructs were extracted from indicator variables, then regressed against the students' bus use which was the dependent variable. They found the TPB framework to be well suited for explaining student bus use behaviour and their findings strengthened previous evidence on the value of TPB and other similar behaviour theory frameworks in the study of travel behaviour (Bamberg & Schmidt 2003).

Several other studies adopted alternative methods for analyzing attitudes and other latent variables that may affect travel mode choice behaviour (Vij et al. 2013; Scheiner & Christian 2007; Idris et al. 2015a; Idris et al. 2015b; Deutch et al. 2013). Among the methods adopted, Structural Equation Modelling (SEM) has been one of the most widely used alternatives to study the effects of non-observable latent factors in shaping travel behaviour. Under the SEM framework, latent factors can be extracted through factor analysis, cluster analysis or descriptive analysis but must be constructed with robust theoretical basis.

Few studies explored the use of latent factors in the study of travel behaviour specifically among students and young adults. However, most such studies analyzed mode choice behaviour of a few selected modes in this demographic cohort. Bamberg, Ajzen, and Schmidt applied the TPB theory within an SEM structure for a pre-post study of a prepaid bus pass program. Their results established causal relationships between attitude, subjective norms and intention as proposed in the TPB. Klockner and Friedrichmeier (2011) applied the similar method in their analysis of car use behaviour of a student sample collected from Ruhr-University. Their findings on the performance of the analytical method were in agreement with Bamberg, Ajzen and Schmidt. They also found trip specific external variables to be significant determinants of mode choice behaviour within the model framework (Klößner & Friedrichsmeier 2011).

While investigating the determinants which affect mode choice behaviour is useful to understand travel

behaviour, an understanding on multimodality for different trip types is lacking in the current literature. This paper will apply the SEM framework to explore the effect of latent factors on the post-secondary students' multimodality as explicit research into post-secondary students' multimodality has so far been restricted to descriptive analysis and discrete choice models.

Ajzen's theory of planned behaviour (TPB) will serve as the theoretical basis for the SEM model structure. Under the TPB framework, any action undertaken by an individual is preceded by the individual's intention to perform such action. The individual's intention is then further controlled by three independent determinants – attitude towards the action, the subjective or social norm concerning the action, and the perceived behavioural control of the individual (Ajzen 1991). Within the context of examining post-secondary student's multimodality, we hypothesize that attitude towards multimodal behaviour can be broken down into attitudes towards more specific travel-related behaviours measured through a set of attitudinal responses. These component attitudes will be constructed from indicator variables collected on student attitudes toward particular travel-related behaviours, then inserted into the SEM framework. Furthermore, the current study will also incorporate other observed external variables to explore their effects on the latent attitudes and on the multimodal behaviour. An ordered probit model will be included for this purpose.

Thus, the goal of the study is threefold. First, the study will try to find latent attitudinal factors that influence post-secondary student travel decisions using exploratory factor analysis. Second, the study will make use of a structural equation model framework to analyze the effects of the attitudinal factors on student multimodality in relation to their indicator variables. The approach should also allow for observations of how the latent attitudinal factors moderate various exogenous variables in the proposed model structure. Finally, the study examines how various exogenous variables affect student multimodality with an ordered probit model.

3. Data for Empirical Investigation

The dataset used for this study was collected through the StudentMoveTO survey, a joint initiative of four universities in the Greater Toronto Region - the University of Toronto, York University, Ryerson University and Ontario College of Arts and Design (OCAD) University. The initiative aims to provide an accurate and consistent source of information on the travel behaviour of students from these universities in order to better understand their transportation needs. StudentMoveTO was designed as a web-based survey to be conducted on a periodic basis. The survey was conducted in the fall of 2015 and is the first of many future surveys of the initiative. It was distributed to all students enrolled in the four universities through an e-mail invitation sent to their school e-mail addresses. Out of more than 180,000 students enrolled in the four universities, a total of 15,226 responses were received, corresponding to a response rate of more than 8% (StudentMoveTO Team 2016; Hasnine et al. 2017). After removing incomplete entries and entries where the respondent did not travel, 9,543 complete responses were used for the study.

The information collected from the survey include a travel diary of a random day from each respondent. Random day data collection facilitates the inclusion of both work/school and leisure/shopping trips in the sample, along with socio-economic information at the household and person level. The travel diary includes all trips the respondent made on their last commuting day to school. Trip specific information, including trip modes, were collected, as were household information such as home location, household size, household composition and dwelling type. Respondents were also asked to provide their affiliated school, campus, faculty, level of study, student status, as well as transportation mobility tool ownership, such as driver's license ownership, transit pass ownership, and car or bike sharing program membership. The raw data required some processing prior to their use in the model estimation stage. In particular, the availability of private automobiles to the respondents required some special attention. Given the fact that the surveyed demographic are university students, a large portion of the surveyed respondents likely do not personally own an automobile. The students were thus both asked about their personal automobile ownership and their

ability to use automobiles owned within the household. Responses to these two questions were combined with the household automobile count collected in the survey to construct the automobile availability of the respondent.

Multimodality is usually defined by the use of various modes of transportation for travel within a certain time period. In this study, multimodality is measured through the number of unique modes utilized by the respondents for their daily travels using information from the travel diaries. While measuring multimodality using this method constrains the time period to be short than some previous studies, it has the advantage of having less respondent bias from recounting long-term memories (Olafsson et al. 2016; Nobis 2007).

In addition to the trip diary and socio-economic information, the survey also included a set of 14 attitudinal questions designed to measure students' attitude towards specific transportation modes and travel related behaviours. Students were asked to indicate whether they agree with a statement presented to them on a five-level likert scale, ranging from "strongly agree" to "strongly disagree". As shown in Table 1, which lists all questions asked in this section of the survey, questions 1 to 3 are particularly concerned with the respondents' sensitivity with travel time; questions 8 to 11 are concerned with modal preference, and question 12 to 14 deals specifically with the respondents' attitude on safety. Note that the mode preference questions specifically ask the respondents to disregard the ownership of the mobility tool required for the use of the mode in question. Responses from these attitudinal questions will form the basis of the latent constructs in the SEM.

The base survey data is further supplemented with land use characteristic information generated using Geographic Information System (GIS) tools based on the postal code of the respondent's home location. This information include the amount of land area used for various land use purposes, employment and population density, average block length, transit-specific information, such as the number of transit stops or

transit departures within a certain radius, and distances to the closest transit stations (bus, street car and subway, and commuter rail).

Table 2 and Figure 1 show the descriptive statistics on the observed mode usage and degree of multimodality from the StudentMoveTO dataset. Table 2 reveals that post-secondary students are heavy users of transit and walking, but are also reliant on the automobile either as a driver or a passenger. Furthermore, it is found that the post-secondary students are predominantly non-multimodal (Figure 1), with over 60% reporting only using one mode in the survey.

4. Model Specifications

Two types of econometric models are used for the investigations in this paper. These are the Structural Equation Model (SEM) and the Bivariate Ordered Probit model.

4.1. Structural Equation Modelling (SEM)

The SEM model framework consists of two components - the measurement model component, and the structural model component. The measurement model component relates a set of latent constructs to their indicator variables. The measurement model component takes the form of:

$$y = \Lambda_y \eta + \epsilon \quad (1)$$

$$x = \Lambda_x \xi + \delta \quad (2)$$

In equation 1, η are the endogenous latent constructs measured by y , the endogenous indicator variables, with Λ_y being the coefficients of η with respect to y and ϵ the error term. Likewise, in equation 2, ξ is the exogenous latent construct, with Λ_x refers to corresponding coefficients and δ the error term. The error terms, ϵ and δ , are, assumed to follow a normal distribution with a standard deviation of σ . In the case of

this study, the latent constructs would be the latent attitudes and the latent mode use intent. The indicator variables would be the observed attitudinal responses and the observed modality. Both the observed attitudinal responses and the observed modality of the students are treated as discrete order variables within the model framework.

The structural model component establishes the relationship between the endogenous and exogenous latent constructs. Its functional form is written as:

$$\eta = \beta\eta + \Gamma\xi + \zeta \quad (3)$$

Where ξ is the exogenous latent construct, β and Γ are the coefficient for the latent constructs, and ζ is the normal error term. In this study, the latent constructs will be further defined by observed exogenous variables in the structural model component of the SEM model, which adds another term to the function:

$$\eta = \beta\eta + \Gamma\xi + \theta z + \zeta \quad (4)$$

Here, z represents the exogenous observed variables that the endogenous latent constructs η would be regressed against, with θ being the corresponding coefficient. Integration of the exogenous variables should reveal the degree to which these variables would shape the latent constructs. Within the context of this study, the latent attitudes, incorporated with the exogenous observed variables, should be able to correlate with the response of the latent mode use intentions directly, and the degree of multimodality indirectly.

The use of this model framework allows for both the definition of underlying latent factors that influences travel behaviour and the establishment of causal relationships between these latent factors, the observed variables and an individual's degree of multimodality. Estimation of the model was carried out through the diagonally weighted least square estimation method using the *Lavaan* package written for *R* (Rosseel,

2012).

4.2. Ordered Probit Model

The ordered probit model is based on the concept of random utility maximization (RUM), which postulates that latent utility of certain behaviour is to be maximized under a given condition (Uddin and Huynh 2017; Li et al. 2017). In this specific case, the latent utility of trip modality is represented by the utility function of:

$$Y_i^* = \beta'X_i + \varepsilon_i \quad (6)$$

Where Y_i^* represents the continuous latent utility of the degree of multimodality for each individual. The degree of multimodality is considered a discrete and ordered variable within this model framework, thus the continuous latent utility Y_i^* needs to be translated to discrete levels separated by a set of threshold values based on the following set of conditions:

$$Y_i = \begin{cases} 0 & \text{if } -\infty \leq Y_i^* \leq \lambda_0 & [1 \text{ mode used}] \\ 1 & \text{if } \lambda_0 < Y_i^* \leq \lambda_1 & [2 \text{ modes used}] \\ 2 & \text{if } \lambda_1 < Y_i^* \leq \lambda_2 & [3 \text{ modes used}] \\ 3 & \text{if } \lambda_2 < Y_i^* \leq \infty & [\text{more than 3 modes used}] \end{cases} \quad (7)$$

Where λ_0 , λ_1 , and λ_2 are the threshold values to be estimated from the model. The values of Y_i^* are assumed to follow a normal distribution, and thus the probability function of Y_i taking discrete level j assumes the form of:

$$Pr(Y_i = j) = Pr(\lambda_{j-1} < Y_{i,1}^* \leq \lambda_j) = \Phi(\lambda_j - \beta'X_i) - \Phi(\lambda_{j-1} - \beta'X_i) \quad (8)$$

The parameters of the models were estimated using the method of maximum likelihood with the

log-likelihood function:

$$\log L = \sum_{i=1}^N \sum_{j=1}^K \delta_{ij} \log [\Phi(\lambda_j - \beta'X_i) - \Phi(\lambda_{j-1} - \beta'X_i)] \quad (9)$$

Where the likelihood is the probability of Y_i taking levels of multimodality j , based on equation 8. N and K are the total number of modelled respondents and the total number of levels of multimodality, respectively. δ_{ij} is the indicator variable, which takes the value 1 when $Y_i = j$ and 0 otherwise. The model was estimated using the NLOGIT 5.0 software package (Greene 2015).

5. Empirical Investigation

5.1. Factor Analysis

An Exploratory Factor Analysis (EFA) is first carried out to extract the set of latent attitudinal factors that would represent the component attitudes to be used for the later stages of the study. An EFA attempts to infer a set of latent factors from a larger set of observed indicators. In particular, EFA tries to find patterned relationships amongst the indicators. Responses from the attitude questions in the StudentMoveTO survey were used as the indicators for the factor extraction. Table 3 provides a summary of the final factors produced by the analysis and their corresponding loadings. The loadings indicate the amount of variance in the indicator that is explained by each proposed latent factor. A higher loading value of an indicator with a particular suggests that greater proportion of the indicator's observed variances are explained by that factor. The EFA model was estimated using the maximum likelihood method and specialized transformation process can Promax transformation (Timm 2002).

The final EFA model extracted four latent attitudinal factors from the indicator variables. They are tentatively named based on the indicator loadings as follows:

- Factor 1: Time Sensitivity

- Factor 2: Active Mode Use
- Factor 3: Auto Use
- Factor 4: Safety Concern

It is found that the first factor, which relates to the student's latent sensitivity to time, is indicated by the student's inertia to making trips, their inclination to telecommuting and their sensitivity to travel time. Among these three indicator variables, inertia to reduce the number of trips and inclination to telecommuting have high loadings which are 0.68 and 0.69 respectively (Table 3). The second factor – active mode usage, is comprised of cycling and walk preference indicators. This finding is intuitive, many studies have stated that cycling and walking mode choice availability largely depends on a travel distance threshold (3 km for walking and 10 km for biking) (Hasnine et al. 2016). The third-factor auto usage constitutes of lifestyle, car use, and transit preference. The indicator variable – “Driving easier than other mode” – has the highest loading (0.86) among other indicators (Table 3). In terms of safety concern factor, the “Driving is safer than walking” indicator has the highest loading (0.98) (Table 3). The “Driving is safer than cycling” and “Driving is safer than transit” factor loadings are 0.45 and 0.55 respectively.

The EFA is followed by a Confirmatory Factor Analysis (CFA) to confirm the initial hypothesis and validate the extracted latent attitudinal factors. The final CFA model path diagram and results, including the final variable parameters, are shown in Figure 3.

The proposed model structure achieved a Comparative Fit Index (CFI) of 0.979 and a Root Mean Square Error of Approximation (RMSEA) of 0.038, suggesting an excellent model fit. The CFA model (Figure 3) produced similar results as the previously estimated EFA model (Table 3). Figure 3 shows that strong positive correlation exists between respondents' attitude towards automobile usage and their concern for safety. This essentially suggests that the perception of safety around automobiles is the strongest motivation behind automobile use among university students. Negative correlations are found between attitude towards active modes and time sensitivity. However, the correlations between attitude towards auto modes

and time sensitivity are positive. This is intuitive, as travel time for active modes is usually much higher than the auto mode for a given distance

5.2. SEM Model

The full SEM model was estimated based on the general theoretical relationship established in the Ajzen's theory of planned behaviour (TPB) and the proposed CFA model structure. Figure 2 shows the general framework of the model. Figure 4 shows the final model structures and result in summaries from the estimated model. RMSEA value for the SEM model is 0.019 and the CFI value for the model is 0.978., indicating very good model fit (Idris et al. 2015a; Long et al. 2011). All parameters in the proposed model are showing correct signs and statistically significant at 95% confidence level.

The complete SEM model produced intuitive results regarding the effect of the four attitudinal factors (time sensitivity, active mode use, auto use, and safety concern) on the multimodality of the respondent. Sensitivity to travel time, attitude towards automobile use and concern for safety all have negative effects on students' intention to use multiple modes. On the other hand, attitude towards active modes affects multi-mode use intention positively. Overall, the four attitudinal factors behaved in expected fashion and in complete agreement with earlier results from the CFA.

Several categories of exogenous variables are also tested in the model, including household characteristics, personal characteristics, built environment characteristics and level of service for various modes as outlined in the initial hypothesis (Figure 4). These exogenous variables are shown at the bottom of Figure 4. The four attitudinal factors (time sensitivity, active mode use, auto use, and safety concern) were influenced by a different set of exogenous variables. This different set of exogenous variables are shown in the left, right and top portion of Figure 4. A few variables are shown to be significant influences at multiple places in the model structure (e.g. age, campus type-urban).

The campus type (urban) is found to be significant for all four attitudinal factors (time sensitivity, active mode use, auto use, and safety concern) in the model structure. The variable distinguishes between university campuses which are located in distinctly urban environments versus, and those that are located in suburban area. Campus location significantly affects students' commuting mode choice behaviour, a finding that is supported by other literature (Hasnine and Habib 2018). Urban campus settings were found to encourage more multimodal behaviour compared to less urbanized settings.

Travel time sensitivity is strongly influenced by the average block length around the student's home location. The average block length directly affects transit stop spacing and the distance between interchange stops, thereby dictating the transit access time of the user. Given that a large proportion of students are likely to transit users, it is intuitive that the block length is a significant determinant of a respondent's time sensitivity. Similarly, the SEM also shows that distance to nearest bus stop affects students' time sensitivity. The dummy variable for living with a partner is another significant variable in respondent's time sensitivity. This is intuitive since students living with partners need to accommodate the schedule of their partners.

Active Mode Preference is influenced by three variables – age, student status, and distance to the streetcar stop. Age is the most significant influence on respondent attitude towards active modes. It negatively influences attitude towards active modes, which is expected as older adults are less likely to have the physical fitness to use active modes for daily travel. Age is also a significant variable in determining the respondents' concern towards safety. Older respondents were more likely to view automobiles as being safer, a perception which could be caused by possibly higher reliance on automobiles.

Variables associated with built environment don't have a significant effect on students' attitudes or intention towards multimodal behaviour. However, it is found that transit stop proximity is a statistically significant variable in affecting student mode choice behaviour. Higher transit stop proximity, in particular,

streetcar stop proximity, have strong negative influences on attitude towards automobile use and in strengthening intention towards multimodal behaviour. This suggests that an increase in transit network density can shift mode use behaviour.

All mobility tool ownership variables' are significant factors that influence student mode choice, except for motorized two-wheeler ownership and bike-share membership. Particularly notable is the influence of smart fare payment card (Presto card) ownership in changing attitudes towards active modes. Students who own Presto cards are much more likely to have favourable attitudes toward active modes in addition to being more likely to use multiple modes for their travels. Traditional transit pass ownership only shows a positive impact on transit mode choice. This finding suggests that students who own Presto card have more flexibility to adopt a more multimodal behaviour in comparison to the students who just own transit passes. The cause of the positive effect of Presto card on attitudes towards transit and other alternatives could come from fare discounts, whether it be flat rate or loyalty based, and the ease of transfers across multiple agencies. Combined with its minimal purchase price, it is a flexible tool with very low initial investment and commitment. By contrast, traditional transit passes offer discounts for a limited time period for a much higher initial investment requiring much higher levels of travel commitment to justify its price. Such findings stress the importance of a well-designed fare payment card system in changing the users' perception of transit and their transit use habit over the long-term.

5.3. Ordered Probit Model

An order probit model is estimated to see how various exogenous variables affect student multimodality. The results from the ordered probit model echo majority of the findings from the SEM model, as seen in Table 4. To better understand the parameters' implications on multimodality, we also calculated partial effects of the parameters at various levels of multimodality (Table 5). Two sets of variables are included in the estimated order probit model: 1) variables which are already adopted in the SEM, 2) new variables from the StudentMoveTo survey which found to be significant in the order probit model.

It is found that average trip distance is the most significant determinant of students' multimodality. From the partial effect of average trip distance, it is evident that students will use more transportation modes with increasing travel distance. Similar to the SEM model, mobility tool ownership (private auto availability, car-sharing membership, and transit pass ownership) also shows a strong positive effect in increasing the degree of multimodality of the students. Students who own transit pass are more likely to use multiple modes, while the same relationship is observed if they have access to a car or they have a car-share membership. The model results suggest that graduate students are more likely to be multimodal than other students. Given that it is only significant in the probit model, it is likely that the trend is a consequence of the difference in the daily routines of graduate students versus undergraduates, and not motivated by any subjective attitudes. Graduate students tend to have more flexible schedules in comparison to undergraduates, which have comparatively rigid class schedules. The model results also show that women are less likely to be multimodal. Built environment variables including campus type, average block length, and transit stop proximity are significant explanatory variables in the estimated ordered probit model. Intuitively, the empirical result suggests that urban settings with better transit stop access and shorter block length increase the probability of a student choosing to use more than one mode.

6. Conclusions and Recommendations for Further Studies

This paper presents a structural equation model (SEM) and ordered probit model for a post-secondary students' travel survey which was conducted among four major universities in Toronto representing over 180,000 students in the region. This paper shows how behavioural theory combined with structural equation modelling framework can be used to better understand students' travel behaviour. Furthermore, the order probit model presented in this paper reveals several major determinants of multimodality. The analysis presented in this paper adds to the growing body of literature by providing valuable insight into the relationship between latent constructs of post-secondary students' travel behaviour and their mode choice

behaviours. This study will be particularly important in anticipating future needs of this population cohort as they become more established members of society.

The findings from this study have shown that the students' mode choice is influenced by their inherent attitudes derived from the personal perception of the surrounding conditions such as a sense of safety and sensitivity in travel time. Results from the proposed structural equation model suggest that students' intention to use multiple modes are negatively affected by their sensitivity towards travel time, concern for safety and attitude towards automobile use while being positively influenced by their attitude towards active modes. The findings also reveal that most observed exogenous variables directly affect university students' mode choice, while some variables also influence their latent attitudinal factors.

Results from the ordered probit model show considerable influence from built environment characteristics, especially the built environment around campuses. Urban settings around campuses are shown to be much more conducive in fostering attitudes which inherently encourages multimodality. Built characteristics near the home, such as street block size and distance to transit, are also shown to be significant. Both also seem to affect students' attitudes and mode use intention.

Mobility tool ownership, such as driver's license ownership, transit pass ownership, and car or bike sharing program membership is also found to have significant effects on forming multimodal behaviour. In particular, ownership of the Presto transit fare card is shown to affect both students' mode choice and attitude towards active transportation modes. This suggests the importance of integrated transit fare payment systems in shaping long-term habits and promote multimodal behaviour. The estimated order probit model shows similar results reinforcing the findings from the structural equation model.

There are few ways in which the current study can be further refined or expanded. First, the StudentMoveTO survey used in this study can be expanded in several ways. Future iterations of the survey

should include questions which would measure a respondent's subjective norm and their behavioural control, allow for modelling of all latent constructs of the TPB framework. The survey sample frame could also be expanded to include other post-secondary institutions, such as technical colleges in the survey area for a complete picture of the post-secondary student demographic. Future studies using this data can explore differences in the effect of both latent constructs and observable variables among further delineated groups of the post-secondary student population. For example, comparisons can be made between students living in urban and suburban neighbourhoods or students commuting to urban and suburban campuses. Another possible extension of this study could be to investigate the effects of latent constructs and observable variables on the mobility tool acquisition of post-secondary students, as the empirical results of this study have clearly shown the importance of mobility tool ownership in mode use behaviour.

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Table 1: List of attitudinal questions

		Question	Response options
Q1	Time Sensitivity	I try to organize my daily activities so that I make as few trips as possible	1. Strongly Disagree 2. Disagree 3. Neutral 4. Agree 5. Strongly Agree
Q2		I often use telephone or internet to avoid having to travel somewhere	
Q3		Time spent travelling is wasted time	
Q4		I try to limit my driving (or being driven) to improve air quality and maintain a low carbon footprint	
Q5		Owning a car contributes to a good lifestyle	
Q6		Driving is easier than using other means of transportation	
Q7		Traffic congestion does not bother me	
Q8	Mode Preference	I prefer to drive (or would prefer if I had a car) whenever possible	
Q9		I prefer to walk whenever possible	
Q10		I prefer to bike (or would prefer if I had a bike) whenever possible	
Q11		I prefer to take transit whenever possible	
Q12	Safety	Travelling by car is safer overall than travelling on foot	
Q13		Travelling by car is safer overall than travelling by bicycle	
Q14		Travelling by car is safer overall than taking transit	

Table 2: Break down of trip mode use for selected modes

Trip multimode categories			Trip mode use		
Car driving	5289	14.7%	Trips involving driving	5714	15.6%
Car passenger	4102	11.4%	Trips involving been driven	5085	13.8%
Transit	11206	31.1%	Trips involving transit	12678	34.5%
Walk	11909	33.1%	Trips involving cycling	2092	5.7%
Cycling	2028	5.6%	Trips involving walking	11909	32.4%
Park and ride	425	1.2%	Total	36740	100%
Kiss and ride	983	2.7%			
Bike and ride	64	0.2%			
Total	36006	100%			

Table 3: EFA final loadings

Indicators	Factor 1 (Time Sensitivity)	Factor 2 (Active Mode Use)	Factor 3 (Auto Use)	Factor 4 (Safety Concern)
1 Organize activity to reduce trips	0.68			
2 Telecommute to avoid travel	0.69			
3 Time spent traveling is wasted	0.43			
4 Limit driving for air quality		0.4		
5 Owning car is good lifestyle			0.57	
6 Driving easier than other modes			0.86	
7 Traffic is not a bother				
8 Driving whenever possible			0.8	
9 Walking whenever possible		0.57		
10 Cycling whenever possible		0.7		
11 Transit whenever possible			-0.4	
12 Driving safer than walking				0.98
13 Driving safer than cycling				0.45
14 Driving safer than transit				0.55
Cumulative Variance	0.15	0.25	0.34	0.41

Note: Based on literature only loadings above 0.40 are shown for purpose of clarity

Table 4: Ordered probit model result summary

Variables	Parameter	z-stat
Average trip distance	0.3200	28.68
Home to campus distance	0.0003	2.25
Private auto availability	-0.1390	-5.6
Car-sharing membership	0.1810	3.91
Transit pass ownership	0.3220	13.3
Number of dependent children	-0.0240	-1.46
Gender (female)	-0.1130	-4.48
Student status (graduate)	0.0710	2.52
# of transit trip in 1200m (24h)	-0.2330	-12.4
Distance to closest streetcar stop	-0.1460	-13.25
Average block length	-0.5760	-4.72
Land area of commercial use	-0.7170	-3.93
Main campus type (urban)	0.4090	16.58
Threshold Values		
Mu (2 modes)	0.9164	64.88
Mu (3 modes)	1.6739	81.14
Mu (4 modes +)	2.472	64.71

Table 5: Partial effect of estimated variables

Variables	1 mode	2 modes	3 modes	4 modes +
Average trip distance	-0.1135	0.03323	0.04411	0.02676
Home to campus distance	-0.0001	0.00003	0.00004	0.00003
Private auto availability	0.0493	-0.01456	-0.01914	-0.04457
Car-sharing membership	-0.0642	0.01611	0.02533	0.01653
Transit pass ownership	-0.1163	0.03333	0.04588	0.0276
# of dependent children	0.0085	-0.00247	-0.00328	-0.00199
Gender (female)	0.0402	-0.01217	-0.01556	-0.00927
Student status (graduate)	-0.0252	0.00714	0.00983	0.00606
Main campus type (urban)	0.0826	-0.02417	-0.03209	-0.01947
# of transit trip in 1200m (24h)	0.0519	-0.0152	-0.02017	-0.01224
Distance to closest streetcar stop	0.2044	-0.05984	-0.07943	-0.04818
Average block length	0.2545	-0.07449	-0.09889	-0.05999
Land area of commercial use	-0.1449	0.04696	0.05573	0.03182

Figure 1: Breakdown of sample population multimodality

Figure 2: General model structure

Figure 3: CFA path diagram and results summary

Figure 4: SEM model path diagram and results summary