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

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Abstract

The study explores the causal relationships between latent attitudinal factors explained by various systematic variables along with their capability in explaining multimodal travel behaviour of post-secondary students in Toronto. Regarding multimodality, the research focused on work/school as well as non-work/school trips. Multimodality is measured by the number of unique modes used by any individual for their daily travels. As opposed to using a single type of mode, use of multiple modes for different trips indicates the degree and nature of multimodality. For the empirical investigation, it uses structural equation modelling (SEM) and bivariate ordered probability model and a dataset collected through large-scale travel diary survey among the students of four major universities in Toronto representing over 0.18 million of post-secondary students in the region. The results reveal that latent attitudes are critical factors in determining the multimodal behaviour of post-secondary students. It is also found that household types, mobility tool ownership, and land use characteristics are key determinants of the latent attitudes as well as direct determinants of the degree of multimodality. In particular, the results seem to indicate considerable effect of intra-household mobility tool sharing and the use of smart fare payment cards on multimodality of post-secondary students.

1. Introduction

Post-secondary students represent a very unique and dynamic group of travellers within many urban contexts. They have been shown to be consistently more multimodal, are more frequent users of public transit and active transportation, and have increasingly been shunning the use of private automobiles *(1, 2, 3)*. This is proven that the travel behaviour of post –secondary students (specifically university students) in their early adulthood could hold even as they transition into later life stages *(2)*. So, habits that are formed during this period can have strong influences on the travel behaviour in later life when they become active in economic sectors and social/family life. In fact, travel behaviour that is in the making during student life is expected to have wide-ranging consequences in the future as this demographic slowly displace the aging baby boomers in the workforce. Thus, it is 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 systematic factors. Such understandings can inform planners and policy makers for developing effective policies with long-lasting consequences.

However, until recently, post-secondary students have been under-represented in travel behaviour research. Though it has been receiving attention in very recent years many questions still remain unexplored. Much of the recent efforts are spent to explore predominant trends in travel behaviour of students, young adults, and late adolescents, while our understandings on the causes of these trends are still far from complete. In particular, existing studies reveal that attitudinal variables affect the multimodality among post-secondary students, but the nature of these attitudes and their precise relationship with multimodality behaviour have not fully explored *(4)*.

Drawing from existing research into latent attitudes and their effect on travel behaviour among the general population, this study explores the effect of latent variables on the multimodality of post-secondary students in general and particularly post-secondary/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 Toronto region. The survey collected a sample of around 8 percent of the region's 0.18 million university student.

The paper is organized as following: Section 2 presents a brief literature review on travel behaviour investigations of post-secondary students; Section 3 presents a brief discussion on the dataset used for current investigation; Section 4 outlines the econometric models that are used for empirical investigation; Section 5 presents a discussion on empirical investigation; Finally, the paper concludes with summary of key findings and recommendations for further research.

2. Literature Review

The existing literature on the travel behaviour of post-secondary or university students is mainly exploratory in nature. There are some applications of discrete choice models but mostly limited to logistic regression analysis. Studies that relied on descriptive statistics identified a decreasing trend in the use and ownership of the automobile among the university/post-secondary students and young adult population, with a corresponding increase in the use of other modes and increasing levels of multimodality *(1, 2)*. Studies that used discrete choice models have identified income, household type, and location as influential factors defining travel behaviour level of multimodality *(5, 6)*. In particular, home location along with built environment characteristics was found as one of the most influential factors defining travel behaviour in terms of distributions of distance travelled and multitudes of travel destinations *(5, 7)*. Studies by Zhou, and Grimsrud and El-Geneidy carried out in Los Angeles and Montreal, respectively, has also revealed a strong correlation between mobility tools ownership and mode choice behaviour (3, 6). Grimsrud and El-Geneidy presented empirical evidence supporting long-term retention of student mode choice habits. The disparity in the larger transportation culture of the two cities (Los Angeles and Montreal) suggests some level of universality in the travel behaviour of post-secondary students regardless of local environmental characteristics.

Using data collected from the students of McMaster University in Hamilton, Lavery et al. investigated multimodality explicitly using an ordered probit model with the inclusion of attitudinal variables *(4)*. They characterized multimodality as the number of modes available to the individual (as elicited directly by the students) students. Such elicited variables were modelled as ordered variables in their regression model. They came to similar conclusions with other discrete choice models in their findings, pointing to demographic, location, and land use as the influential factors on students' multimodality. The study also investigated effects of an attitudinal factor and found them significantly influencing students' multimodality along with the observable exogenous variables. However, they considered the attitudinal factors as exogenous inputs to the econometric model. Such treatment of attitudinal factor implies that attitude is directly measurable rather than latent, which may be counter-intuitive.

Structural Equation Models (SEM), along with other hybrid econometric model approaches, can integrate attitudes as latent factors. These factors are usually constructed through factor analysis, cluster analysis or other similar approaches. Such frameworks have been successfully applied in studies of travel behaviour of the wider population *(8, 9, 10, 11)*. However, there has been little research on the travel behaviour of young adults or post-secondary students with a similar approach. Among the exceptions, Klockner and Friedrichmeier used data collected from Ruhr-University and examined the travel mode choices of students through the use of a SEM model incorporating latent attitudinal factors. They found that latent attitudes shaped both the mode use intent and norms of the individuals *(12)*. Other studies used latent attitudinal factors in similar model frameworks, but only to examine post-secondary students' usage of a chosen mode *(13, 14)*. While investigations on mode choices of specific trip types are very useful to understand travel behaviour, a comprehensive understanding on multimodality for different trip type is also necessary.

To contribute to the literature on the travel behaviour of post-secondary students, in this study we seek to build a comprehensive understanding of multimodal travel behaviour and its determinant. We explicitly focus on understanding how latent factors/variables define travel behaviour, while at the same time study how different systematic variables can be used to explain those latent factors/variables. Two separate approaches are taken. SEM is used to investigate how latent attitudes affect multimodality. Bivariate ordered probit model is used to investigation the correlation between the degrees of multimodality of work/school and non-work/school trips. After all, the study used a recently collected large-scale dataset from four major universities in Toronto.

3. Data for Empirical Investigation

The dataset used for this study was collected through a survey named StudentMoveTO, a joint initiative of four universities in Toronto - the University of Toronto, York University, Ryerson University and OCAD University *(15)*. The initiative aims to study the travel behaviour of students from these universities in order to better understand their transportation needs. StudentMoveTO was a web-based survey conducted in the fall of 2015 among all students enrolled in the four universities. Out of more than 0.18 million students enrolled in the four universities, a total of 15226 responses were received, corresponding to a response rate of more than 8%. After removing incomplete entries, 11,167 complete responses were used for this investigation.

The information collected from the survey includes a daily travel diary of a typical day from each respondent along with socio-economic information at the household and person level. The daily travel diary includes all trips the respondent made on their last commuting day to school. Data were collected on modes used, trip distance, trip starting time, origin, destination among others. Students were asked for information indicating their home location, household size, household composition, dwelling type, household income level and age of the household members. Respondents were also asked to provide their affiliated school, campus, and faculty, the 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.

Multimodality is normally 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 being shorter than some previous studies *(16, 17)*, it has the advantage of having less respondent bias.

In addition to the trip diary and socio-economic information, the survey also included a set of 14 attitudinal questions which are designed to measure students' inherent attitudes towards different transportation modes and travel in general. Students were asked to indicate whether they agree with a statement presented to them on a five-level scale ranging from "strongly agree" to "strongly disagree". Table 1 shows the list of questions asked in this section. Here, a response of 5 indicates “strongly agree” and a response of 1 indicates “strongly disagree”. Responses from these attitudinal questions form the basis of the latent constructs in the measurement model portion of the SEM.

The base survey data is further supplemented by land use characteristic information generated using Geographic Information System (GIS) tools based on the postal code of the respondent's home location. These information include the amount of land area used for various land use purposes, the employment and population density, the average block length, and transit-specific information such as the number of transit stops or transit departures within a certain radius, and the distance to the closest transit station (bus, streetcar and subway, and regional rail). Table 2 shows a selected list of variables from the base dataset and the supplementary data. Besides preliminary investigation through descriptive statistics, an Exploratory Factor Analysis (EFA) of the responses to the attitudinal questions is conducted to identify latent and unique factors defining travel attitudes. This EFA guides us in developing the appropriate Structure Equation Model.

Table 1: List of attitudinal questions

	Question	Response
Q1	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 the 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	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	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: Descriptive statistics for selected variables

Variables	% Share	Variables	Mean	Std. dev.
Personal characteristics		Household characteristics		
Gender		Income level	1.29	1.96
Male	32.52	Number of males	1.58	1.22
Female	66.6	Number of females	1.94	1.17
Student status		Household average age	31.69	9.02
Undergraduate	77.42	Mode ownership		
Graduate	22.58	Number of cars in household	1.34	1.12
Student status		Travel characteristics		
Full-time	93.15	Average trip straight line distance (m)	12758.25	50405.7
Part-time	6.85	Land use characteristics (within residence postal code area)		
Household characteristics		Residential area (sq. km)	0.94	0.42
Living alone	0.8	Parks and recreational area (sq. km)	0.1	0.11
Living with roommates	22.41	Transit access		
Living with partner	13.2	Number of stops within 400m	6.58	6.19
Living with family	63.59	Number of stops within 800m	25.63	18.13
Living with both parents	45.82	Number of stops within 1200m	56.88	37.14
Mode ownership		Distance to closest bus stop (m)	329.5	714.53
Car owner	18.13	Distance to closest streetcar stop (m)	11728.02	12087.27
Bike owner	49.3	Distance to closest subway stop (m)	8755.75	10980.31
Presto card owner	40.96	Number of departures within 400m (24h)	568.88	863.28
Transit pass owner	40.54	Number of departures within 800m (24h)	1261.41	1258.63
Car sharing program member	5.61	Number of departures within 1200m (24h)	1903.92	1566.52
Bike sharing program member	1.12			

4. Econometric Models

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

4.1. Structural Equation Modelling (SEM)

The SEM framework consists of two components - the measurement model, and the structural model. The measurement model component relates the set of proposed latent factors, constructed through the EFA, to the indicator variables. The measurement model component takes the functional form of:

$$x = \beta\eta + \varepsilon \tag{1}$$

Where x is the indicator variable, β the coefficient and η the latent factor? The error term, ε, is assumed to follow a normal distribution with a standard deviation of σ.

The structural model component establishes the relationships between the latent factors, the dependent variables, and any other exogenous variables that may be incorporated.

$$U = \sum \gamma\eta_i + \varepsilon \tag{2}$$

Where U is the dependent variable or other endogenous latent factors. In this case, it is the latent utility of the degree of multimodality. γ is the coefficient for the exogenous latent factors.

In this study, the attitudinal responses from the survey are used as the indicator variables to construct the latent factors. The resulting latent factors are assumed to be the base attitudinal preferences of the sample population. As seen from Figure 1, the latent factors are further defined through regression of the observed variables in the structural model component of the SEM model, which takes the form of:

$$\eta = \sum \theta m_i + \varepsilon \tag{3}$$

Where m_i are the systematic exogenous variables and θ refers to corresponding coefficients. The integration of exogenous observed variables reveals the effect these variables have in shaping the individual latent attitudinal preferences.

The latent variables are finally incorporated with the exogenous observed variables to model the response of latent utility directly and the degree of multimodality, y, indirectly:

$$y = U + \varepsilon \tag{4}$$
$$U = \sum \gamma\eta_i + \sum \theta m_i + \varepsilon \tag{5}$$

The use of this model framework allows for both the definition of underlying latent factors that influences travel behaviour, and to draw causal relationships between these latent factors, the observed variables and an individual's degree of multimodality. Estimation of the model was done through the maximum likelihood method using the Stata statistical analysis software *(18)*.

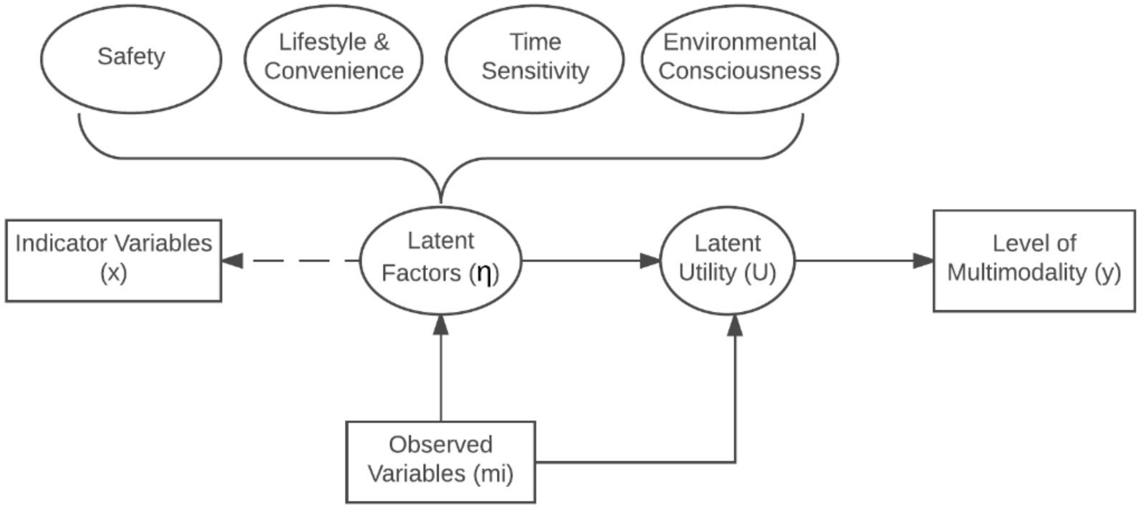


Figure 1: General model structure

4.2. Bivariate Ordered Probit Model

The bivariate ordered probit model is based on a set of latent utility functions, with work/school trips, and non-work/school trips each represented by their own utility functions, which takes the general form of:

$$Z_i^* = \beta' X_i + \varepsilon_i \tag{6}$$

Where Z_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 Z_i^* needs to be translated based a set of threshold values and the following set of equations:

$$Z_i = \begin{cases} 0 & if -\infty \le Z_i^* \le \lambda_0 & [no\ trips\ taken] \\ 1 & if\ \lambda_0 < Z_i^* \le \lambda_1 & [1\ mode\ used] \\ 2 & if\ \lambda_1 < Z_i^* \le \lambda_2 & [2\ modes\ used] \\ 3 & if\ \lambda_2 < Z_i^* \le \infty & [3\ modes\ used] \end{cases} \tag{7}$$

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

$$Pr(Z_i = j) = \phi(\lambda_j - \beta' X_i) - \phi(\lambda_{j-1} - \beta' X_i) \tag{8}$$

The parameters of the models, including the variable coefficients and the threshold values, were jointly estimated using the method of maximum likelihood with the likelihood function *(19, 20)*:

$$L = Pr(Z_{i,1} = j \cap Z_{i,2} = k) = Pr(\lambda_{j-1} < Z_{i,1}^* \le \lambda_j \cap \lambda_{k-1} < Z_{i,2}^* \le \lambda_k) \tag{9}$$

Where the likelihood is the joint probability of $Z_{i,1}$ and $Z_{i,2}$ taking levels of multimodality j & k, respectively based on the equation (8), and can be further expanded into the probability density function of:

$$L = \int_{\lambda_{j-1}-(\beta_1' X_{i,1}+u_i)}^{\lambda_j-(\beta_1' X_{i,1}+u_i)} \int_{\lambda_{k-1}-(\beta_2' X_{i,2}+v_i)}^{\lambda_k-(\beta_2' X_{i,2}+v_i)} \phi_2(u,v,\rho)dudv \qquad (10)$$

Where u and v are the error terms for work/school trips, and non-work/school trips respectively, with ρ as the co-relation coefficient between unobserved factors influencing two ordered variables. The model was estimated using the NLOGIT software package *(21)*.

5. Empirical Investigation

The EFA is first carried out to establish the set of latent attitudinal factors to be used in the later stages of the study. An EFA attempts to infer a set of unobserved factors from a larger set of observed indicators. Table 3 gives a summary of the factors produced from the analysis and their final loadings. The indicators used in this analysis are the responses from the attitude questions from the survey. The loadings indicate the amount of variance in the each indicator explained by each proposed latent attitudinal factor. A higher loading of a factor on an indicator indicates that higher variances of the indicator in question are explained by the factor. The uniqueness indicates the amount of variance in the indicators not explained by the proposed factors. Question 7 from the survey, which asks for the respondents' attitude towards traffic congestions, was excluded from the final analysis due to very high uniqueness (>0.9). The EFA was estimated using the principle component approach with Varimax rotation.

Table 3: EFA final loadings

Indicator	Safety	Lifestyle and Convenience	Time Sensitivity	Environmental consciousness	Uniqueness
Q1	0.014	0.032	0.804	-0.019	0.352
Q2	0.062	0.026	0.807	-0.015	0.344
Q3	0.253	0.140	0.613	-0.005	0.540
Q4	-0.424	0.007	0.098	0.531	0.529
Q5	0.573	0.312	0.149	-0.213	0.506
Q6	0.704	0.328	0.169	-0.067	0.364
Q8	0.71	0.330	0.159	-0.206	0.319
Q9	-0.123	-0.127	-0.015	0.743	0.416
Q10	-0.059	-0.142	-0.047	0.802	0.331
Q11	-0.689	0.107	0.083	0.028	0.506
Q12	0.163	0.832	0.058	-0.147	0.256
Q13	-0.013	0.738	0.058	-0.094	0.444
Q14	0.315	0.736	0.011	-0.040	0.357

A few points can be noted here. First, responses to the question 7, which concerns attitude towards traffic congestion, did not produce significant loadings on any of the four factors. Second, while most factors are loaded with an expected grouping of variables, factor 1, which largely correlates with questions of convenience and lifestyle in car usage, has a very high negative loading on responses to the Q11, "I prefer to take transit whenever possible."

The latent attitudinal factors constructed from the EFA are then fed into the SEM model. Two separate models for work/school related trips and for non-work/school trips are estimated. Figure 2 and Figure 3 show the final model structures and result in summaries from these two models. The Root Mean Square Error of Approximation (RMSEA) of 0.054 and 0.058, and a Comparative Fit Index (CFI) of 0.837 and 0.844 for the work/school trip model, and the non-work trip models, respectively, suggests a good level of fit *(22, 23)*. Coefficients of all variables in the models produced intuitive signs and all variables are statistically significant at a 95% confidence level.

Each model could have two latent factors: ‘safety’, and ‘lifestyle and convenience’, as significant in the respondents' general behaviour when it comes to multimodality. Both affect the multimodality of the respondent in an expected fashion, with the positive attitudes towards automobiles negatively affecting the degree of multimodality of the students. The latent attitude “Environmental Consciousness” was not at all significant in either model and seems to play no role in the determination of the students’ degree of multimodality. Slight differences do exist between the two models.

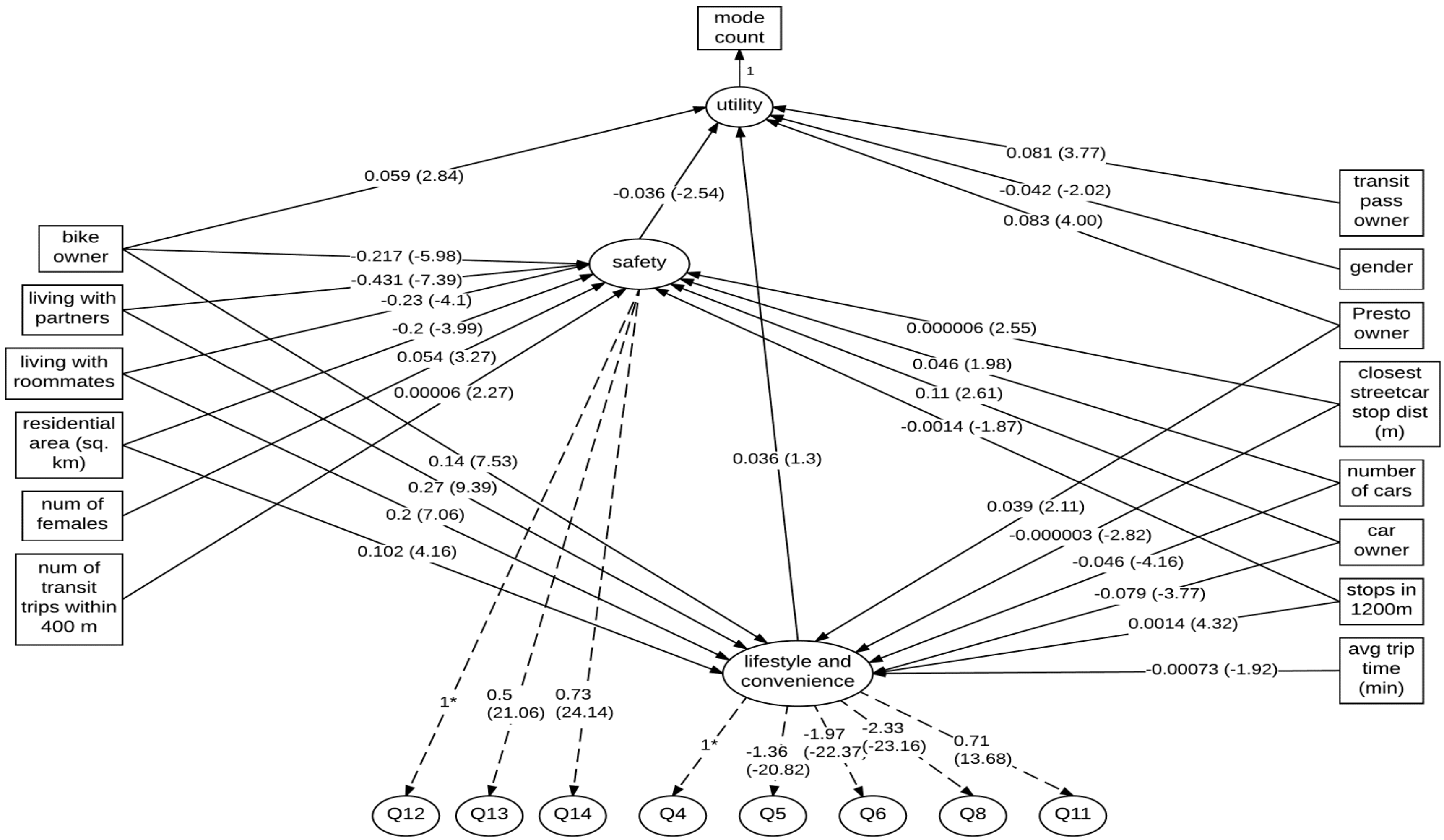
The latent safety factor carries marginally higher influence on non-work/school trips than work/school trips. The opposite is true with the lifestyle and convenience factor, which shows higher influence against work/school trips. The results also indicate that the observed variables mostly exert influence on multimodality indirectly through the mediation of the latent factors, while some also directly affect multimodality.

Most notably, mobility tool ownerships are significant factors that both influences students' latent attitudes and their multimodality. Predictably, those who own cars or have access to cars in their household show more favourable attitude towards cars and are less likely to be users of multiple modes. The opposite is true for those with ownership of other mobility tools.

Particularly notable is the influence of owning a smart fare payment card (Presto card) in changing attitudes in terms of lifestyle choice and convenience. Students who own Presto cards less likely to prefer the car for its convenience and are much more likely to use multiple modes for their travels. Traditional transit pass ownership only shows a positive impact on the latent utility term. These results suggest that while transit pass ownership is influential in the immediate term, ownership of smart fare payment cards like Presto affects mode preference and multimodality in the medium and long term through latent attitudes. Such findings point to the importance of a well-designed fare payment card system in changing the latent perception of transit in terms of convenience and flexibility.

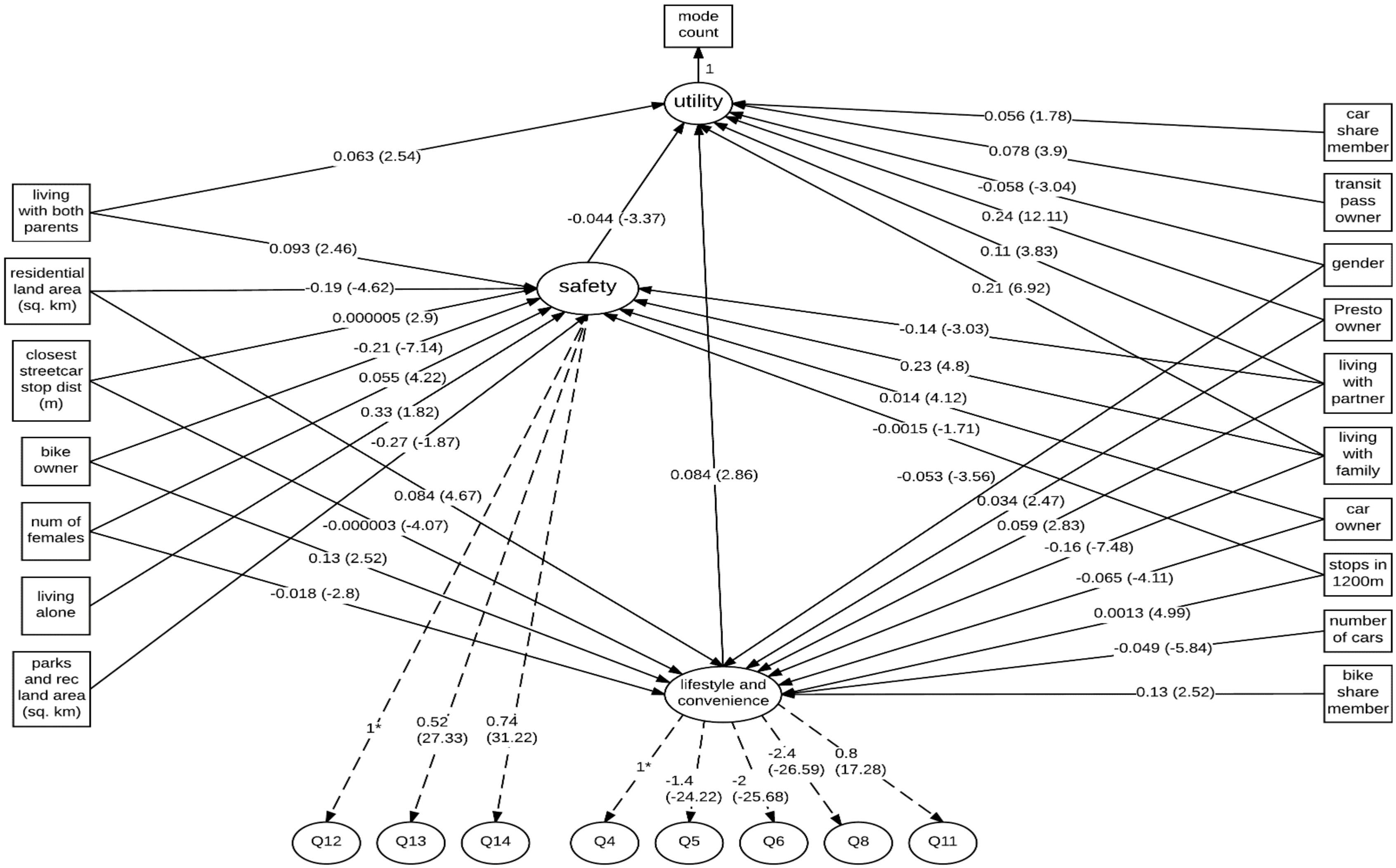
The cause of this positive effect of Presto card on attitudes towards transit and other alternatives could come from the fare discounts that it offers, whether it be a flat rate or loyalty based, across multiple agencies and the ease of transfers, especially when travelling with multiple agencies. Combined with its purchase price of $6, it represents a flexible tool with very low-level entry investment and commitment *(24)*. By contrast, traditional transit passes offers discounts for only one transit agency and is valid for only a limited time period, requiring a much higher level of travel commitment from the individual to justify its investment.

Also notable is the positive influence of having a bike sharing membership in shaping the latent attitude of a student, despite the fact that only a very low percentage of the student actually has a membership. Conversely, car sharing membership did not prove significant in the same regard.



Parameters (t-stat)
*Constrained

Figure 2: SEM work/school trip model result summary



Parameters (t-stat)

*Constrained

Figure 3: SEM non-work/school trip model result summary

Household characteristics are another category of variables which influence the degree of multimodality both directly and indirectly. The model results suggest that those living with roommates or partners are less likely to have latent attitudes that are partial towards the car in terms of safety or preferential attitudes favouring the car for its convenience or as a lifestyle choice. On the other hand, students living with parents/family are more likely to have attitudes that prefer the car over other modes for safety, convenience and lifestyle reasons. The same variables also hold more immediate influence on a student's degree of multimodality when it comes to routine work or school trips. Those who live with close families, be it a partner or parents, are more likely to use multiple mobility tools. This would suggest the presence of resource allocation and share within households for routine daily travels, especially among close family members.

Influences of the built environment near home locations also shape students' latent attitudes towards multimodality with mostly expected outcomes. Neighbourhoods with more parks, recreation, and residential land use as well as higher transit stop density are generally conducive to shifting latent attitudes from being favourable to cars to favouring other active modes (walk, bike and transit) with regards to both safety and convenience. This indicates the need to both increase transit network density and creates safe and pleasant environments to shift long-term habits in modality style.

Overall, the two models captured similar effects of the variables that were considered. The similarity between the two models supports the initial hypothesis that the unobserved factors influencing the degree of multimodality for work/school and non-work/school trips are correlated. However, SEM models have an inherent limitation in capturing such correlations. As such, a bivariate order probit model is used.

The results from the bivariate ordered probit model echo some of the findings from the SEM model, as seen in the summary shown in Table 4. The jointly estimated model shows a strong correlation between the between unobserved factors affecting multimodality of the two trip types. Once again, mobility tool ownership and transit network density variables show a strong positive effect in increasing the degree of multimodality of the student population. Also significant were the trip distance which negatively affects multimodality, and household characteristics such as the level of income which increases multimodality. It is possible that the cost of owning multiple mobility tools means that wealthier households can more easily absorb those costs. For non-work/school trips, whether or not a student is a graduate level student seem to play a role in determining multimodal behaviour.

Average probabilities of individual utilizing different levels of multimodality are compared for various levels of the included observed variables (Table 5). In addition, the partial effects of various variables are shown in Table 7. In general, students tend to be more multimodal when making school and work trips. Particularly high levels of multimodality can be observed for students with transit passes, and for students making regular trips between 5 to 10 kilometres. Those who live more than 1km away from a subway also tend to commute using multiple modes, which likely reflects high usage of park & ride, and kiss & ride users at major terminuses, while also being in agreement with the aforementioned presence of mobility tool sharing within households. The same trends generally hold for non-work travels as well, with the one exception being student status. Graduate students seem to have a particularly high probability of making non-work/school trips and for using multiple modes for those trips. This is most likely the consequence of the higher level of independence that graduate students tend to have and the amount of personal administrative tasks that comes with that independence (Table 5, Table 6).

Table 4: Bivariate ordered probit model result summary

	Work/school trips		Non-work/school trips	
	Parameter	t-stat.	Parameter	t-stat.
Household characteristics				
Income level	0.0203	2.45	0.037	4.67
Number of males			-0.055	-4.37
Personal characteristics				
Student status (undergraduate/graduate)			0.175	5.15
Mobility tool ownership				
Driving licence owner	1.225	17.19	0.218	6.92
Transit pass owner	0.155	4.66		
Travel characteristics				
Average trip straight line distance (m)	-0.0000043	-11.8		
Transit access				
Distance to closest bus stop (m)	-0.00013	-7.33		
Distance to closest subway stop (m)	0.0000167	12.25		
Threshold values				
λ_0	0	-------	0	-------
λ_1	2.242	59.32	1.345	53.54
λ_2	3.246	75.43	2.265	34.23
Correlation Coefficient	0.362	22.29		

Table 5: Probability of multimodality level

	Probability of # of modes used for work/school trips				Probability of # of modes used for non-work/school trips			
	0 (no trip taken)	1	2	3+	0 (no trip taken)	1	2	3+
Benchmark	4.46	63.39	24.66	7.49	40.90	45.58	11.32	2.19
Undergrad	4.30	63.31	24.88	7.51	43.26	44.61	10.27	1.86
Grad	4.81	64.66	23.75	6.78	35.53	47.81	13.68	2.98
Transit pass (yes)	3.70	61.80	26.22	8.29	41.16	45.49	11.19	2.15
Transit pass (no)	4.88	64.79	23.60	6.74	40.76	45.64	11.38	2.22
Average trip distance (less than 1km)	5.24	67.25	21.89	5.62	40.47	45.75	11.52	2.26
Average trip distance (1 to 5km)	4.27	64.45	24.26	7.02	39.96	45.98	11.73	2.33
Average trip distance (5 to 10km)	3.76	62.86	25.58	7.80	41.20	45.47	11.18	2.15
Average trip distance (less than 10km)	4.70	62.35	25.13	7.82	41.67	45.27	10.98	2.09
Closest bus stop (less than 400m)	4.44	63.85	24.48	7.22	40.69	45.68	11.41	2.23
Closest bus stop (400 to 1000m)	4.39	63.22	24.85	7.54	41.62	45.27	11.01	2.10
Closest bus stop (less than 1000m)	5.79	63.42	23.39	7.40	42.15	45.06	10.77	2.02

Closest subway stop (less than 400m)	6.35	67.45	21.05	5.15	39.35	46.27	11.98	2.41
Closest subway stop (400 to 1000m)	5.74	67.41	21.48	5.36	39.18	46.30	12.07	2.44
Closest subway stop (greater than 1000m)	3.84	62.19	25.86	8.12	41.59	45.29	11.02	2.10

Table 6: Partial effect of estimated variables

	Work/school trips				Non-work/school trips			
Variables	0	1	2	3+	0	1	2	3+
Household characteristics								
Income level	-0.002	-0.006	0.005	0.003	-0.014	0.006	0.006	0.002
Number of males					0.022	-0.010	-0.010	-0.003
Personal characteristics								
Student status (graduate)					-0.075	0.031	0.032	0.011
Mode ownership								
Driving licence owner	-0.411	0.116	0.228	0.067	-0.084	0.044	0.031	0.009
Transit pass owner	-0.014	-0.045	0.037	0.022				
Travel characteristics								
Average trip straight line distance (m)	0.0000006	0.170	-0.000002	-0.0000008				
Transit access								
Distance to closest bus stop	0.00001	0.00004	-0.00003	-0.00002				
Distance to closest subway stop	-0.000002	-0.000005	0.000004	0.000002				

6. Conclusions and Recommendations for Further Studies

The findings of this study confirm the initial hypothesis that latent attitudes play a significant role in shaping the level of multimodality among university students. Empirical investigations reveal that post-secondary/university students are affected by their latent attitudinal preference for safety, convenience, or certain lifestyles. This is in general agreement with existing research into the role of latent attitudes on travel behaviour *(8, 9, 10, 11)*. The findings also reveal that most observable variables affect multimodality indirectly through the latent attitudes, while some influences multimodality both directly and indirectly. Notably, the results show considerable influence from household types and mobility tool ownership. Living in traditional households (with family/parents) and the ownership of a fare payment card positively influences both the latent attitudes towards alternative modes and the choice to use multiple modes. This would suggest the importance of intra-household resource allocation and the use of integrated transit fare payment systems in shaping both latent attitudes and mode choice decision-making processes of students. This lesson should be used to inform the design of future transportation demand management programs and transit fare collection framework. The strong influence of the Presto card on latent attitude, in particular, would indicate the need for good integration and wide adoption of smart fare payment in promoting multimodal behaviour.

Land use characteristics are also determinants of the student attitudes, and should be an important consideration in the planning policy context. Residential, parks and recreational land use were found to positively impact students' perception of the safety and convenience of alternative modes. As such, land use strategies that combine high transit density with safe and pleasant built environments could go a long way to shaping student mode use in the long term. These insights warrant further investigation and more advanced research on the topic. Results from the bivariate order probit model show a high level of correlation in the degree of multimodality between the work and non-work trip types, as was initially hypothesized. The model also found similar groups of explanatory variables responsible for the multimodality of the students under study, echoing the results from the SEM model. These two models, in fact, identify the same latent and observed variables that affect the multimodality of the university students.

Future studies could explore differences in the effect of both latent and observable variables among further delineated groups of the university student population. For example, comparisons can be made between students living in urban and suburban or students commuting the urban and suburban campuses. Another possible extension of this study could be the integration of the latent attitudinal variables proposed here into the bivariate ordered probit model or other discrete level models structure to investigate the influence of these latent attitudes in more specific decision scenarios. These are considered as the recommendations for further research on this topic.

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