TRAVEL LIFESTYLES AND THE BUILT ENVIRONMENT – EXPLORING HOW POST-SECONDARY STUDENTS NAVIGATE THE GTHA

by

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Abstract

This study explores the relationship between travel lifestyles and the built -environment in post-secondary students - a historically understudied section of the population- in the Greater Toronto and Hamilton Area, Canada. An extensive, data-driven was used to classify students based on their travel patterns and neighbourhoods based on their built environment characteristics and explore correlations between the two. We identified five very distinct student travel lifestyles – Car users, Occasional Drivers, Transit Users, Cyclists and Walkers. Only 33% of Post Secondary students were identified as car dependent and a very high proportion of them are systematically multi-modal in their travel pattern. Alternatively, there is some indication that these changes may be a function of vehicle access. Atypically strong correlations between traveller types and the built environment in which they reside were also identified, particularly in certain neighbourhood types suggesting student travel may be more influenced by their environment.

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Table of Contents

Lists of Tables and Figures

Tables — Page

Figures

1 Introduction

1.1 Background

The link between built environment and travel behavior has been subject to a great deal of research and debate over the last 20 years (Ewing & Cervero, 2010). Beyond simply measures of neighbourhood density, characteristics of the street network such as intersection densities, the mixing of land uses, and even the architectural character of buildings within a neighbourhood have all been demonstrated to have a modest influence on the means that residents utilize to travel from one place to another (Cao, Mokhtarian, and Handy 2009; Ewing and Cervero 2010). In 1997, Cervero and Kockelman distilled the factors that influence travel behaviors into what are called the Three D's; Density, Diversity and Design (Cervero and Kockelman 1997). Over the years more D's such as Distance to transit, Destination accessibility have been added to the equation as more research found increasing complexities between built environment and travel behavior (Ewing and Cervero 2001).

Decades of research and more than 200 individual publications have demonstrated modest correlations between the characteristics of an individual's neighbourhood and various indicators of travel behaviour (Ewing & Cervero, 2010). For example, findings suggest declines in vehicle miles travelled in neighbourhoods with higher density and transit access (Holtzclaw, 1994; Holtzclaw et al. 2002), significantly higher levels of transit usage in neighbourhood with transit- oriented design as opposed to auto- oriented designs (Cervero and Gorham, 1995), and greater overall levels of walking and other street level activities in neighbourhoods with regular street crossings and connected sidewalks (Hess et al., 1999). Research has even found correlations between levels of active transportation - transportation completed using human powered means such as walking and cycling– and the topography of the land (Rodríguez and Joo 2004).

More recent work has begun the exploration of the influence of individual preferences and behaviors on transportation decision making. A ground-breaking study by Kitamura, Mokhtarian and Laidlet (1997) explored the influences of attitudes and behaviors of decision making and found that an individual's travel related preferences may better explain travel behavior than the built environment. Similar findings have also be These findings influenced further studies, which suggested that the role of built environment in determining travel behaviors may not be quite as strong as initially believed and in-fact, may be significantly moderated by endogenous preferences and attitudes leading to residential self-selection (Bagley and Mokhtarian 2002; Boarnet and Crane 2001).

1.2 Millennial Travel Behavior

Compared to adults, millennials' travel behavior and the influence of the built environment therein, have been less thoroughly examined. In the past decade, a great deal of attention has been paid to indications that millennial travel patterns are shifting significantly from those of the previous generations. Research clearly points to declining rates of drivers licensing and car ownership amongst millennials and in some studies significant reductions in the overall vehicle miles travelled (Ralph et al. 2016; McDonald 2015; Polzin, Chu, and Godfrey 2014; Shults and Williams 2013; Shay and Khattak 2007; Myers 2016; Sivak and Schoettle 2012; Schoettle and Sivak 2014). While there is some research that has explored the broad differences between millennials and the older generations with regard to transportation behaviors, detailed examinations of these differences have been limited (Ralph et al. 2016). Further, those that have explored the phenomenon have reported differing results, many of which have not considered the influence of the built environment characteristics (Ralph et al. 2016).

Studies have indicated changing attitudes toward travel in light of virtual mobility, such as online shopping, as one of the primary causes of declining mobility among millennials and have found that economic constraints and joblessness only explain a small proportion of millennials who choose to travel by modes other than the car (McDonald 2015). Research by Ralph et al (2016) exploring millennial travel behavior represents one of the first significant explorations of the influence of the built environment on millennial travel patterns. Determining neighbourhood "typologies" utilizing census data from across the entire United States, and comparing these to millennial traveler typologies, the authors sought to estimate how differences in the built environment may explain millennials' travel patterns (Ralph et al. 2016). Their findings suggest that the built environment does play a modest role in shaping travel behavior; particularly, car travel was found to be significantly reduced for individuals living in "old urban" neighbourhoods (Ralph et al. 2016). However, beyond just the built environment, their findings indicated that the majority of car-less millennials could be found in the lowest income brackets (Ralph et al. 2016), contradicting previous research on this topic (e.g., McDonald, 2015). Further, they found that trip making among these low income car-less travelers was the lowest off all identified traveler types (Ralph et al. 2016). If the assumption was that these individuals were changing their travel habits and choosing *alternative* modes, then logically there should be no significant difference in the degree of travel, only in the modes utilized (Ralph et al. 2016).

These findings indicate that for a steadily growing segment of the millennial population, travel is in decline, and that this decline may have less to do with changing attitudes towards travel or the built environment and more to do with the declining middle class (Ralph et al. 2016). Others still have suggested that changes in life stages brought about by factors such as increasing levels of post-secondary education combined with more time consuming graduated drivers licensing schemes and higher auto travel costs discourage the use of cars as a means of travel, and may explain the movement away from car-focused travel (Delbosc and Currie 2013). In conjunction with these finding it is important to keep in mind that millennials are pursuing post-secondary education at rates higher than any other generation in history and in doing so also accruing personal debt at unprecedented levels (LendingTree, 2016).

1.3 Research Gap

Post-secondary students comprise a significant proportion of the millennial generation. Research on post-secondary students' travel behavior is only just emerging. Existing research has indeed demonstrated that post-secondary students do indeed have very different travel behaviors than the older population (Chen 2012; Das et al. 2016). Housing and living situations have been found to have extremely important influence on travel behaviors, with student pooling expenses to afford accommodations that reduce commute times and allow for alternative means of travel (Zhou 2014). Existing research has also often explored specific aspects of travel behavior, such as cycling patterns among post-secondary students (Emond and Handy 2012) and certain subsets of student populations, such as students attending private schools (Danaf, Abou-Zeid, and Kaysi 2014) or students living in certain spatial contexts, such as rural areas (Limanond, Butsingkorn, and Chermkhunthod 2011). Comprehensive studies of post-secondary student travel behavior that factor in individual travel behaviors and the way these behaviors correlate with the built environment are required in order for urban and transportation policies to address the needs of this important segment of urban population in big metropolitan regions. Even more important are studies that address the complicated nature of the relationship between the built environment and travel, and account for the fact that particular combinations of built form characteristics combined together can have a significant influence on behavior where, taken individually, they may not (Ewing and Cervero 2010; Bento et al. 2005).

1.4 Research Questions

By performing a comprehensive examination of travel data on post-secondary students, this research paper seeks to examine the following questions, in relation to travel behavior in the Greater Toronto and Hamilton Area (GTHA), Canada:

1) Do patterns of transportation lifestyles exist among post-secondary students?

2) Are transportation lifestyles different across socio-demographic groups and between neighbourhood types?

By identifying differences in the ways that students travel, and how these differences may correlate with the built environment, we can also provide valuable evidence for housing policies and initiatives aimed and encouraging certain types of travel, and developing long term habits in young adults. This study may also shed light on the potentially beneficial or harmful impacts of future changes in programs and policy, as well as indications of whether students are moving towards more healthy and sustainable means of travel in their daily lives.

2 Method

In order to explore post-secondary students' travel behavior, distinct patterns with regard to travel outcomes (i.e., transportation lifestyles or traveler types), among groups of students, were identified, following a methodical approach that was somewhat inspired by that of Ralph et al (2016). Their study, which explored millennial travel patterns and the built environment, utilized a unique typology-based analytical approach which began with the determination of traveler and neighbourhood types using an extensive, data driven approach (Ralph et al, 2016). In the creation of typologies, which represent the inherit or 'latent' characteristics of the each dataset, correlations and co-variances between all of the variables are accounted for when determining type membership, which accounts for things that may vary in tandem. By isolating and separating these complex interactions into unique types for both travels and their built environment, a clearer picture of association can be drawn. To do this, traveler types, along with a series of socio-demographic control variables, were then included in a series of multinomial logistic regressions to estimate the degree with which changes in millennial travel behavior could be explained by built environment types (Ralph et al, 2016).

This study uses a similar approach, creating traveler lifestyle and neighbourhood typologies for post-secondary students and the GTHA. However, unlike the study of Ralph et al, variables included in our neighbourhood typology will be a significantly smaller areal resolution and will include a much wider range of transportation accessibility measurements, including access to cycling and transit infrastructure. In this way we will be defining neighbourhood types not only by the characteristics of their built environment, but also by the degree with which they facilitate certain types of travel. The differences in identified traveler types across these various neighbourhood types will then be examined statistically. This approach is differs from the majority of transportation literature which typically examines the correlation between specific travel outcomes (e.g., mode choice) and individual neighbourhood environmental characteristics (e.g., land use mix). By including measures of transportation accessibility, we can also assert the degree with which specific infrastructure may be influencing travel decisions.

2.1 Dataset

The StudentMoveTO survey is a large survey of post-secondary student travel behavior completed in Fall of 2015. The data was the result of a large collaborative study by researchers from four universities located within the City of Toronto, namely: OCAD University, Ryerson University, University of Toronto and York University. Each student registered in these universities received an email from their university administration with invite to participate in an online survey, which collected retrospective travel data in the form of a travel diary for one full day (i.e., the day prior to the date when the invite was sent). The emails were sent every day to a randomly selected group of students, over a period of one month and-a-half to ensure a random distribution of travel experiences. By the close of the survey a total of 15,226 individuals responded to the email and filled out the survey (a response rate of 8.3%).

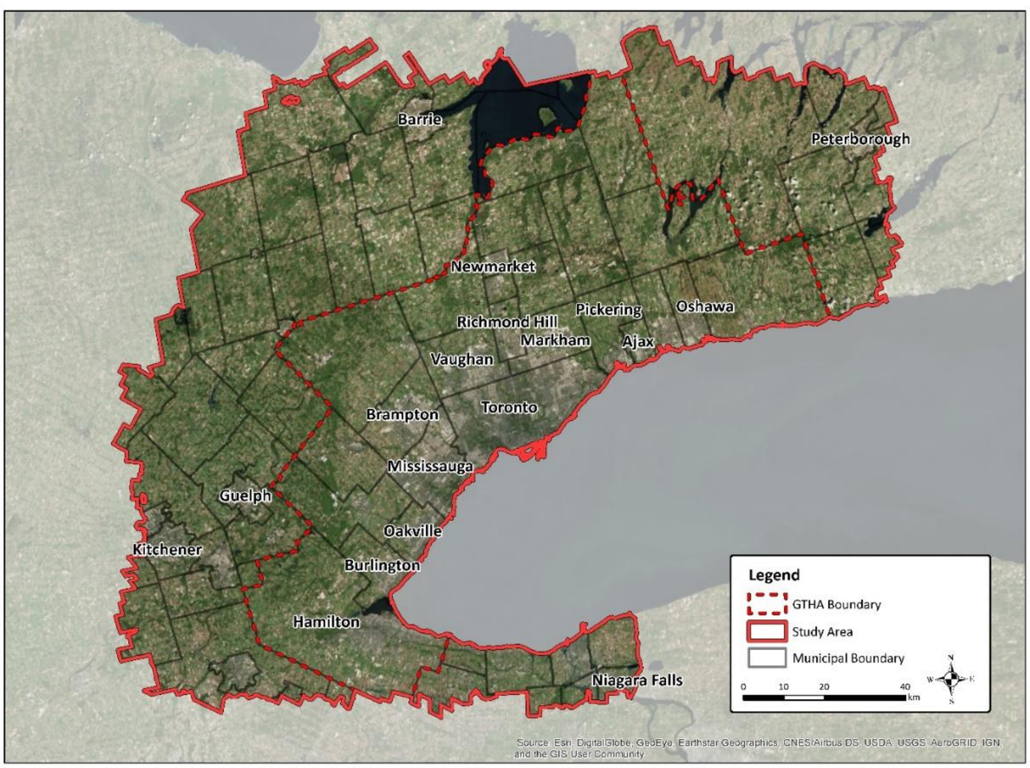
The StudentMoveTO survey provides a unique and rich data source, including questions covering attitudes towards travel, socio-demographic characteristics of the students, and residential and/or activity locations, in addition to a travel diary that includes details relating to all trip taken during a one-day period. The four participating universities combined operate a total of seven campuses, three of which are located in suburban communities (University of Toronto the Mississauga and Scarborough campuses and York university), while the remaining campuses are located in downtown Toronto, representing a wide diversity of urban contexts within the sample. This dataset allows a comprehensive and robust analysis of travel behavior focusing on post-secondary students in particular, and the millennials in general.

Prior to analysis, data was cleaned of outliers and individuals who reported no travel in the day prior to the study or did not complete the attitudes and perceptions questions were removed from the analysis leaving a total of 8486 individuals. In addition, all students who reported having no choice in their residential location were removed from the dataset (n=1983) in order for our sample to be more representative of the working millennials who would likely be able to choose their residential locations based on their abilities). The final dataset consisted of 6502 individuals.

2.2 Study Area

As opposed to limiting our study area to arbitrary municipal boundaries our approach to creating a study area focused on the household locations of students in our dataset. This was defined by the minimum bounding geometry rectangle encompassing the households of our dataset. All dissemination areas (DAs) intersected by this rectangle were selected and utilized as a final study area. The final areas, which can be seen in Figure 2.1 is representative of a significant proportion of southern Ontario, and represents a wide variety of diverse built environments. Ranging from the city of Toronto, one of the most densely populated cities in Canada as well as the suburban sprawl surrounding it, to the rural farm lands of southern Ontario and their rural town centers the diversity of uses in the study area ensures that our classification of neighbourhood typologies will be robust and account for all environments that a student may be living in.

Figure 2.1: Map showing the study area relative to the outline of the GTHA



2.3 Identifying Traveler Types

Our first step was to explore how post-secondary students were travelling in our study area. This is essential for determining prevalent patterns or commonalities in travel among post-secondary students. Further, identified student travel types will be the outcome variable in our regression models exploring the impact of the built environment on travel behaviors.

Utilizing a deconstructed approach to SEM, where 'latent classes' are identified independently, we created two distinct typologies. First, student traveler types were identified utilizing Latent Class Analysis (LCA) on disaggregate travel related data, including trip specific characteristics, short and long term mode choices and travel related attitudes and behaviors (Appendix 1). LCA is a subset of SEM and is utilized to identify discreet latent variables within a dataset based on the collective probabilities of the variables used in the analysis. Classes are latent because the classes themselves are not directly observed, but are determined through an iterative probability algorithm that estimates the probability of class membership independently for each variable based on cross classifications and assigns a maximum likelihood membership based on the collective summation of these probabilities (Goodman 1974). The result is that within each class, variables are statistically independent (Goodman 1974). There are a variety of benefits of LCA over other methods of data grouping - such as cluster analyses – which include the ability to utilize ordinal and nominal data due to the use of iterative cross tabulations to identify class membership (Schreiber and Pekarik 2014). Further, the ability to measure the fit of models and produce maximum likelihood estimations allow for more informed optimal class selections and also allow researcher to identify individuals who are poorly classified (for example, if an individual had a < 0.5 chance of belonging to any group) (Schreiber and Pekarik 2014)

The number of classes was determined by comparing the Akaike Information Criterion (AIC), and the Bayesian Information Criterion (BIC) combined with a 'sanity test' placing a limit on classifications when classes become uninterpretable (Lin and Long 2008; Schreiber and Pekarik 2014). The results of the study were 5 unique student traveler types which characterize the ways students are travelling.

2.4 Identifying Neighbourhood Typologies

Our second step was the identification of neighbourhood typologies. The identification of such neighbourhood types is essential for determining the degree with which the built environment is influencing a student's travel behaviors. The results of our neighbourhood typologies will be included as explanatory variables in out regression analysis in an effort to identify correlations between certain identified neighbourhood types and specific types of travelers.

To create the neighbourhood typologies for the entire study area a two-step approach was utilized. A total of 16 variables describing the built environment of 11,519 DAs across the study area. DAs are the smallest areal unit of statistical measure utilized by Statistics Canada and represent spatial areas containing between 400-700 individuals (Statistics Canada 2017). Dissemination areas were utilized for two reasons: First, being the smallest areal unit at which aggregate data is widely available, DA's significantly reduce the degree of error created by aggregation relative to larger areal unit, such as the more frequently utilized Census Tracts. This allows for a more detailed exploration of neighbourhood variability, particularly in urban areas where DA's are quite small due to very high population densities. The second reason DA's were utilized is that, unlike census tracts, they are available for the entirety of Canada, include remote and rural areas.

Creating typologies of neighbourhoods, as opposed to simply including built environment variables themselves as explanatory variables has a number of advantages (Sarjala, Broberg, and Hynynen 2015; Song and Knaap 2007). First, given the complexity involved in measuring the built environment, a total of 16 variables were measured to describe various aspect of the built environment (Appendix 1). Including 16 variables in a regression analysis not only produces results that may be difficult to interpret and fails to account for the fact that many of these measures may be correlated with each other in certain spatial contexts and vary in concert with each other (Ralph et al. 2016; Lin and Long 2008). To address this a Principal Component Factor (PCA) analysis is utilized to identify these correlations, and the resulting factor scores are then utilized in a k-means cluster analysis to identifying the final neighbourhood typologies. This two-step process is advantageous as it considers the complex manner in which variable measuring neighbourhood characteristics can and do vary in tandem with each other (Ralph et al. 2016). Further, by scaling the data and passing it through a factor analysis, we address some of the shortfalls associated with a k-means cluster analysis, namely, that data be relatively normally distributed (Schreiber and Pekarik 2014; Eshghi et al. 2011; Lin and Long 2008).

The principal component analysis was utilized to create built environment "factors" from the 16 built form variables. Data was mean centered and scaled before being analyzed and factorization was completed using a correlation matrix to ensure variables were standardized. Kaiser-Meyer-Olkin's test of sampling adequacy was 0.822, and Bartlett's test of sphericity was significant (p = 0.00) indicating the data was suitable for factorization. All of the 16 variables displayed diagonal correlations above 0.4 in the anti- image correlation matrix. The factor scores were then subjected to a varimax rotation to facilitate factor interpretation. Factors with eigenvalues greater >= 1 were then selected and interpreted. This PCA procedure produced 6 principal components or built environment "factors".

These six factor scores derived from the built form variables were then subjected to a k-means cluster analysis with the goal of creating DA bound neighbourhood typologies based on the characteristics of their built environment. K-means cluster analysis has been a "go-to" method of data grouping for many years (Eshghi et al. 2011). It is achieved using an iterative algorithm that centers data points around a set of randomly seeded 'centers' in the dataset. Using voronoi diagrams, the dataset is initially split into k planes where k = the number of clusters being fit (Lloyd 1982; Schreiber and Pekarik 2014). All observed data points contained within a plane are then utilized to recalculate the mean 'centroid' of the data as well as the within-cluster sum of squares (WCSS) (Lloyd 1982; Schreiber and Pekarik 2014). The process is then iteratively reapplied, with new voronoi cells being created around the new centroids until the data converges on the least sum of squares solution. The end result is a set of defined clusters defined as all observations that fall within the voronoi cells created around the converged cluster centers (Lloyd 1982).

While cluster analysis is an extremely valuable tool for the clustering of multidimensional data, it does have shortfalls as well. Because cluster centers are defined as centroids they are heavily influenced by outliers and non-normal data distributions (Schreiber and Pekarik 2014; Eshghi et al. 2011). There are also very few guidelines regarding the selection of the ideal number of clusters (Eshghi et al. 2011). In our case, the use of factor scores as inputs into the cluster analysis addresses concerns over outliers and data scaling. Non-normal distributions are also addressed as any non-normal distributions in factor scores would be reflective of inherit qualities in the data. For example, factor scores for 'intensity of use' should have a natural positive skew, as wide swaths of the study area contain flat rural land while proportionally smaller areas highly intensified areas (such as downtown cores) will have significantly higher scores. A natural positive skew to this variable is not only inevitable, but essential for proper cluster differentiation.

2.5 Exploring Correlates of Transportation Lifestyles

Finally, a series of multinomial logistic regressions were estimated. Using traveler type as our outcome variable, and of 11 sociodemographic variables (See Appendix 1) as well as our identified neighbourhood typologies as explanatory variables, we explore the correlation between a student's travel behaviors, their socio-demographic characteristics, and the neighbourhood they live in. The use of logistic regression is common in travel mode choice modelling as it allows for the estimation of discreet results reflecting the binary nature of decision making (Voulgaris et al. 2016; Sarjala, Broberg, and Hynynen 2015). Utilizing individual travel classes as dependent variables allows for the exploration of whether a student's travel characteristics are influenced by the neighbourhood in which they live in. In addition, a total of 11 socio-demographic variables such as living situation, household size and number of dependent children are included to explore whether the living situation or stage of life influences the way a person travels.

2.5.1 Trip Characteristics

Trip records from the StudentMoveTO travel diary were utilized to identify and distinguish between commute (defined as a trip that begins at home and ends at school) and non-commute (A trip beginning at home, and ending at a non-school destination) trips. The primary travel mode for each of these trips was also recorded by the respondents.

Using the origin/destination data, the network distance of every recorded trip in the survey was calculated using ArcGIS. For commuter trips, the shortest path network distance of the trip from home to school was used for further analysis. For non-commuter trips, the average distance of all non-commute trips was calculated. In addition, the total number of non-commute trips made by each individual, during a one-day period, was counted and used as an explanatory variable in our multivariate analysis.

2.5.2 Socio-economic Characteristics

Socio-economic variables were measured through the respondents' answers in the survey. The living situation (i.e. who, if anyone, they lived with e.g. parents, roommates, partner) were reported and utilized as is in the model. The number of dependent children a respondent was responsible for was also documented. Student Status was reported as Full or Part Time Graduate or Undergraduate as well as continuing education. This data was then categorized into three groups, namely- Full Time, Part Time and Continuing Education students.

Income and Work status questions were too sporadically answered to be useable, and thus, were excluded from the analysis. Instead, student status was utilized as a rough proxy for employment (assuming full time students were not likely to work full time).

2.5.3 Attitudes and Perceptions

A total of 14 statements relating to individual attitudes and perceptions about the use of transportation modes and trip-making behaviour, were explored for each respondent in the survey. In the survey, the level of agreement to the statements were measured on a 5-point Likert scale ranging from (1) strongly disagree to (5) strongly agree.

2.5.4 Built Environment

Built environment variables were measured at the dissemination area level to provide the highest possible resolution while also ensuring data availability for rural as well as urban areas (Statistics Canada 2017). The selected variables reflect built form measures that have been demonstrated to significantly influence travel behavior in the general population as well as amongst millenials (Ewing et al. 2011; Sarjala, Broberg, and Hynynen 2015; Ralph et al. 2016; Voulgaris et al. 2016; Lin and Long 2008). An overview of the 16 selected variables, the methods utilized to calculate/create them, and data sources can be found in Appendix 1. The following paragraphs will describe the method utilized to calculate the more complex measures of the built environment.

2.5.5 Transit Accessibility

Transit accessibility was measured utilizing public available General Transit Feed Specification (GTFS) data files. GTFS is test based file system developed by Google for transit routing and scheduling in Google Maps software (Google 2017). GTFS data from all regions within the study area (with applicable transit systems) as well as from the regional GO service were included in the analysis. Using ArcGIS, GTFS files were converted into vector data (transit stop points) with each point represents a transit stop and contained information on the corresponding transit schedules at that stop. To sufficiently measure transit accessibility, measures must consider more than just the number of transit stops and must also take into account the *frequency* of service. As a result, two measures of transit accessibility were decided: (1) The total number of stops in the 1km service area (measuring accessibility), and (2) The average number of transit trips per hour during the peak morning rush hour (6am-9am) (measuring frequency of service) Measuring transit accessibility is particularly challenging because access to transit is significantly influenced by spatial location. Measuring transit accessibility over wide areas (e.g. census tracts and larger dissemination areas) may fail to address disproportionate levels of accessibility across a larger area.

To address the spatially uneven nature of transit accessibility, particularly within larger dissemination areas (typically rural areas), a 500m x 500m grid was overlaid on the study area and all transit accessibility measurements were measured from the centroids of each of these cells, similar to the methodology utilized by Harding et al. (2012) in their study exploring activity spaces. A network distance of 1km from each centroid was utilized to estimate the accessible 'service area' of each centroid, and the number of stops/frequency of service for each centroid was determined. Transit measures for each DA would then be calculated as the mean values of all points located within the boundaries of the DA.

2.5.6 Building Heights

While structure massing data is readily available for the City of Toronto through its open data portal, similar data is not for the remainder of the study area and had to be measured. A well-defined methodology for estimating the height of man-made structures through remotely sensed data is through the use of Synthetic Aperture Radar (SAR) (Qian, Tang and Zhao 2015). Data acquired from SAR satellites is utilized to produce high resolution Digital Elevation Models (DEM) which represent 'bare earth' land elevations, as well as Digital Surface Models (DSM) which represents the raw surface elevations including the canopies of trees and man-made structures. The Ontario Ministry of Natural Resources produces both DEM and DSM's annually and these models were accessed utilizing their publically available open data portal (Ontario Ministry of Natural Resources 2016). By subtracting the values of the DEM from those of a DSM, the remainder represent the heights of any objects present on the surface, including tree canopies and man-made structures (QIAN Yao, TANG Lina, and ZHAO Jingzhu 2015).

To differentiate tree canopy and man-made structures a two-step process was utilized. To begin, the heights layer was clipped using a data layer created by DMTI spatial identifying the 'built up areas' in Ontario (DMTI Sptial Inc., 2014). The second step involved removing tree canopies from the calculations, as tree canopies would significantly influence average heights, particularly in more suburban areas where canopy coverage is higher and building heights often less than that of the canopy. To achieve this a Normalized Differential Vegetation Index (NVDI) was calculated using LANDSAT 8 satellite imagery which was accessed through the USGS Earth Explorer website (USGS 2017). A NDVI is a frequently utilized and well-studied vegetation index that is utilized to measure the health and density of vegetation using the absorption and reflective characteristics of the chlorophyll in plant leaves (Bino et al. 2008). It is calculated as a ratio between the Near Infrared (NIR) and infrared (IR) spectral bands in a multispectral satellite image with the resulting values can ranging from -1 to 1 (Bino et al. 2008). To remove tree canopy heights from the calculations of building height, a general cut-off NDVI value of > = 0.3 was utilized with all such areas being classified as vegetation and being removed from the analysis (Gandhi et al. 2015). The resulting layer represents the heights of all non-vegetative objects on the surface of the study areas. The mean values of these heights were then calculated for each DA and utilized in the analysis.

3 Results

3.1 Traveler Lifestyle Typologies

A total of five classes was determined as the ideal solution for the LCA, representing five distinct traveler types based on post-secondary students' transportation lifestyles. As table 3.1 shows, both the AIC and the BIC declined as the number of classes increased, suggesting a constant improvement in model fit. However, an upper limit of 5 classes was determined as cross tabulated item-response probabilities in models predicting > 5 classes became too fine to produce logical interpretation. The outputs of a latent class analysis (Table 3.2) include the item-response probabilities for *each* variable by class expressed as a percentage likelihood of membership in each factor (Schreiber and Pekarik 2014; Goodman 1974). Utilizing these variables as an interpretive guide, 5 classes was determined as cross tabulated item-response probabilities in models predicting > 5 classes became too fine to produce logical interpretation. Each of these 5 classes represented a clearly distinguishable group of post-secondary students in terms of their daily and long term travel characteristics (or lifesyles), namely: Transit riders (33%), walkers (19%), cyclists (15%), occasional drivers (11%), and drivers (22%) (Table 3.2).

The outputs of a latent class analysis include the item-response probabilities for *each* variable by class expressed as a percentage likelihood of membership in each factor (Schreiber and Pekarik 2014; Goodman 1974). Utilizing these variables as an interpretive guide, the five lifestyle groups estimated by the final model represent the following characteristics:

Table 3.1: Measure of Latent Class Model Fit

Number of Classes	residual	df	BIC	aBIC	AIC	cAIC	likelihood-ratio
2	-117594	6393	236145.1	235798.7	235406.1	236254.1	121177.6
3	-114216.8	6338	229873.4	229352.3	228761.5	230037.4	114423.1
4	-112799.8	6283	227522.5	226826.5	226037.7	227741.5	111589.2

	-						
5	111878.2	6228	226162	225291.3	224304.3	226436	109745.9
6	-110979	6173	224846.7	223801.2	222616.1	225175.7	107947.6

Table 3.2: Latent-Class Analysis Results: Characteristics of the Five Student traveler/ lifestyle groups

(n = 6502)	Transit Riders	Walkers	Cyclists	Occasional Drivers	Drivers
	33%	**19%**	**15%**	**11%**	**22%**
Have used a Car in the last Month	0.2218	0.1105	0.0944	0.4674	**0.6242**
Have used Public Transit in the last Month	0.9393	0.3541	0.5078	**0.957**	0.7121
Have Active Transit in the last Month	0.2054	0.8497	**0.9449**	0.1878	0.1198
Number of trips made on day of travel diary					
1-2 Trips	**0.5924**	0.5761	0.0904	0.3241	0.4709
3-4 Trips	0.2981	0.2977	0.3384	**0.3982**	0.3211
> 4 Trips	0.1095	0.1262	**0.5713**	0.2777	0.208
Distance travelled on day of diary					
Less than 2km	0.0009	**0.2671**	0	0	0.0146
Between 2-5km	0.0273	**0.5828**	0.113	0.0339	0.039
Between 5-10km	0.1161	0.1357	**0.4878**	0.0922	0.0833
Greater than 10km	0.8557	0.0144	0.3992	**0.874**	0.8632
Time spent travelling on day of diary					
1-29 minutes	0.0037	**0.2305**	0	0.0042	0.0791
30 - 59 minutes	0.0668	**0.5032**	0.0984	0.0574	0.1634
> 60 minutes	0.9294	0.2663	0.9016	**0.9383**	0.7575
Percent of travel completed using Public Transit					
0-20%	0.0118	0.9874	0.7501	0.1191	**1**
20-40%	0	0	0.0743	**0.1216**	0
40-60%	0	0.0126	0.053	**0.5744**	0
60-80%	0	0	0.1062	**0.185**	0
80-100%	**0.9882**	0	0.0165	0	0
Percent of travel completed using active transit					
0-20%	**1**	0.0028	0.0864	0.8117	**1**
20-40%	0	0	**0.1236**	0.0886	0
40-60%	0	0.0271	0.0892	**0.0981**	0

60-80%	0	0	**0.0709**	0.0016	0
80-100%	0	**0.9702**	0.6299	0	0
Percent of travel completed by Car					
0-20%	**1**	0.9909	0.916	0.2458	0
20-40%	0	0	0.0181	**0.1349**	0
40-60%	0	0.0091	0.0228	**0.5163**	0.004
60-80%	0	0	0.0237	**0.103**	0.0009
80-100%	0	0	0.0193	0	**0.995**
Attitudes and perceptions: I prefer to drive when possible					
Strongly disagree	0.1027	0.1593	**0.3608**	0.0719	0.0404
Disagree	0.237	0.3081	**0.4176**	0.2116	0.1927
Neutral	0.2417	**0.2432**	0.1428	0.238	0.2143
Agree	0.2562	0.2114	0.0687	0.2941	**0.3311**
Strongly agree	0.1625	0.078	0.0101	0.1843	**0.2214**
Attitudes and perceptions: I prefer to walk when possible					
Strongly disagree	0.0379	0.0212	0.0159	0.0394	**0.0475**
Disagree	0.1272	0.0921	0.1205	**0.1496**	0.1486
Neutral	0.2364	0.2179	0.1414	0.2416	**0.2741**
Agree	0.4036	**0.4467**	0.4086	0.4061	0.3787
Strongly agree	0.1949	0.2222	**0.3136**	0.1634	0.1511
Attitudes and perceptions: I prefer to bike when possible					
Strongly disagree	0.1203	0.0982	0.0454	0.1404	**0.1618**
Disagree	0.2186	0.1899	0.1281	0.244	**0.2764**
Neutral	**0.2856**	0.2605	0.1685	0.2526	0.2728
Agree	0.2488	**0.2912**	0.2805	0.2785	0.2052
Strongly agree	0.1267	0.1601	**0.3775**	0.0845	0.0838
Attitudes and perceptions: I prefer transit when possible					
Strongly disagree	0.0727	0.1002	0.0906	0.0859	**0.1502**
Disagree	0.1832	0.2954	**0.3248**	0.2117	0.2701
Neutral	0.3054	**0.3378**	0.2858	0.3134	0.288
Agree	**0.3539**	0.2291	0.2479	0.3248	0.2388
Strongly agree	**0.0848**	0.0375	0.0508	0.0642	0.0529
Attitudes and perceptions: Time spent travelling is wasted time					
Strongly disagree	0.0351	0.0379	**0.0764**	0.019	0.0229
Disagree	0.1485	0.2172	**0.3565**	0.1181	0.1392
Neutral	0.244	**0.3031**	0.2592	0.2525	0.2372
Agree	0.3143	0.297	0.2149	**0.3601**	0.3478
Strongly agree	**0.2581**	0.1449	0.093	0.2503	0.2529

Attitudes and perceptions: I limit my driving to improve air quality					
Strongly disagree	0.0821	0.056	0.0275	0.0813	**0.0831**
Disagree	0.1551	0.1389	0.0747	0.2188	**0.2418**
Neutral	**0.4417**	0.4173	0.2782	0.3961	0.3695
Agree	0.2251	0.2608	**0.3639**	0.2355	0.2369
Strongly agree	0.096	0.127	**0.2557**	0.0683	0.0687
Attitudes and perceptions: Car safer overall than transit					
Strongly disagree	0.1368	0.1235	**0.2999**	0.103	0.0857
Disagree	0.3464	0.3561	**0.425**	0.3437	0.3137
Neutral	0.358	0.3763	0.2256	0.3551	**0.3967**
Agree	0.1151	0.1163	0.0441	**0.1498**	0.1375
Strongly agree	0.0438	0.0279	0.0054	0.0484	**0.0664**
Attitudes and perceptions: Car is safer overall than cycling					
Strongly disagree	0.0361	0.034	**0.0876**	0.0146	0.0156
Disagree	0.1244	0.1151	**0.1792**	0.1093	0.0912
Neutral	0.2413	**0.2604**	0.1573	0.2405	0.2185
Agree	0.4274	0.4381	0.4494	0.4505	**0.4696**
Strongly agree	0.1707	0.1524	0.1264	0.1852	**0.2051**

Note: Bolded values are the highest probabilities for that parameter, and are bolded to facilitate interpretation **only.**

The majority of Transit Riders utilized transit for nearly all of their daily travel (Table 3.2). While they are extremely dependent on transit use, a slightly higher 20.54% reported using active modes of transportation in the last month, suggesting that 1 in 5 transit users may walk or cycle to their origin and/or destination (Table 3.2). They are the most likely to express a preference for transit when possible and were also the most likely to perceive travel as wasted time (25.81% strongly agree) (Table 3.2). Transit users make up the largest proportion of travel types in the High Density Urban Core neighbourhoods.

Walkers were heavily dependent on walking as their sole method of travel with 97.02% using active transit to complete the majority of their travel. Walkers are distinct from cyclists by their significantly shorter average trip distance (58.28% had average trips of 2-5km and 26.71% had trips less than 2k) (Table 3.2). Walkers were also spending the least amount of time traveling per day of all traveler types with almost 1 in 4 spending less than

30 minutes travelling in a full day (Table 3.2). They are also far more preference neutral regarding their travel preferences than any other traveler type.

Similar to walkers, the majority of cyclists complete almost all of their travel using active transportation (Table 3.2). However, unlike the walkers slightly over 10% of cyclists complete some of their daily travel utilizing public transit as well (Table 3.2). Cyclists also travel significantly longer distances per trip with half making average trips between 5-10km (Table 3.2). They also express the greatest overall preference for cycling as well as walking, and are the most likely to report limiting their driving to reduce air pollution (Table 3.2). Interestingly, they are also the least likely of all groups to disagree that travelling is wasted time (Table 3.2).

Occasional drivers, unlike the previous two classes demonstrated more flexibility in their reported travel patterns with 57.44% completed roughly half of their travel by transit, 51.63% completing half of their travel by car and an estimated 9.81% completed 40-60 percent of their travel using active transportation (Table 3.2). It is also important to note that no individuals in the occasional driver class were estimated to complete more than 80% of their travel using only one mode, cementing them as multimodal travelers (Table 3.2). Occasional drivers were the most likely individuals to have average trips greater than 10km and correspondingly, were the most likely to spend greater than 60 minutes travelling (Table 3.2).

Drivers are differentiated from occasional drivers by the degree of their automobile dependency. The clear majority of their travel is completed utilizing a private vehicle, and had an average trip length greater than 10km (Table 3.2). Only 11.98% reported active travel in the last month, the lowest of all of our groups, and they are the most likely to see driving as the safest overall form of transportation (Table 3.2).

3.2 Neighbourhood Typologies

3.2.1 Factor Analysis

The results of our principal component factor analysis produced 6 clearly identifiable factors, which were interpreted and defined as follows: Density, mix of uses, transit accessibility, intensity of use, neighbourhood maturity and cycling access. These six factors explain a total of 85% of the variance in the data (Table 3.3).

Table 3.3: Principal component factor analysis results

	Factor					
	Density	**Mix of Uses**	**Inaccess ibility of Transit**	**Intensity of use**	**Neighbo urhood Maturity**	**Cycling Access**
Intersection Density (km²)*	.513		-.613			
Population Density (km²)*	.915					
Housing Density (km²)*	.892					
Street Network Density (km²)*	.863					
Percent of Roadways > 60km/h (%)	-.892					
Activity Density (Emp+Pop)	.901					
Employment Density (km²)*	.404	.735				
Percent of Residential Area (%)	.494	-.567				

Jobs Housing Balance (Shannon Entropy)		.880				
Job Activity Share (%)		.853				
Average Number of Transit Trips per hour (Weekday/ PeakAM)			-.839			
Average Number of Transit Stops (DA)			-.776			
Average Building Height (Dissemination Area)				.770		
Proportion of Single Family Housing (%)				-.591		
Proportion of Residential built in the last 10 years (%)					.867	
Proportion of Residential Older than 35 Years (%)					-.748	
Dedicated Cycling Infrastructure Density (km²)*						0.98
SS Loadings	4.914	2.591	2.495	1.477	1.353	1.014
Proportion of Variance	28.9%	15.2%	14.7%	8.7%	8.0%	6.0%
Cumulative variance	28.9%	44.1%	58.8%	67.5%	75.5%	81.5%

*Note: * Log of variable was taken*
Extraction Method: *Principal Component Analysis.*
Rotation Method: *Varimax with Kaiser Normalization.*

3.2.2 Cluster Analysis

These six factor scores were then utilized in a k-means cluster analysis. Clusters were created using the 16 built form characteristics of our 11,519 dissemination area's resulting in the highest resolution neighbourhood typology analysis possible using spatially aggregated data in Canada. A combination of internal cluster indices along with a visual "sanity check" of the results in a GIS environment was utilized to determine the final number of clusters for the 11,500 DA's (Lin and Long 2008). There exist a wide variety of both internal (data driven) and external (results driven) indicies to identify the ideal number of clusters to use in an analysis (Ralph et al. 2016; Eshghi et al. 2011; Schreiber and Pekarik 2014; Lin and Long 2008). Given that our analysis is estimating an unknown number of clusters from our built environment characteristics, we calculated a total of 9 internal cluster indices. While most of the indices indicate an ideal cluster size of < 5, "sanity tests" on these clusters conducted using orthophotography in neighbourhoods we know very well (a type of ground-proofing, if you will) found that 4 clusters were not adequately describing the varieties of built form. The second most common index result was 7 clusters, which was reported by both the "Ball-Hall" and "Calinski-Harakasz" indices.

Plotting the result of indices can also provide insights into the selection of clusters; in particular, looking for "elbows" or points of significant declines in model fit can act as guides for selection (Lin and Long 2008). Plotting the result of the "C' Index", which was the only index to indicate a solution with > 7 clusters, a significant 'elbow' at 7 clusters can be observed, with the ideal estimate of 12 clusters being only marginally better than 7 (Figure 3.1). Given that two other indices suggested a 7-cluster solution, and 7 clusters were also found to produce well defined neighbourhood types which pass sanity checks it was then selected as the final cluster model.

Figure 3.1: Plot of the Calinski-Harabasz and C'Index internal cluster indices

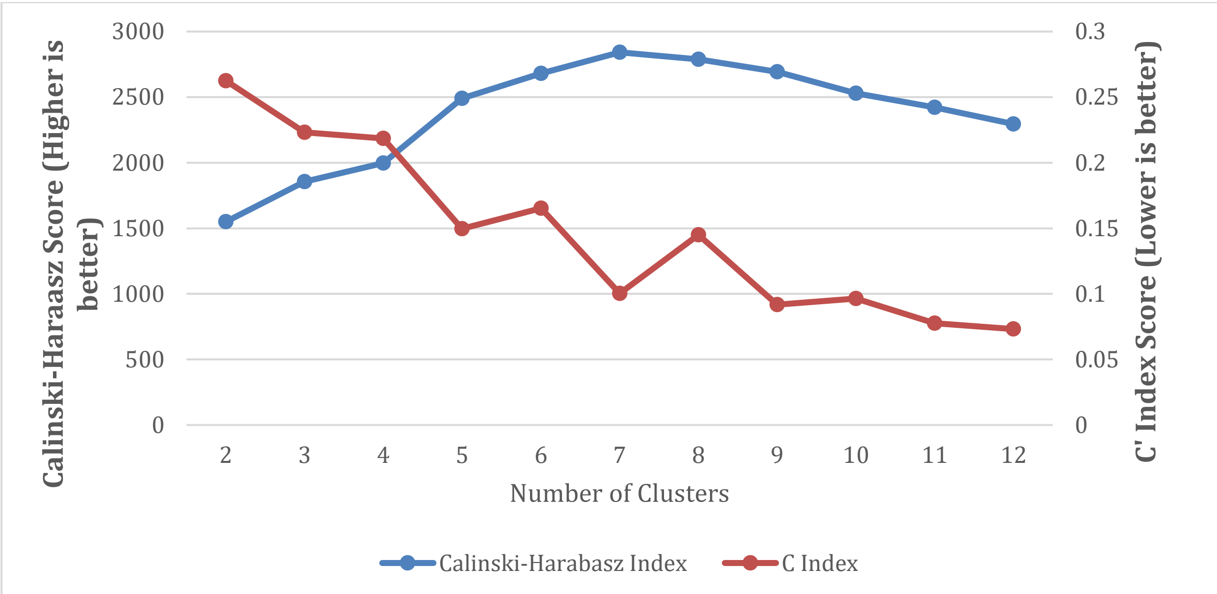


Figure 3.1 shows the identified cluster centers which were interpreted into the following 7 neighbourhood types. These clusters can be seen in Figure 3.2 and the characteristics of each neighbourhood can be found summarized in Table 3.4. All variables were subjected to a one-way ANOVA and statistically significant differences were found between all neighbourhoods ($p < 0.000$).

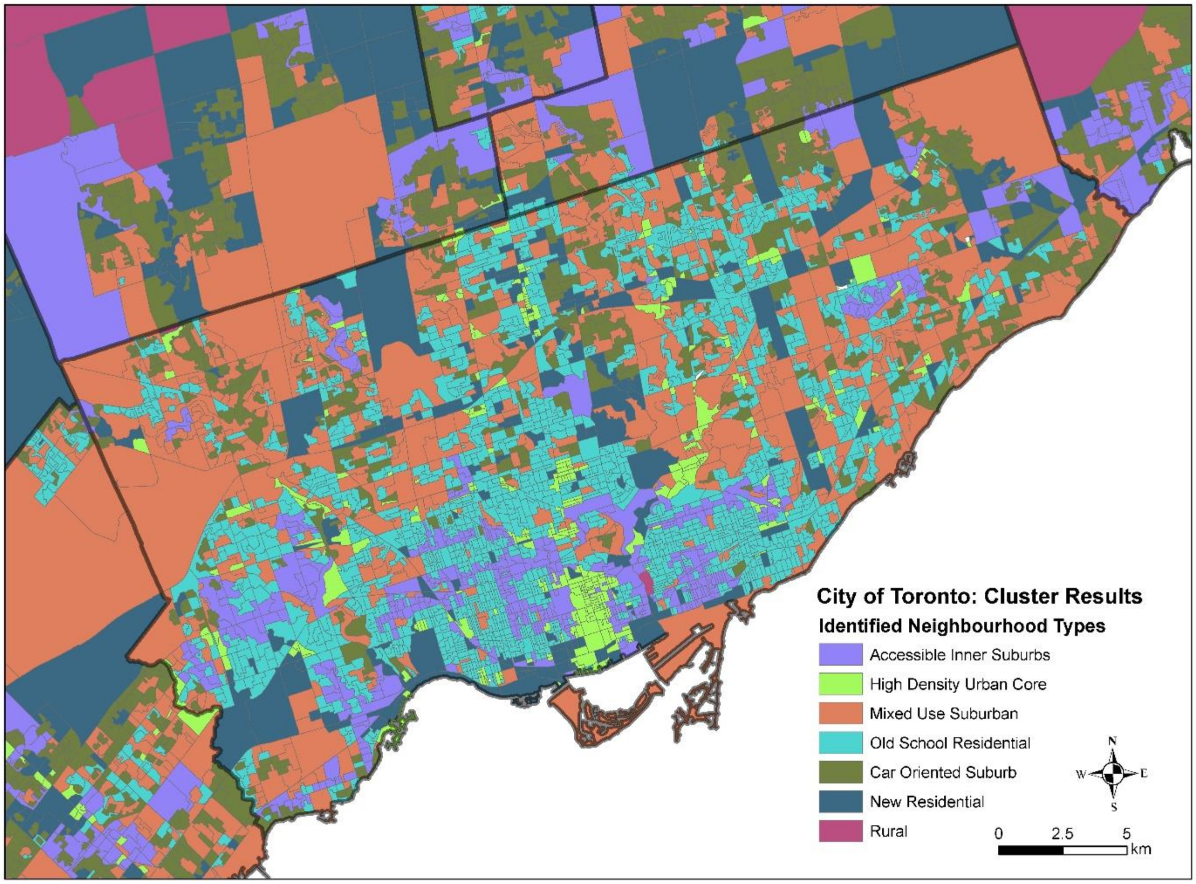
Table 3.4: Built environment characteristics of identified neighbourhood types

(N = 11519)	Rural	Car oriented suburbs	Mixed Use Suburban	Accessible Inner Suburbs	New Residential	Old Urban Residential	High Density Urban Core
	Mean (StDev)	Mean (StDev)	Mean (StDev)	Mean (StDev)	Mean (StDev)	Mean (StDev)	Mean (StDev)
Percentage of DA's	6.78%	33.82%	18.81%	11.23%	6.58%	18.93%	3.81%
Percentage of Land Area	78.74%	4.33%	6.10%	2.49%	6.89%	1.21%	0.21%
Average Building Height (Meters/Dissemination Area)	0.15 (0.26)	0.43 (0.47)	0.59 (0.57)	0.8 (0.83)	0.59 (0.68)	0.6 (0.58)	4.54 (3.55)
Activity Density (Jobs+Population)	69.18 (94.05)	4928.63 (3182.16)	5149.09 (7751.44)	7278.25 (14682.6)	5694.58 (11329.75)	7990.34 (6334.25)	41043.64 (48689.26)
Employment Density (km²)	17.25 (71.82)	213.94 (602.37)	1987.62 (6286.4)	1832.75 (12979.78)	2003.13 (7989.3)	1284.3 (3010.19)	14626.97 (37835.38)
Street Network Density (km²)	1731.73 (899.39)	13157.44 (4081.11)	10793.59 (4030.48)	13945.48 (5798.12)	10290.26 (5768.8)	16304.62 (5052.05)	13287.98 (7136.87)
Intersection Density (km²)	3.62 (5.36)	101.69 (44.63)	85.65 (43.12)	129.22 (90.03)	74.28 (75.15)	171.81 (94.7)	169.24 (112.19)
Population Density (km²)	51.93 (60.36)	4714.68 (3054.32)	3161.47 (3382.13)	5445.49 (5672.17)	3691.46 (6697.94)	6706.04 (4941.46)	26416.68 (30262.19)
Housing Density (km²)	19.62 (23.26)	1612.13 (1231.19)	1364.59 (1897.64)	2422.9 (3301.94)	1955.66 (4276.82)	2825.19 (2521.57)	14625 (13863.96)
Proportion of Single Family Housing (%)	0.96 (0.09)	0.86 (0.21)	0.66 (0.31)	0.7 (0.33)	0.74 (0.34)	0.65 (0.29)	0.04 (0.07)

Average Number of Transit Trips per hour (Weekeday/PeakAM)	0.37 (3.76)	16.33 (17.92)	23.65 (29.17)	47.84 (47.87)	33.36 (51.3)	81.57 (47.3)	120.08 (66.38)
Average Number of Transit Stops (DA)	0.35 (1.66)	13.79 (11.37)	14.97 (14.28)	30.72 (18.88)	18.66 (17.9)	37.79 (15.03)	52.61 (30.99)
Percent of DA dedicated to Parks/Rec (%)	0.36 (0.43)	0.05 (0.13)	0.13 (0.2)	0.09 (0.19)	0.1 (0.2)	0.04 (0.1)	0.08 (0.19)
Percent of Residential (%)	0.4 (0.44)	0.93 (0.17)	0.54 (0.3)	0.79 (0.28)	0.69 (0.36)	0.93 (0.15)	0.59 (0.43)
Percent of Commercial/Government (%)	0.01 (0.06)	0 (0.02)	0.16 (0.22)	0.06 (0.15)	0.07 (0.17)	0.03 (0.09)	0.15 (0.3)
Percent of Industrial (%)	0.05 (0.2)	0 (0.05)	0.17 (0.28)	0.05 (0.16)	0.11 (0.25)	0.01 (0.06)	0.17 (0.34)
Jobs Housing Balance (Shannon Entropy)	0.23 (0.23)	0.18 (0.16)	0.69 (0.21)	0.42 (0.28)	0.45 (0.26)	0.36 (0.23)	0.35 (0.24)
Job Activity Share (%)	0.13 (0.2)	0.03 (0.05)	0.35 (0.22)	0.16 (0.2)	0.24 (0.26)	0.08 (0.1)	0.29 (0.27)
Proportion of Residential built in the last 10 years (%)	0.08 (0.09)	0.04 (0.05)	0.05 (0.07)	0.07 (0.09)	0.5 (0.2)	0.04 (0.05)	0.12 (0.14)
Proportion of Residential Older than 35 Years (%)	0.58 (0.23)	0.39 (0.37)	0.7 (0.28)	0.56 (0.37)	0.15 (0.17)	0.86 (0.15)	0.54 (0.3)
Proportion of Roadways > 60km/h	0.85 (0.23)	0.01 (0.06)	0.03 (0.09)	0.02 (0.08)	0.09 (0.18)	0.01 (0.05)	0.02 (0.08)
Dedicated Cycling Infrastructure Density (km^2)	84.13 (757.23)	0.02 (0.36)	1.79 (29.49)	443.91 (683.24)	223.12 (899.51)	0.11 (2.02)	28.81 (110.69)

Note: Values show

Figure 3.2: Map showing the clustering results for the city of Toronto



<u>Rural</u> – Characterized by large open areas and farmland. Poor land use mixing due to the size of dissemination areas, but a relatively high non-residential intensity representative of the industrial/farming activities (Table 3.4, Figure 3.3).

<u>Car Oriented Inner Suburbs</u> – Car oriented inner suburbs are characterized by a relatively high residential density, and a nearly complete focus on car travel. They have very low transit accessibility, poor cycling infrastructure access and a very low mix of land uses (Table 3.4, Figure 3.3).

Mixed Use Sub-Urban - Mixed use suburban landscapes are defined by a higher jobs/housing balance than typical suburban neighbourhoods combined with a relatively poor transit accessibility, suggesting potential dependence on privately owned automobiles for everyday travel needs (Table 3.4, Figure 3.3).

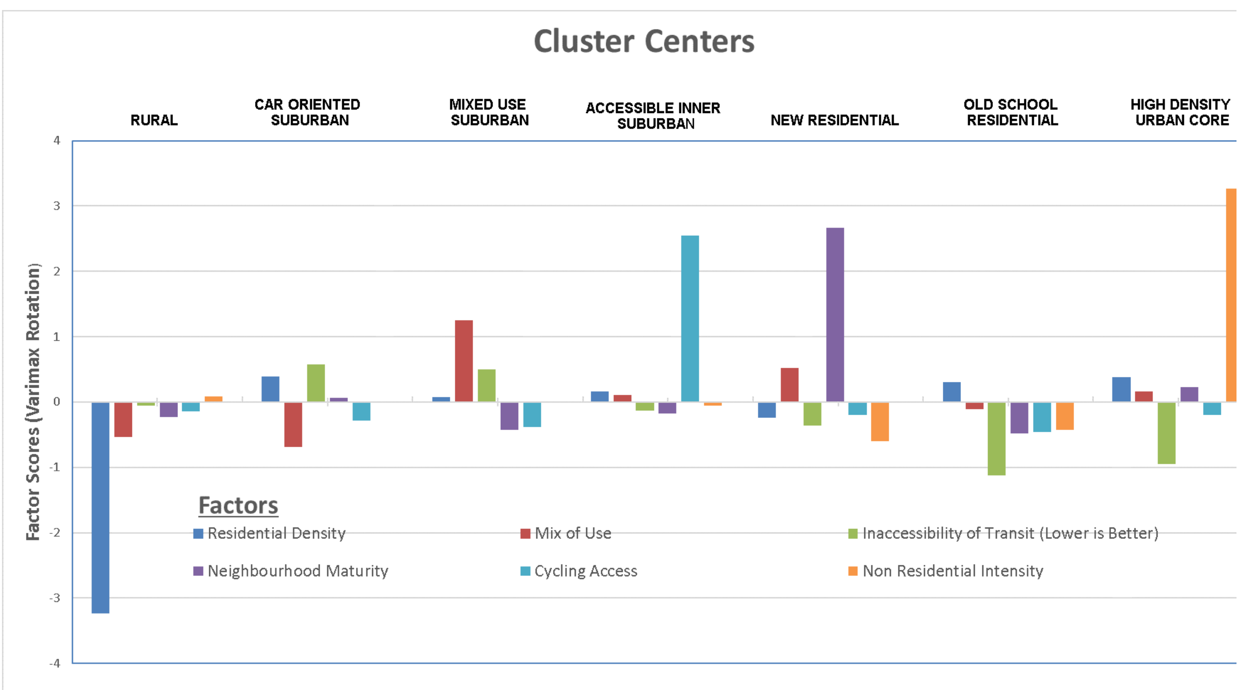
New Residential – New Residential neighbourhoods are identified by a high proportion of development in the last 10 years. Very low non-residential intensity and a high land use mix suggest a focus on residential land use combined with low intensity commercial and retail (Table 3.4, Figure 3.3).

Accessible Inner suburbs – Sharing many traits in common with their less accessible cousin, accessible inner suburbs are characterized by higher transit accessibility and a much higher access to cycle friendly built form. A slightly higher maturity may indicate closer proximity to main streets and the benefits that brings for mobility.

Old Urban Residential – These neighbourhoods are characterized by their age, with most of the residential developments being 35+ years old. Post-war suburbs with little land use mixing and very little non-residential intensification, but generally with very good transit service (Table 3.4).

High Density Urban – High density urban areas are defined very high residential densities; very high intensity non-residential land uses and excellent transit and cycling access. These neighbourhoods can take a variety of forms depending their location; Residential tower block in the suburbs, central business districts in the downtown core, or highly mixed use areas, such as North York and Scarborough centers (Table 3.4, Figure 3.3).

Figure 3.3: Identified cluster centers (k-means cluster analysis)



Correlates of Transportation Lifestyles and Neighbourhood Types

Table 3.5 contains summary statistics for each of the variables as well as the neighbourhood distributions of each traveler type, defined on the basis of their transportation characteristics/ lifestyles. Statistically significant differences between classes were analyzed using Chi-square (categorical variables) and one-way ANOVA's (continuous variables) and all were found to be significant p < 0.000; Table 3.5).

Table 3.5: Characteristic profiles for each of the identified traveler types

			Latent Class			
(N = 6502)	**Transit Riders**	**Walkers**	**Cyclists**	**Occasional Driver**	**Drivers**	**p-Value**
	Mean (StDev)	Mean (StDev)	Mean (StDev)	Mean (StDev)	Mean (StDev)	
Percentage of Individuals	**33%**	**19%**	**15%**	**11%**	**22%**	
Household Size	3.18 (1.57)	2.67 (1.86)	2.53 (1.34)	3.46 (1.57)	3.61 (1.61)	**0.000**
Number of Dependant Children	0.14 (0.34)	0.05 (0.21)	0.04 (0.21)	0.16 (0.37)	0.20 (0.4)	**0.000**
Mean Trip Length (km)	12.29 (10.84)	1.31 (1.43)	3.41 (8.54)	13.02 (12.85)	16.78 (19.29)	**0.000**
Total Number of Trips	2.82 (1.35)	2.84 (1.41)	4.34 (2.27)	3.77 (1.99)	3.3 0(1.78)	**0.000**
Respondent Age (years)	23.65 (6.75)	23.43 (5.89)	25.58 (7.2)	23.46 (6.71)	25.73(9.74)	**0.000**
Possess a Drivers License (%)						
Yes	51.4%	56.5%	66.8%	60.4%	81.1	**0.000***
Access to a Vehicle (%)						
No vehicle	40.7%	75.7%	73.4%	23.5%	8.2	**0.000***
One vehicle	36.6%	18.3%	20.6%	37.3%	31.8	

Two or more	22.7%	6.0%	6.0%	39.2%	60	
Owns a bike (%)						
Yes	42.1%	38.2%	61.5%	50.3%	50.8	**0.000***
Owns a transit pass (%)						
Yes	66.1%	14.1%	12.3%	54.4%	27.9	**0.000***
Owns a Presto card (%)						
Yes	33.6%	29.9%	25.8%	44.8%	47.2	**0.000***
Mode choice by gender (%)						
Male	35.6%	20.9%	14.6%	9.6%	19.4%	**0.000***
Female	32.0%	18.1%	14.1%	12.3%	23.5%	
Living situation (%)						
Live alone	12.9%	24.1%	17.9%	7.3%	6.5%	
Live with family/parents	53.4%	11.5%	10.2%	65.8%	58.2%	
Live with partner	12.6%	13.8%	21.6%	11.7%	16.9%	**0.000***
Live with roommates	21.1%	50.6%	50.3%	15.2%	8.4%	
Neighbourhood Distribution (%)						
Poor Mobility Inner Suburb	35.8%	3.1%	1.6%	17.4%	42.2%	
High Density Urban Core	27.5%	35.9%	22.2%	6.4%	8.0%	
Accessible Inner Suburbs	24.0%	30.2%	21.2%	8.8%	15.9%	
Residential Redevelopment	33.4%	18.2%	7.1%	14.1%	27.2%	**0.000***
Mixed Use Suburban	33.4%	18.2%	7.1%	14.1%	27.2%	
Old School Residential	41.1%	14.1%	19.9%	10.5%	14.4%	
Rural	12.2%	0.0%	2.4%	19.5%	65.9%	

*Note: *p-values for variables with an asterisk are from a Chi-Square Test. All others were tested using a one-way*

3.3 Regression Results

Results from multinomial regression models suggest a strong correlation between an individual's travel characteristics and the neighbourhoods they live in (Table 3.5). An individual's travel type was estimated in relation socio-demographic and built form characteristics and the log-likelihood estimations of outcomes were made with car focused travellers as a reference.

Table 3.6: Multinomial regression results: Factors Associated with Traveler Types (Reference: Drivers)

(n = 6502)	Transit Riders	Walkers	Cyclists	Occasional Drivers
	Coef (S. E.)	Coef (S. E.)	Coef (S. E.)	Coef (S. E.)
Transit Pass Owner - Ref: No	**1.263 (0.083)*** **	**-0.726(0.120)*** **	**-0.910 (0.134)*** **	**0.923 (0.100)*** **
Presto Pass Owner - Ref: No	-0.084 (0.084)	**-0.356(0.107)*** **	**-0.496(0.116)*** **	**0.171 (0.100)* **
Bike Owner - Ref: No	0.088 (0.081)	**0.185 (0.104)* **	**0.955(0.110)*** **	**0.237(0.097)** **
University Affiliation (Ref: Full Time) - Continuing Education	0.141 (0.289)	-0.187 (0.395)	-0.006 (0.370)	-0.483 (0.436)
University Affiliation (Ref: Full Time) - Part Time	**-0.272(0.151)* **	-0.307 (0.201)	-0.040 (0.194)	-0.158 (0.185)
Possess a Driver License (Ref: No) - Yes	**-0.960(0.093)*** **	**-0.924 (0.115)*** **	**-0.721(0.124)*** **	**-0.711(0.111)*** **
Respondent Age	**-0.021(0.006)*** **	**-0.033(0.008)*** **	**-0.007 (0.008)**	**-0.017(0.008)** **
Gender (Ref: Female) - Male	**0.457(0.085)*** **	**0.440(0.105)*** **	**0.267(0.112)** **	0.033 (0.105)
Household Size	0.003 (0.032)	0.027 (0.038)	**-0.091(0.044)** **	-0.016 (0.039)

Number of Dependent Children	-0.031 (0.111)	0.072 (0.183)	-0.261 (0.211)	-0.015 (0.131)
Vehicle Access (Ref: None) - One Car	**-1.226(0.132)*** **	**-1.746(0.145)*** **	**-1.826(0.150)*** **	**-0.813(0.161)*** **
Vehicle Access (Ref: None) - Two or More Cars	**-2.102(0.149)*** **	**-2.681(0.191)*** **	**-2.762(0.207)*** **	**-1.340(0.179)*** **
Living Situration (Ref: Alone) - Family/Parents	-0.025 (0.178)	**-1.140(0.208)*** **	**-0.662(0.231)*** **	0.360 (0.228)
Living Situration (Ref: Alone) - Partner	-0.280 (0.174)	**-0.451(0.187)** **	0.159 (0.193)	-0.016 (0.228)
Living Situration (Ref: Alone) - Roomates	0.231 (0.186)	0.195 (0.192)	**0.808(0.205)** **	**0.437(0.237)* **
Lives in an Accessible Inner Suburb (Ref: Poor Mobility Inner Suburb)	-0.011 (0.139)	**1.470(0.251)*** **	**1.613(0.305)*** **	0.078 (0.164)
Lives in a High Density Urban Core (Ref: Poor Mobility Inner Suburb)	**0.259(0.157)* **	**1.780(0.258)*** **	**1.739(0.313)*** **	0.127 (0.193)
Lives in a Mixed Use Sub-urban Neighbourhood (Ref: Poor Mobility Inner Suburb)	**0.350(0.137)** **	0.280 (0.309)	0.460 (0.373)	0.246 (0.163)
Lives in an Old Urban Neighbourhood (Ref: Poor Mobility Inner Suburb)	**0.468(0.130)*** **	**1.296(0.252)*** **	**1.946(0.301)*** **	0.258 (0.157)
Lives in New Residential Neighbourhood	-0.036 (0.132)	**0.917(0.254)*** **	**0.569(0.320)* **	0.106 (0.153)

(Ref: Poor Mobility Inner Suburb)				
Lives a Rural Area (Ref: Poor Mobility Inner Suburb)	**-0.862(0.507)***	-3.189 (4.049)	0.038 (1.071)	0.199 (0.398)
Primary Moving Factor is Walkability/Cyclability (Ref: Other reason)	0.108 (0.148)	**1.322(0.152)*****	**1.190(0.158)*****	0.172 (0.185)
Primary Moving Factor is Cost of Housing (Ref: Other reason)	0.092 (0.089)	0.142 (0.130)	0.062 (0.138)	0.120 (0.106)
Primary Moving Factor is Transit Access (Ref: Other reason)	**0.796(0.147)*****	0.293 (0.209)	0.213 (0.226)	**0.621(0.175)*****
Constant	**1.884(0.272)*****	**1.533(0.371)*****	0.037 (0.417)	0.166 (0.340)
Akaike Inf. Crit.	*15,117.400*	*15,117.400*	*15,117.400*	*15,117.400*
Null Deviance				*14917.4*
Residual Deviance				*10014.58*
McFadden's R2				*0.255*
Note:				**** p<0.1 **p<0.05*** p<0.01***

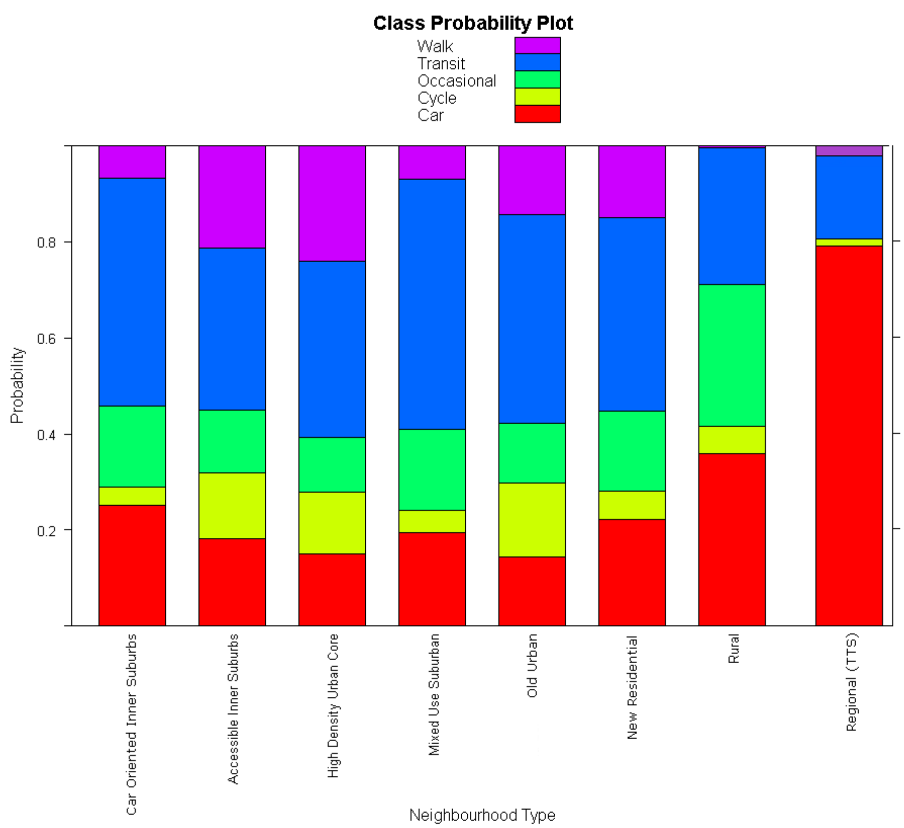
Neighbourhood built form characteristics were found to significantly correlate with different types of travel. A stacked probability plot, created from observed probabilities of each traveller type in each neighbourhood clearly demonstrates the differential distributions of traveller types in different neighbourhoods across the study area, compared with regional mode shares from the 2011 Transportation Tomorrow Survey (the TTS is the key travel behavior survey used for studying transportation in the GTHA (Figure 3.2) (Data Management Group, 2012).

Unsurprisingly, living in a high density urban core neighbourhood was found to increase the odds of active transportation (walking and cycling) more than any other neighbourhood type (Table 3.6). Interestingly, despite having the highest overall transit accessibility, high density urban core neighbourhoods only slightly increased the odds of being a transit user relative to a car use (Table 3.6). Students living in accessible inner suburban neighbourhoods had significantly higher odds of both walking and cycling in reference to car users, however once again, despite relatively high transit accessibility and service, transit use was found to be no more likely than car usage (Table 3.6). It was those living in an Old Urban neighbourhood that demonstrated the highest overall likelihood of utilizing car-alternative modes; Here students had greatest odds of being a cyclist and were also the most likely to be transit users (Table 3.6). The New Residential neighbourhoods demonstrate a strong focus on walkability, with the odds of being a walker significantly higher relative to car users (Table 3.6). Students living in mix-use suburban neighbourhoods significantly increased the odds of being a transit user relative to car users, but are no more likely to walk, cycle, or be occasional drivers in comparison to other neighbourhood types (Table 3.6). Occasional drivers were not found to be significantly more or less likely live in any particular neighbourhood type , when compared to drivers (Table 3.6).

With regard to socio-demographic characteristics of travellers, student status was found to significantly influence traveller types, with part time students being less likely to be transit users than full time students (Table 3.6). Age was found to significantly correlate with travel behaviors; the odds of being an occasional driver, transit user or walker declined with age, in reference to car users (Table 3.6). An increase in household size significantly reduced the odds of cycling (Table 3.6). Gender of traveller also appears to have an influence on travel behavior, with males having significantly higher odds of walking, cycling and public transit than females (Table 3.6). Finally, living situations were found to have varying impacts on travel behaviors. For those living with family, the odds of utilizing active transportation declined significantly in reference to those living alone (Table 3.6). Living with a partner significantly reduced the odds of being a walker (Table 3.6) and living with roommates increased the odds of being a cyclist (Table 3.6) or an occasional driver (Table 3.6).

Unsurprisingly, possessing a bus pass increases the likelihood of being classified as a transit user *or* an occasional driver however, interestingly, also significantly decreased the odds of walking or cycling (Table 3.6). Possessing a regional transit pass (such as a Presto card), has a similar but less substantial decrease in the likelihood of active travel as well (Table 3.6). However, possessing a regional transit pass significantly increases the odds of being an occasional driver (*Coef* = 0.171, p = 0.088; Table 3.6). As would be expected, bike ownership increases the likelihood of being an cyclist or a walker but surprisingly also increased the odds of being an occasional driver (Table 3.6). Having access to a vehicle was found to drastically change travel behaviors, as access to a vehicle decreased the odds of all

Figure 3.3: Probability plot showing observed probabilities of traveler types in each neighbourhood compared with regional mode shares



non-car related travel (Table 3.6). This decrease was *substantially* higher if students had access to 2 or more vehicles, particularly in respect to active transportation (Table 3.6). Similarly, the possession of a driver's license was found to significantly decrease the odds of all traveller types when compared to car users (Table 3.6).

Finally, strong correlations were observed between the primary reason for an individual's chosen housing location and their travel type; those who reported choosing their neighbourhood for it's walkability or cyclability was indeed more likely to be walkers or cyclists relative to drivers (Table 3.6). The same can be said for those who reported moving for better transit accessibility, these individuals were more likely to be transit users or occasional drivers as opposed to dedicated car users (Transit: *Coef* = 0.796, p = 0.000; Occasional Driver: *Coef* = 0.691, p = 0.000; Table 3.6). Moving due to housing costs appears to have no correlation with travel behaviors.

4 Discussion and Implications

The results from this study clearly indicate that unique transportation lifestyles exist within post secondary students and that these lifestyles contribute to significantly different travel profiles. The observed differences between each of the traveller types were in some cases substantial, and the relationship with the built environment much less modest than what is suggested in the existing literature (Ewing and Cervero 2010; Bento et al. 2005). Further, significant differences in the socio-demographics paint very different pictures about the lives of these students, and shed some light on how travel behavior is likely the result of a complex set of factors.

What is encouraging is that in comparison to findings from the United States (Ralph et al., 2016), the millennials in Canada appear to be a significantly less car dependent. However, this difference, at least to some degree, can relate to less personal wealth, as this study only looks at millennials who are post-secondary students.

Similar to the findings of Kitamura et al (1997), students in the GTHA appear to hold very strong preferences toward specific types of travel which contribute significantly to their overall decision making; (Tables 3.2, 3.6). Specifically, cyclists have very strong preferences for active transportation, show a marked disinclination toward other forms of travel (particularly the car) and as such are least likely to perceive their travel time as being wasted (Table 3.5). Powerful attitudes such as this clearly demonstrate that the decision to cycle over driving is about more than simply finances or convenience, and while attitudes are much less vigorous in the other lifestyles, they are not absent and demonstrate that to varying degrees, attitudes and preferences are playing some role in travel patterns. They also emphasize the tremendous complexity in drawing causal conclusions when examining travel behaviors, as each traveler type is likely motivated by different factors and to varying degrees. This also underlines the value of creating traveler typologies, as it allows the exploration of these differing motivating factors. Such as how cyclists appear to be heavily driven by attitudes and perceptions, while transit users a

However, these findings do not necessarily indicate the establishment of fundamental changes in travel behavior. For example, it was found that students having access to any number of vehicles *significantly* decreased the likelihood of being anything but a car user. Similarly, possessing a driver's license significantly decreased the likelihood of being anything other than a car user (Table 3.5). There is also indirect evidence suggesting that the changes may, at least to some degree, be explained by vehicle access. For example, as age increases the likelihood of being a transit, walker or occasional driver declined relative to being a car user (Table 3.5). Keeping these findings in mind, while our results do indicate that post-secondary students are highly diverse in their travel preferences and subsequent activities, this diversity may not be indicative of a major shift away from car travel. In this regard, our findings are provides evidence to what has been previously hypothesized by Ralph et al. (2016), who noted that the changes in millennials' travel appear to be less about changes in attitudes, and more about access to a vehicle.

The implications of these findings are significant, as they may lend further credence to the assertion that the changes in travel behavior we are seeing have less to do with fundamental shifts in the attitudes and perceptions towards travel or the proliferation of multi-modal built environments, and more to do with vehicle access.

Mirroring the results of the substantial existing research base, we found significant correlations between our identified neighbourhood typologies and the travellers types that reside within them (Ewing et al. 2011; Ewing and Cervero 2010; Krizek 2003; Cao, Mokhtarian, and Handy 2009). However, in contrast to research that has typically found only modest correlations between built environment and travel behaviors, our results show a greater variety and magnitude of associated correlations. Interestingly, much like the findings of Ralph et al. (2016), "Old Urban" neighbourhoods identified in our typology appear to be the most attractive overall neighbourhood type from the perspective of non-car travel (Ralph et al. 2016; Voulgaris et al. 2016). With the exception of occasional drivers, students living in an old urban neighbourhood had significantly higher odds of using all car-alternative modes of travel (Table 3.5). Paradoxically Old urban neighbourhoods identified in Toronto have the highest odds of cycling of all neighbourhood types identified in our study, and yet possess the second lowest dedicated cycling infrastructure densities only ahead of Car oriented inner suburbs (Table 3.4). While Old Urban neighbourhoods may lack dedicated cycling infrastructure, they have the highest street network and intersection density of all neighbourhoods in our study area, as well as the lowest proportion of >60km/h roadways; all factors which have been demonstrated to be significant contributors to all forms of active transportation (Cervero et al. 2009; Charreire et al. 2012). As has been noted by many authors, certain characteristics of the built environment only demonstrate significant influences on travel behavior in specific combinations (Ewing and Cervero 2010; Bento et al. 2005; Ralph et al. 2016). It is often the case that, as we see in older urban neighbourhoods here in Toronto and elsewhere in North America, a built environment does not necessarily have to include dedicated infrastructure to be a suitable environment for various modes of travel.

The relationships observed between transit use and built form is more typically modest (Ewing and Cervero 2010). In this study, a variety of neighbourhood types, including mixed use suburban, Old Urban, and high density urban core neighbourhoods, appear to influence transit use, and the probability plots indicates that poor mobility inner suburban neighbourhoods have the highest proportion of transit users overall (Figure 3.3).

Further, transit accessibility does appear to positively correlate with transit use as the two highest transit access neighbourhood types also have the highest odds of having transit users living in them. However, we also find that mixed use and poor mobility suburban neighbourhoods, both of which display very poor transit access represent some of the highest overall probabilities of transit users in our study (Figure 3.3). These findings are concerning as they suggest that a very large number of transit using students are living in neighbourhoods with very poor overall transit access, and are likely suffering with longer and more strenuous commutes thus. In fact, potential indications of this can be found in transit user attitudes, which found that transit users were the most likely of all five types to perceive travel as wasted time (table 3.2). In circumstances, such as these such as these, accounting for decision making becomes difficult as factors such as family and neighbourhood characteristics can and likely do play a significant role that is not accounted for in our study. For example, transit users may weigh factors such as proximity to family or lower neighbourhood density higher than convenient and accessible transportation, and as such are willing to make trade-offs. In this case, students with higher income may be more likely to have access to a vehicle (the other primary mode of travel in these neighbourhoods), while those in the lower end will be left with public transit. This scenario reflecting findings identified in Ralph et al. (2016)'s American study, however lacking sufficiently detailed data on the economic characteristics of our students, any such explanations are little more than speculation.

4.1 Policy Implications

From the view of a University in the GTHA, our results demonstrate that post-secondary students demonstrate very strong and highly variable preferences in regards to the way they choose to travel, and that considerations of these preferences should be considered when considering the provisioning of student housing. While on campus residences may represent the most convenient locations for students, the prohibitively high costs of land, particularly for Urban campuses, presents a significant barrier to the construction of suitable accommodation for ever growing universities in the GTHA. Further, the location of all student residences on campus neglects to address that students demonstrate a preference for a variety of environments and type of travel, and may prefer to live in a neighbourhood that, while further from campus, may better suit their preferred patterns of travel. As an example, "Old Urban" or "Accessible Suburban" neighbourhoods identified through our typology analysis represent excellent neighbourhoods for the provisioning of off campus student housing that retains accessibility and encourages active transportation.

Given the wide spatial distribution of these two neighbourhood types it is possible for Universities to provision student housing in neighbourhoods where land values are lower, thereby reducing the costs for students and Universities in the provisioning of Student housing. Given that many students, and particularly transit users, are living in neighbourhoods that are poorly serviced these options have the potential to improve the quality of life for some students who may not want to live in the more accessible neighbourhoods, or be able to afford the higher expense that come with them.

The results of our study have also identified that possessing a city transit pass (for example, a TTC Metropass) significantly increases the likelihood of an individual being a transit user or occasional driver (Table 3.5). These findings should be of concern to policy makers because, as of July 2017, the TTC's Metropass program is slated to be discontinued. As we can see, removing the option of the Metropass has the potential to reduce the overall number of students utilizing transit as occasional drivers may make the transition into dedicated car users. Further, this change will also increase the financial burden of transit users, many of whom already have some of the longest commutes and are living in some of the least accessible segments of the city (Table 3.5).

Considering these findings and the importance of the metropass, it is recommended that policies must be put in place to accommodate students and address the financial burdens that the elimination of bus passes are going to place on university students. If the goal of policy in the city of Toronto is to reduce the overall levels of personal automobile use of it's citizens, it is not going to achieve this by making alternative means of travel significantly more expensive; particularly for segments of the population who are already struggling to make ends meet.

Conclusions

This study explored travel lifestyles in post-secondary students in the GTHA and how they correlate with the built environments of the neighbourhoods in which they live. Our findings indicate that post-secondary students demonstrate significant variations in their travel patterns, and these patterns are likely strongly influenced by their attitudes and perceptions towards travel and preferences for specific modes. Further, contrary to evidence from the United States, our results indicate that post-secondary students (who are primarily millennials) appear to be less car dependant and a very high proportion of them are systematically multi-modal in their travel. Findings however also suggest that at least some of these travel patterns can be associated with vehicular access and socio-demographic characteristics that relate therein, although inadequate data prevents us from exploring this robustly.

Correlations with the built environment were found to be strong and varied. In other words, post secondary students were found to travel very differently depending on the neighbourhoods they lived in, and certain neighbourhood types were identified as being more amenable to specific modes over others. For example, students living in rural and car oriented suburbs were significantly more likely to be drivers, either dedicated or occasional, while those living in the downtown core were found to be highly active and largely reliant on public transit. Most importantly however, our study identified that some less dense older urban residential and even suburban neighbourhoods can be attractive to students who prefer car-alternative modes of travel, such as public transit, walking and cycling.

However, when generalizing the findings from this study, a number of limitations should be considered. The lack of data regarding student income levels drastically reduced our ability to explore the impacts of economic ability on student travel behavior. Another limitation to our study can be found in the cross-sectional nature of our dataset. Our exploration of student travel behavior explored data collected over the course of only one day in the lives of post-secondary students in the GTHA. The result is that it is difficult to surmise whether the previous day's travel reported by the individual represents their typical travel behavior, or is an outlier due to unusual origins, destinations or circumstances. Further, given that students often operate on schedules that deviate from the typical 9-5, a significant number of the respondents in the survey reported no travel the day before, and were thus excluded from our analysis. Most importantly, while post-secondary students constitute a significant proportion of the millennial generation, travel behaviour of working millennials can be significantly different from what we have observed here.

Keeping in mind these limitations, the results of this study shine a light on the potential for change that is latent in the Post-secondary students of our region. Our results clearly demonstrate that post-secondary education is drastically changing the way students travel during their tenure as students; changes that, for all intents and purposes represent positive shifts away from automobile dependence that we as planners would like to see adopted as much as is possible in the general population. While we cannot comment as to whether these changes influence the long term habits of students after they graduate, the fact that they are present for these four years represents an excellent opportunity to promote positive habit, and encourage the use of alternative means to automobile.

Appendix

Appendix 1: Independent Variables

Latent Class Analysis	Description	Source/Method
Trip Characteristics		
CARLASTMONTH:	Respondents were asked whether they had used a car as a primary mode of travel over the last month (Binary)	StudentMOVETO
TRANSITLASTMONTH:	Respondents were asked whether they had used public transit as a primary mode travel in the month prior to the survey date (Binary)	StudentMOVETO
ACTIVELASTMONTH:	Respondents were asked whether they had walked or cycled as a primary mode of travel in the month prior to the survey date (Binary)	StudentMOVETO
SUM_TRIPS:	Calculated number of trips completed on survey day for each individual. Three bins based on number of trips: 1-2 Trips, 3-4 Trips, > 4 Trips	StudentMOVETO
AVG_TRIP_DISTANCE[1]	Average trip distance on the day of the travel diary. Trip distance calculated using ArcGIS network analyst and For Car mode, time impedance used to simulate highway usage, for all other mode, length impedance used. Four bins based on calculated trip length; Less than 2km, between 2km and 5km, between 5-10km, greater than 10km	StudentMOVETO DMTI Spatial's Route Logistics File (DMTI 2014)
TRAVEL_TIME:	Reported time spent travelling on the day of the travel diary (Minutes)	StudentMOVETO
PUBLIC_TRANSIT_PERC:	The percentage of travel reported in the travel diary completed using public transit. Five bins based on Quintiles	StudentMOVETO
CAR_PERC:	The percentage of travel reported in the travel diary completed using a car (driver or passenger). Five bins based on Quintiles	StudentMOVETO
ACTIVE_PERC:	The percentage of travel reported in the travel diary completed using active transportation (walking or cycling). Five bins based on Quintiles	StudentMOVETO
Attitudes/Perceptions		
TIMESPENTTRAVELINGWASTETIME[3]:	The degree to which an individual agrees with the statement "Time spent travelling is wasted time." Measured on a five point Likert Scale	StudentMOVETO
ITRYLIMITDRIVIMPRAIRQUALITY[3]:	The degree to which an individual agrees with the statement "I try to limit my driving (or being driven) to improve air quality and maintain a low carbon footprint." Measured on a five point Likert Scale	StudentMOVETO
IPREFERDRIVEWHENPOSSIBLE[3]:	The degree to which an individual agrees with the statement "I prefer to drive (or would prefer if I had a car) whenever possible." Measured on a five point Likert Scale	StudentMOVETO
IPREFERWALKWHENPOSSIBLE[3]:	The degree to which an individual agrees with the statement "I prefer to walk whenever possible." Measured on a five point Likert Scale	StudentMOVETO
IPREFERBIKEWHENPOSSIBLE[3]:	The degree to which an individual agrees with the statement "I organize my daily activity to reduce trips." Measured on a five point Likert Scale	StudentMOVETO
IPREFERTRANSITWHENPOSSIBLE[3]:	The degree to which an individual agrees with the statement "I prefer to take transit whenever possible." Measured on a five point Likert Scale	StudentMOVETO
CARSAFERTHANBICYCLE[3]:	The degree to which an individual agrees with the statement "Travelling by car is safer overall than travelling by bicycle." Measured on a five point Likert Scale	StudentMOVETO
CARSAFEROVERALLTHANTRANSIT[3]:	The degree to which an individual agrees with the statement "Travelling by car is safer overall than taking transit." 'Agree' for those answering Strongly agree or Agree, 'Neither or disagree' otherwise	StudentMOVETO

Neighbourhood Typology	Description	Source/Method
AVG_BUILDING_HEIGHT:	Average of all building heights in a Dissemination area (meters)	Ontario Digital Elevation Model, Digital Surface Model, DMTI Built up area file, USGS Landsat 8 Imagery (DMTI 2014; Ontario 2016; USGS 2017)
ACTIVITY_DENSITY[1]:	A density measure describing the number of job and people in a dissemination area. (Jobs+population/km^2)	Environics Analytics 2015 census population projections, 2015 Daytime population data (Environics Analytics, 2017)
JOB_DENSITY[1]:	A density measure describing the number of jobs in a dissemination area. (Jobs /km^2)	2015 Daytime population data (Environics Analytics, 2017)
STREET_DENSITY[1]:	A density measure describing street network density in a dissemination area (street length/km^2)	DMTI Spatial's Route Logistics File (DMTI 2014)
INTERSECTION_DENSITY[1]:	A density measure describing the number of intersections in a dissemination area (intersections/km^2)	DMTI Spatial's Intersection File (DMTI 2014)
POPULATION_DENSITY[1]:	A density measure describing the number of people in a dissemination area. (People/km^2)	Environics Analytics 2015 census population projections (Environics Analytics, 2017)
HOUSING_DENSITY[1]:	A density measure describing the number of household in a dissemination area (HH/km^2)	Environics Analytics 2015 household projections (Environics Analytics, 2017)
SINGLE_FAMILY_PROP:	Proportion of single family households in a dissemination area (%)	Environics Analytics 2015 household projections (Environics Analytics, 2017)
NUM_TRIPS_PEAKAM:	The average number of transit trips made at all stops within 1km in the peak AM (6-9AM)	Publicly available General Transit Feed Specification (GTFS) Data, ArcGIS (ESRI 2017) (See write-up for methodology)
NUM_STOPS_IN_RANGE:	The number of transit stops within 1km	Publicly available General Transit Feed Specification (GTFS) Data, ArcGIS (ESRI 2017) (See write-up for methodology)
PERC_RESIDENTIAL:	Percent of total dissemination area dedicated to residential land-use (%)	DMTI Spatial's LUR File (DMTI 2014)
JOBS_HOUSING_BALANCE:	Shannon Entropy Index between the number of Jobs and number of households in a DA. Calculated using $ENT = -\frac{\sum[\mathrm{pj}\ln(\mathrm{pj})]}{\ln(\mathrm{k})}$ p^j = Percentage of land use in DA j k = The number of land use types per j	DMTI Spatial's LUR File (DMTI 2014); Daytime population data (Environics Analytics, 2017)
JOB_ACTIVITY_SHARE:	The proportion of jobs relative to population in the DA (%)	Daytime population data (Environics Analytics, 2017)
PROP_35_YEARS:	Proportion of residential households older than 35 years (%)	Household Projections (Environics Analytics, 2017)
PROP_10_YEARS:	Proportion of residential households built in the last 10 years (%)	Household Projections (Environics Analytics, 2017)

DEDI_CYCLE_DENSE:	Density of dedicated cycling infrastructure in the DA (m/km^2)	
Regression Analysis	**Description**	**Source/Method**
TRAVEL_TYPE	Traveler type determine by the latent class analysis	
PSDRIVINGLICENSEOWNER:	Possession of a valid driver's license. 1 if possesses driver's license, 0 otherwise (binary)	**StudentMOVETO**
PSUNIVERSITYAFFILIATION:	The student's status with the university – Full time, part time, or continuing education (categorical)	**StudentMOVETO**
HHCARNUMBER:	The number of cars in the household – No Cars, One car, Two or more cars (categorical)	**StudentMOVETO**
RESPONDENT_AGE:	Repondent age (years)	**StudentMOVETO**
GENDER	Respondents Gender	**StudentMOVETO**
HOUSEHOLD_SIZE	Number of people in respondent's household	**StudentMOVETO**
DEPENDENT_CHILDREN	Number of dependent children (if any)	**StudentMOVETO**
LIVING_SITUATION	The currently living situation for the respondent, as selected from the following options (Living alone, Living with family/parents, Living with partner, Living with roommates.	**StudentMOVETO**
MOVING_FACTOR	Th primary Factor for moving to their current location Binned into the following options (Public Transit Access, Active Transit Accessibility, Cost, Other)	**StudentMOVETO**
NEIGHBOURHOOD_TYPE	The seven neighbourhood types determined by the cluster analysis	**StudentMOVETO**

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