

# **An Activity-Based Approach of Investigating Travel Behaviour of Older People: Application of a Time-Space Constrained Scheduling Model (CUSTOM) for Older People in the National Capital Region (NCR) of Canada**

Khandker Nurul Habib, PhD, PEng ([Khandker.nurulhabib@utoronto.ca](mailto:Khandker.nurulhabib@utoronto.ca))

Vivian Hui, M.A.Sc ([vivian.hui@mail.utoronto.ca](mailto:vivian.hui@mail.utoronto.ca))

**Khandker M. Nurul Habib** is an Associate Professor of Civil Engineering at the University of Toronto. He works in the area of travel demand modelling, econometric choice modelling, micro-simulation and sustainable transportation planning. He has received numerous awards for his contribution to travel demand modelling and travel behaviour research, which include honorable mention in 2007 Eric I Pass Award from IATBR, 2008 Pyke Johnson Award from TRB and 2013 Minister's Award of Excellence from Alberta Ministry of Transportation.

**Vivian Hui** is a graduate student in Civil Engineering at the University of Toronto. Her research interests include equity and sustainability in urban transportation with special focus on elderly, disabled and homeless individuals. She plans to work in the area of urban transportation policy development to minimize transport-related social exclusion across the broad spectrum of socio-demography in urban areas of North America.

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## **Abstract**

The paper presents the results of an investigation on daily activity-travel scheduling behaviour of older people by using an advanced econometric model and a household travel survey, collected in the National Capital Region (NCR) of Canada in 2011. The activity-travel scheduling model considers a dynamic time-space constrained scheduling process. The key contribution of the paper is to reveal daily activity-travel scheduling behaviour through a comprehensive econometric framework. The resulting empirical model reveals many behavioural details. These include the role that income plays in moderating out-of-home time expenditure choices of older people. Older people in the highest and lowest income categories tend to have lower variations in time expenditure choices than those in middle-income categories. Overall, the time expenditure choices become more stable with increasing age, indicating that longer activity durations and lower activity frequency become more prevalent with increasing age. Daily activity type and location choices reveal a clear random utility-maximizing rational behaviour of older people. It is clear that increasing spatial accessibility to various activity locations is a crucial factor in defining daily out-of-home activity participation of older people. It is also clear that the diversity of out-of-home activity type choices reduces with increasing age and older people are more sensitive to auto travel time than to transit or non-motorized travel time.

**Key Words:** Elderly mobility, activity-travel scheduling, out-of-home activity participation, activity duration, trip chaining

## **1. Introduction**

An enhanced understanding of the travel behaviour of older people is necessary for policy makers and planners to better allocate public resources to meet the mobility needs of an aging society. As such, there has been a renewed concern for understanding the travel demand of older people (Moniruzzaman et al. 2013). In particular, the older population (65+ years old) in Canada is rapidly increasing. By 2036, the older population will comprise of around 25% of Canada's population. It is speculated that an increasing population of older people implies inefficient utilization of existing transportation systems and/or increasing transport-related social exclusion (Mercado et al. 2010, Ravulaparthi et al. 2013). Such speculations are mostly based on investigations of very specific dimensions of travel demand of older people, for example, only trip frequency or only travel mode choice along with travel distance. However, travel behaviour of older people in the context of their home locations, accessibility (urban forms) and time constraints imposed by transportation system performances can define their transport-related social exclusion. Thus, the exploration of time-space constrained activity-travel demand of older people is key to the understanding of the transport-related social exclusion of elders (Farber et al. 2011).

Most of the travel behaviour related investigations on older people in existing literature focus on specific dimensions of behavioural processes of activity-travel demand. While research on trip generation rates and trip distances reveal valuable information on activity-travel behaviour, a complete understanding requires a robust analytical framework of travel demand analysis. This paper contributes to the research gap of older people's travel behaviour through the investigation of daily activity-travel scheduling processes using a comprehensive behavioural econometric model. The model employs a random utility maximization based approach to jointly capture activity type choices, activity duration choices, activity start time choices and activity location choices within a 24-hour time frame. Through such an approach, the model also reveals the tradeoffs that older people make between their activity location choices and their activity duration choices.

Data from the 2011 household travel survey of the National Capital Region (NCR) of Canada was used for empirical investigation in this study. A subset of the travel diary dataset belonging to individuals with 65 years of age or more was taken to reconstruct their daily

activity-travel scheduling information. This dataset was used to estimate the parameters of the joint activity-travel scheduling model. The empirical model captured behaviour through parameterized functions of continuous time expenditure choices under time budget constraints and activity location choices in the context of time-constrained urban activity spaces (potential path area: PPA). The behaviour of optimizing/utility-maximizing in activity-travel scheduling behaviour was captured through parameterization of the choice model scale parameters.

The paper is organized as follows: the next section presents a literature review on older people's activity-travel behaviour. This is followed by a discussion on datasets available for empirical investigation, description of the econometric modelling framework and the empirical model. The conclusion discusses key findings and their relevancy to planning and policies.

## **2. Activity-Travel Demand of Older People: A Literature Review**

Recent interest in older people and their travel behaviour has been fuelled by the challenges associated with aging populations in developed countries (Mercado et al. 2007). In response, early literature, such as Tacken's (1998) study, has mainly focused on the descriptive analysis of older people's travel behaviour in correspondence to their personal attributes. Metz (2000) presented a theoretical investigation (without empirical evidence) on the travel demand of older people, proposing that mobility needs decrease with increasing age and eventually affects older people's quality of life. Yet another example of the use of descriptive analysis is exhibited in Rosenbloom's (2001) study, which found that older people all over the world are more private-car dependent than ever before. In addition, Alsnih and Hensher (2003) used descriptive analysis to investigate mobility needs and travel patterns of people over 64 years of age. Complementary to Rosenbloom's (2001) results, Alsnih and Hensher (2003) found that older people in Australia are mostly captive to the private automobile than to public transit. As such, the authors recommended a specialized transit system to cover the mobility needs of the elderly. Finally, Newbold et al. (2005) used descriptive analysis to investigate cohort effects on older people's travel demands in Canada. Similarly, Newbold et al's (2005) analysis of older people in Canada, classified into the categories of 'younger-aged', 'transitional old' and 'old' cohorts, revealed that the mobility needs of the elderly also reduce with age.

While descriptive analysis of travel demand may uncover patterns and correlations from observed data, it does not investigate the causal linkages and relationships between travel behaviour and various attributes of older people. In response to the lack of systematic analysis in this field, a concern voiced by Kim (2003) and Paez et al. (2007), recent research has incorporated a greater use of quantitative methods. These methods mostly include the use of linear or log-linear regression, binary logit or probit logit and ordered probability regression models. Such models are used to investigate causality between various attributes of older people and their trip distances, trip frequencies, mode choices, trip timing and trip chaining complexities.

Smith and Sylvestre (2001) presented one of the first Canadian studies using multiple linear regression analysis to investigate variables that affect trip frequencies of older people in Winnipeg. Their regression model revealed a correlation between older people's trip-making frequency and variables related to health characteristics, living arrangements and income levels. Consequently, they also found that such causal relationships were contextualized by trip destination categories. Boschmann and Brady (2013) used binary logit and linear regression models to investigate mode choices and travel distances of older people in Denver, Colorado. Their study confirmed the complexities of older people's travel behaviour, implying the difficulty of capturing such complexities with simple univariate models.

Overcoming the limitations of simple linear regression analysis, Mercado and Paez (2009) employed a multi-level econometric approach to model the mean trip distances of older people travelled by different modes. They found that the 'age' effect was significant in all mode-specific travel distance determinations, but was especially influential on private car-based trips.

Morency et al. (2011) adopted a multivariate regression technique, enhanced by means of spatially-expanded coefficients, to examine the factors that impact the distances travelled by elderly people in three Canadian cities. Their finding highlighted that elderly people residing in suburbs have significantly different travel distance patterns than other population segments.

Building upon linear regression analysis, Paez et al. (2007) and Schmöcker et al. (2005) presented ordered probit models as contributions to the literature on older people's travel behaviour. Paez et al. (2007) used ordered probit models to examine spatial variability in elderly trip-making frequency. The research revealed general trends of older people's travel behaviour, namely that trip-making frequency decreases with age, but increases with license-holding status, auto ownership and other variables. Likewise, Schmöcker et al. (2005) used ordered probit models to investigate trip generation rates of older people in London, UK. The investigation identified household structure, car ownership and driving license ownership as critical factors that influence trip generation rates of older people.

Progressing towards more comprehensive models, Kim and Ulfarson (2004) used a multinomial logit approach to investigate mode choice behaviour of older people for all trip purposes. Kim and Ulfarson's (2004) findings revealed that the mode choice behaviour of older people is mostly defined by their place of residence and the transportation system performance in the respective region. Scott et al. (2009) used a binary probit model to examine peak versus off-peak trip-making by older people in Canada. Results showed that older people in Canada are increasingly using private automobiles and making trips during peak periods, revealing the dependency of older people on the car for mobility purposes, even during the most congested times of the day. Subsequently, Kim (2011) investigated the trip-making behaviour of older people in the US by modelling transportation deficiency as a binary logit model. Kim's (2011) investigation revealed the logical and necessary dependency of older people on the private automobile in the context of poor transit services. Finally, Hensher (2007) developed a comprehensive nested logit model of mode and trip chain choices by using pooled repeated cross-sectional travel survey data from Sydney. Complementary to Kim's (2011) results, Hensher (2007) found that the dependence of older people on the private car and on other household members to access mobility needs may eventually lead them to social isolation.

Among the more comprehensive modelling structures, Hildebrand (2003) used a simplified activity-based approach to investigate travel behaviour of older people and used a series of conditionally independent models to jointly capture each individual's demographic category (e.g. workers, mobile widows, mobility impaired, affluent males and disabled drivers), activity pattern choice, pattern adaptation choice and trip tour choice. Consequently, more recent studies, such as Moniruzzaman et al. (2013) and Habib's (2014) works, have offered comprehensive approaches to investigating older people's travel behaviour in Canada. Both studies made use of joint discrete-continuous models to account for endogeneity between older people's mode choice and trip length decisions. The specific advantage of using joint econometric models is that such an approach deals explicitly with the issue of sample selection (Moniruzzaman et al., 2013). Thus, both Moniruzzaman et al. (2013) and Habib's (2014) studies were able to demonstrate the complexity of travel behaviour resulting from multifaceted trip-making decisions. However, the major limitation of such an approach is that it concentrates on one or two dimensions of travel behaviour alone, treating decisions on trip distances, trip frequencies, mode choices and trip timing as separate entities.

By considering trip-making decisions as joint discrete-continuous choices, there is opportunity to simulate a dynamic activity scheduling process to realistically portray the travel behaviour of the elderly. Habib (2011) presents such an activity scheduling process modelling approach, which relies more on probabilistic econometric formulations in comparison to other activity-based approaches (e.g. models presented by Joh 2004, Roorda 2005, Arentze and Timmermans 2011). This paper uses the Comprehensive Utility maximizing System of Travel Option Modelling (CUSTOM) approach (Habib, 2015). The CUSTOM approach endogenously

captures multidimensional interactions of activity-travel scheduling and allows better understanding of older people's travel and time expenditure behaviour.

### 3. Data for Empirical Investigation

This study uses the 2011 household travel survey dataset of the NCR of Canada for empirical investigation on older people's activity-travel scheduling behaviour. The survey is the latest of a 5-year cycle 4% household travel survey of the NCR that is conducted and maintained by a joint transportation planning committee serving the NCR<sup>1</sup>. The large collected dataset serves the purpose of passenger travel demand investigation that is used for transportation and infrastructure planning by all government planning agencies and private organizations in the NCR of Canada. The dataset, along with the survey statistics, are well documented<sup>2</sup>.

The region is expected to witness growth in both employment opportunities (University of Ottawa 2002) and an aging population (National Capital Commission 2012). As such, there is interest in complementing the sole existing research on the travel behaviour of older people residing in the NCR (Habib 2014). The dataset consisted of 9,918 individuals, aged 65 or above. For this study, the dataset was "trimmed" by eliminating records with missing socio-economic and personal attributes. The empirical model was estimated with a sample of 8,430 individuals, representing 6,331 households. Table 1 summarizes the key descriptive statistics of the sample individuals used for empirical investigation.

**Table 1: Socio-demographic Characteristics of Sample Individuals**

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Average household size	2.00				
Average household auto ownership	1.29				
Household income/year	below \$29,999 (12% of the sample); \$30,000 – \$59,999 (23% of the sample); \$60,000 – \$89,999 (16% of the sample); \$90,000 – \$119,999 (8% of the sample); \$120,000 – \$149,999 (3% of the sample); \$150000 – \$179999 (1% of the sample); \$180,000 – \$209,999 (0.6% of the sample); \$210,000+ (1.3% of the sample); no income or unknown(35% of the sample)				
Dwelling types	Single-detached (59% of the sample); Semi-detached (7% of the sample); Row/Townhouse (7% of the sample); Apartment/Condo (tenant) (15% of the sample); Apartment/Condo (owner) (12% of the sample)				
Male: Female	46% : 64%				
Driver's license	Having driver's license (79% of the sample); no driver's license (21% of the sample)				
Transit passes	Senior's pass holders (6.7% of the sample); no pass holders (92.0% of the sample); others (1.3% of the sample)				
Occupation status	Retired (89.5%); full-time worker (5.4%); part-time worker (2.6%); homemaker (1.8%); others (0.7%)				
Trip purposes	Work and school; shopping, household maintenance; restaurant; recreation; visiting friends/family; health and personal care; facilitating passenger; picking someone; return home; other				
Out-of-home trip-making	No trip-making (36%); 2 trips per day (33%); 3 trips per day (11%); 4 trips (12%); 5+ trips per day (8%)				
Mean Number of Trips by Age Cohort					
Age cohort →	65–69	70–74	75–79	80–84	85+
Male	2.23	2.00	2.00	1.70	1.35
Female	2.01	1.96	1.65	1.41	0.99

<sup>1</sup> <http://www.ncr-trans-rcn.ca/en/> (Accessed in May 2015)

<sup>2</sup> <http://www.ncr-trans-rcn.ca/surveys/o-d-survey/o-d-survey-2011/> (Accessed in May 2015)

All	2.12	1.98	1.81	1.54	1.13
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#### 4. Econometric Modelling Framework for Activity-Travel Scheduling

A Random Utility Maximization (RUM) based modelling framework was used to investigate daily activity-travel scheduling processes of older people. The modelling framework used the Comprehensive Utility maximizing System of Travel Option Modelling: CUSTOM approach (Habib 2015). Figure 1 presents the schematic diagram of the scheduling stems and feedback mechanisms. Two aspects of activity-travel scheduling were taken into consideration: increasing time constraint defined with time-of-day as the 24-hour time budget depletes, and space constraint shaped by time availability and travel time needed to get to potential activity locations (Potential Path Areas: PPA). After each activity completion, both time budget availability and PPA shrink. The proposed joint econometric model jointly modelled activity type choices, time expenditure choices and activity location choices sequentially with consideration of expectations of later activities and locations to visit. The activity-travel scheduling process was composed of a number of scheduling cycles, with three assumptions: 1) each person starts and ends the day at home; 2) the day begins at home; and 3) at-home activity type choices are not specifically modelled. More specifically, at-home activity referred to any time spent at home. In addition, the indication of the start of the day included time spent at home before making the first trip. In the case that no out-of-home trips were made, the whole day was spent at home. In the case that there were multiple home-based trip chains, at-home time occurred between two trip chains. Finally, a scheduling cycle was considered as a unit comprised of three components: 1) time expenditure choice of the current activity; 2) activity type choice of next activity; and 3) activity location choice of next activity.

For any trip maker, the first scheduling cycle was composed of time expenditure of at-home activities before the first trip, activity type choice of the first trip and activity location choice of the first trip. At the end of the first scheduling cycle, the time budget was reduced by the time expenditure at-home before the first trip and the travel time needed to get to the succeeding activity location. PPA for the first trip was defined by the time budget available just after spending time at home and the travel time required to get to different potential activity locations. For any scheduling cycle that did not start at home, activity type choice included two return home options: return home temporarily and return home for the rest of the day. The return home temporarily option referred to returning home in between two consecutive home-based trip chains. Returning home for the rest of the day referred to the end of the out-of-home scheduling process.

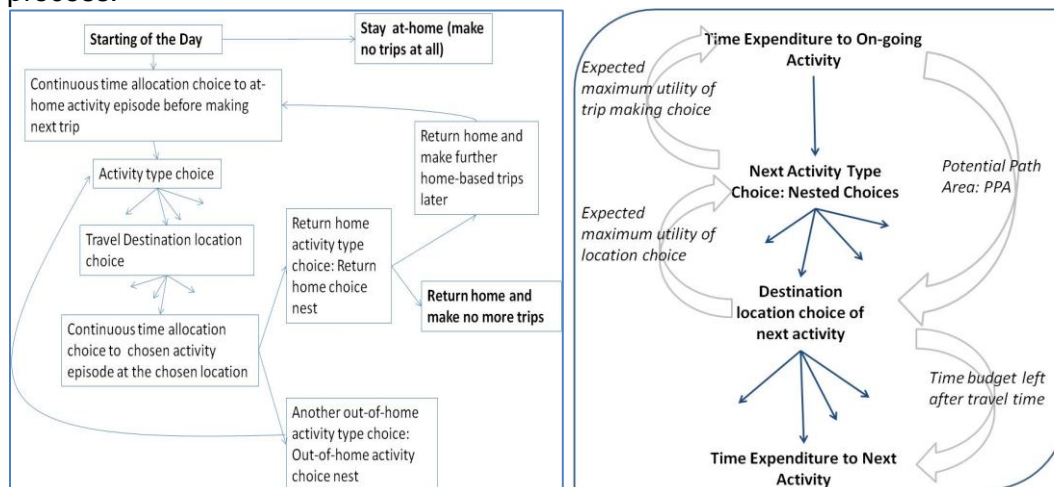


Figure 1: CUSTOM Scheduling Process

Daily activity-travel scheduling was considered to be a panel of multiple scheduling cycles. Consecutive scheduling cycles were nested through choice model scale parameters. The RUM approach was considered for both continuous time allocation choice and discrete activity type and location choices. As described in Habib's (2011, 2013 and 2015) works, the RUM-based choice of spending  $t_i$  amount of time to  $i$  activity under a total time budget constraint ( $t_i + t_c$ ) can be defined as follows:

$$\Pr(t_i) = \left( (1 - \alpha_i) / t_i + (1 - \alpha_c) / t_c \right) \mu_{t_i} \exp(-\mu_{t_i} (V_c - V_i)) \left( 1 + \exp(-\mu_{t_i} (V_c - V_i)) \right)^{-2} \quad (1)$$

$$V_c = (\alpha_c - 1) \ln(T - t_i) \quad \& \quad V_i = \psi_i z_i + (\alpha_i - 1) \ln(t_i) \quad (2)$$

here:  $t_i$  = time expenditure to activity  $i$

$t_c$  = time available for composite activity

$\alpha_i$  = satiation parameter for time expenditure to activity type  $i$

$\alpha_c$  = satiation parameter for time allocation to composite activity type  $c$

$\psi_i z_i$  = linear-in-parameter function of variable set  $z_i$ ; corresponding coefficients representing the systematic component of the baseline utility of continuous time expenditure choice

$\varepsilon_i$  = random component of the baseline utility of continuous time expenditure choice

$T$  = total time from the start of the activity to the end of the 24 hours

$\mu_{ti}$  = scale parameter of time expenditure ( $t_i$ ) choice

For any scheduling cycle that occurred out-of-home, the two-level nested choice models assumed three discrete alternative choices. The first level consisted of the choice of returning home for the rest of the day ( $RH_{i+1}$ ), returning home temporarily ( $R_{i+1}$ ) and the choice of another out-of-home activity type ( $a_{i+1}$ ). The second level consisted of the choice of a specific activity type ( $a_{i+1}$ ). These choices followed the Generalized Extreme Value (GEV) model formulation (Habib and Sasic 2014):

$$\Pr(RH_{i+1}) = \frac{\exp(\mu_{h_{i+1}} V_{rh_{i+1}})}{\exp(\mu_{h_{i+1}} V_{rh_{i+1}}) + \exp(\mu_{h_{i+1}} V_{h_{i+1}}) + \exp(\mu_{h_{i+1}} I_{A_{i+1}} / \mu_{a_{i+1}})} \quad (3)$$

$$\Pr(R_{i+1}) = \frac{\exp(\mu_{h_{i+1}} V_{h_{i+1}})}{\exp(\mu_{h_{i+1}} V_{rh_{i+1}}) + \exp(\mu_{h_{i+1}} V_{h_{i+1}}) + \exp(\mu_{h_{i+1}} I_{A_{i+1}} / \mu_{a_{i+1}})} \quad (4)$$

$$\Pr(a_i) = \frac{\exp(\mu_{h_{i+1}} I_{A_{i+1}} / \mu_{a_{i+1}})}{\exp(\mu_{h_{i+1}} V_{rh_{i+1}}) + \exp(\mu_{h_{i+1}} V_{h_{i+1}}) + \exp(\mu_{h_{i+1}} I_{A_{i+1}} / \mu_{a_{i+1}})} \times \frac{\exp(\mu_{a_{i+1}} V_{a_{i+1}})}{\sum_{A_{i+1}} \exp(\mu_{a_{i+1}} V_{a_{i+1}})} \quad (5)$$

here:  $\mu_{h_{i+1}}$  = root scale parameter of activity type choice

$\mu_{a_{i+1}}$  = scale parameter of out-of-home activity type choice

$V_{rh_{i+1}}$  = systematic utility of returning home for the rest of the day

$V_{h_{i+1}}$  = systematic utility of returning home temporarily

$V_{a_{i+1}}$  = systematic utility of out-of-home activity type choice that includes expected maximum utility of destination location choice,  $I_{l_{i+1}}$

$I_{A_{i+1}}$  = expected maximum utility of out-of-home activity type choice

Considering a similar GEV formulation, the activity location choice model was defined as:

$$\Pr(l_{i+1}) = \exp(\mu_{l_{i+1}} V_{l_{i+1}}) / \sum_{L_{i+1}} \exp(\mu_{l_{i+1}} V_{l_{i+1}}) \quad (6)$$

here:  $V_{l_{i+1}}$  = the systematic utility function of activity location choice

$L_{i+1}$  = the choice set for activity location choice, consisting of 10 randomly chosen locations (inclusive of the actual chosen location) from the feasible choice set

The expected maximum utility of activity location choice for the feasible choice set stood as follows:

$$I_{l_{i+1}} = \ln \left( \frac{\text{Number of locations in feasible set}}{L_{i+1}} \times \sum_{L_{i+1}} \exp(\mu_{l_{i+1}} V_{l_{i+1}}) \right) \quad (7)$$

Here,  $I_{l_{i+1}}$  gives the expected maximum utility of location choices based on the weighted sum of  $L_{i+1}$  random alternative location.

The joint likelihood of the RUM-based model scheduling retained a closed form by assuming the day as a panel of multiple scheduling cycles. The maximization or optimization of random utility in daily scheduling might be different at various levels of scheduling processes. For example, RUM might happen only at one scheduling cycle, at multiple scheduling cycles or it might happen at a complete day's scheduling level. Such varieties of possible optimizing behaviour were accommodated by parameterizing the scale parameter of the choice model components. Scale parameters of all choices were fixed to the first scheduling cycle that started at home. The proposed model was of closed form and was estimated by using the classical maximum likelihood estimation method. The likelihood function of the joint model was programmed in GAUSS (Aptech System 2014).

## 5. Empirical Model

The empirical model of daily activity-travel scheduling of older people jointly modelled activity type choices consisting of home-based tour/trip chaining choices, time expenditure choices and activity location choices. Mode choice was considered exogenous to the model as a majority of older people were private car users. Separate mode-specific travel time coefficients were accommodated to capture modal influences on activity-travel scheduling. Scale parameters of the choice model components were expressed as exponential functions of different parameters maintaining a hierarchical relationship to capture RUM activity-travel choice behaviour. The empirical model revealed that older people of the NCR optimize daily activity-travel scheduling choices and furthermore, that considerable heteroskedasticity existed in such optimizing behaviour. The final specification was based on theoretical expectation of the effects and statistical significance of different parameters. A 95% confidence limit ( $t$ -statistics = 1.96) was considered for testing statistical significance. Some variables with lower  $t$ -statistics values were retained considering that these variables contributed to the explanations of behavioural processes. It was also expected that such variables would appear more significant with a larger dataset.. The final model consisted of 114 parameters. A summary of the statistics of the estimated model parameters are presented in Table 2.1. In addition, the Rho-Squared value was calculated against a null model. The null model considered all discrete choice alternatives as equally likely options and explained all continuous choices through constants alone. The goodness-of-fit of the final model was 0.18. To put it in perspective, a goodness-of-fit value of 0.3 for a single discrete choice model is considered a high value. As such, a goodness-of-fit value of 0.18 for a multilevel nested discrete-continuous model was favourable. Finally, empirical model parameters explained activity-travel scheduling behaviour of older people in the NCR.

**Table 2.1: Summary Statistics of the Estimated Model**

Number of observations	8220
Loglikelihood of full model	-131971
Loglikelihood of null model	-160197
Rho-Squared values	0.18

### 5.1 Scale Parameters of Choice Model Components: Choice Stability, Randomness and Choice Optimization



Four types of scale parameters were parameterized: scale parameter for time expenditure choices; scale parameter for return home activity type choices; scale parameter for out-of-home activity type choices; activity location choices. The scale parameters explained the choice heteroskedasticity and correlations among alternative choices of older people in the NCR. Table 2.2 presents the estimated parameters of the scale functions. The scale parameter of the time expenditure choice was measured as the inverse of time expenditure variations. This scale parameter explained any existing heteroskedasticity in time expenditure choices, in which a higher scale parameter referred to a lower variance and less randomness in time expenditure choices. People of the same age, but in different income groups, exhibited different time expenditure choice behaviours. The highest and the lowest income groups showed the least randomness in time expenditure choices. For those who belonged to the income groups in between the highest and lowest income groups, there was a gradual increase in variances of time expenditure choices with increasing income. Consequently, for any income group, it was clear that variance of time expenditure choices (to different activities) reduced with increasing age. For example, people of age 70+ had less variance in activity durations than people younger than 70, irrespective of income. Possibly, older people seek less variety in activity-travel behaviour and therefore, have longer activity durations.

Estimated scale parameters revealed that older people in the NCR optimized their engagements with activity types and activity locations on a daily basis. Such optimization was established with the objective of choosing activity types and activity locations that maximize one's activity-travel needs over the day rather than by one's individual activity engagements. However, considerable heteroskedasticity (sources of such variations) existed in such behavioural linkages.

**Table 2.2 Parameterized Scale Functions**

	Parameter	t-statistics
<i>Exponential scale parameter function of time expenditure choices</i>		
Logarithm of age interaction with		
Annual income: \$150,000-\$179,999	0.07	1.20
Annual income: \$120,000-\$149,999	-0.06	-1.29
Annual income: \$90,000-\$119,999	-0.01	-0.46
Annual income: \$60,000-\$89,999	-0.05	-1.78
Annual income: \$30,000-\$59,999	-0.01	-0.68
Annual income: \$0-\$29,999	-0.02	-0.42
Additional exponential component (to location choice scale of previous activity)		
Logarithm of age x Household size	0.02	19.85
<i>Additional exponential component (to activity type choice for next activity) for destination location choices</i>		
Time-of-day x logarithm of activity number	-1.76	-14.85

Age, household size and number of activities performed in a specific time-of-day were key variables that defined various levels of relationships between activity type choice, location choice and daily optimization of activity-travel scheduling of older people. It was clear that for the same age group, older people in larger household sizes had a lower increase in scale parameter with increasing number of activities scheduled with time-of-day than older people in smaller household sizes. For the same household sizes, age and household size jointly explained the changes in one's activity type choice randomness. In further investigation, lower rates of increasing scale referred to weaker hierarchical relationships among the activity types chosen in a day. An increasing scale portion tending to zero suggested that activity type choices

were made almost independent of each other throughout the day. This meant that individual activity types were not linked or correlated. In addition, it was clear that with increasing time-of-day and activity number, the rate of increase in activity location choice scale over activity type choice scale tended to zero (simultaneous choices). The empirical model showed that activity type and location choices were more closely coupled during the latter part of the day than during the earlier part of the day. Older people with larger household sizes tended to have lower variance in activity type and location choices with increasing time-of-day and activity number. On the other hand, older people with lower age and with smaller household sizes showed more variety seeking behaviour in activity type and location choices with increasing time-of-day and activity number.

### **5.2 Time Expenditure At-Home before First Out-of-Home Activity of the day**

Time expenditure at-home before first out-of-home activity was explicitly modelled if the individual made any out-of-home trips in the modelled day. Table 2.3 presents the estimated parameters of time expenditure of at-home activities before the first out-of-home activity of the day. The time expenditure choice model had two components, comprised of the baseline utility function and the satiation parameter. Baseline utility defined the marginal utility of time expenditure for a specific activity, whereas the satiation parameter defined the rate of change in marginal utility of spending more time. A higher marginal utility of time expenditure referred to the baseline choice of spending longer durations at home. A lower satiation parameter value referred to a lower rate of decreasing one's marginal utility of spending time and thereby, referred to longer durations at home. In addition, a constant satiation parameter was identified for older people in the NCR. The constant parameter implied that older people in the NCR did not show any significant variations in satiations of spending time at home before their first trip.

**Table 2.3 Time expenditure choice model component for at-home before first out-of-home activity of the day**

	Parameter	t-statistics
<i>Satiation parameter, <math>\alpha</math></i>	-1.85	-273.36
<i>Baseline utility of time expenditure choice for at-home activities before the first trip</i>		
Age less than 70 years	0.24	2.82
Age greater than or equal to 75 years	0.52	5.72
Gender: male	0.19	2.81

The baseline utility function was parameterized as a function of age and gender. Compared to people of age 70 to 75 years, those below 70 years or above/equal to 75 years had significantly higher marginal utility in spending longer durations of time at home before their first trip. Older people of age greater than or equal to 75 had the highest marginal utility of spending time at home before their first trip and also had a tendency of spending longer durations than all other age groups. Lastly, males had higher marginal utility of spending time at home before their first trip than females.

### **5.3 Activity Type Choice for the first Out-of-home Activity of the Day**

The activity type choice for the first out-of-home activity was modelled separately from all other activities of the day as it defined the patterns of activity-travel scheduling and also included the choice of not making any out-of-home trips. Table 2.4 presents the estimated parameters of this model component. The expected maximum utility of the location choice of the first out-of-home activity significantly defined the first out-of-home activity type choices. The effects of this expected maximum utility was moderated by the inverse of the scale parameter of location choice, defined by time-of-day interaction with the activity number. It was found that the choice of the first activity was defined by constant utility and time-of-day. The choice of staying home for the whole day had the highest constant utility. Furthermore, time-of-day effects were positive

for all out-of-home activity types and the highest effect was for other activity types. This suggested that the other activity type was the most preferable one when older people started their first trip during the latter part of the day. In comparison, the work activity at a non-fixed location was the least preferable one when the first trip began during the latter part of the day. The choices of all other activities seemed to be affected similarly by the time-of-day of the start of the first trip.

**Table 2.4 Activity type choice model component for first out-of-home activity of the day**

	Parameter	t-statistics
Alternative specific constant (asc)		
Work	25.83	70.19
Work-related	10.17	21.59
Work at non-fixed location	8.53	17.09
School	4.38	3.18
Shopping	11.33	49.03
Restaurant	8.81	24.20
Recreation	10.78	44.79
Visiting friends and family	9.17	23.77
Health and personal care	10.90	38.12
Dropping someone/something	9.22	13.79
Picking someone/something	6.03	6.65
Staying home whole day	29.97	139.13
Other activities	0.00	---
Time of day (as a fraction of 24 hour)		
Work	11.23	11.60
Work-related	21.77	19.04
Work at non-fixed location	0.00	---
School	27.95	9.05
Shopping	24.79	61.65
Restaurant	25.51	34.49
Recreation	24.19	46.32
Visiting friends and family	25.31	33.94
Health and personal care	23.32	39.22
Dropping someone/something	21.93	14.72
Picking someone/something	27.83	16.72
Staying home whole day	0.00	---
Other activities	40.11	85.10

#### **5.4 Time Expenditure Choice for Activities Subsequent to the First Trip of the Day**

Table 2.5 presents the estimated parameters of time expenditure choices for all activities subsequent to the first out-of-home trip of the day. Activity type specific constants in the baseline utility function indicate relative preferences of time expenditure choices for different activity types. Large marginal utility refers to longer duration for time expenditure choices and vice versa. Results revealed that older people tended to spend the longest duration of time for work activities.

**Table 2.5: Time expenditure choice model component for activities subsequent to first out-of-home trip**

	Parameter	t-statistics
<i>Baseline utility function</i>		
Constant for activity types		
Work	9.58	7.28
Work-related	-5.56	-8.34
Shopping	-0.93	-1.49
Recreation	-1.47	-4.58
Visiting friends and family	-4.10	-9.20
Health and personal care	-0.18	-0.33
Dropping	-8.47	-21.80
Picking	-8.14	-14.60
Other activities	-3.22	-6.89
Time-of-day (as fraction of 24 hour) interaction with		
Shopping	-6.55	-5.77
Health and personal care	-5.32	-7.78
At-home in between two home-based tours/trip chains	-3.90	-5.82
Other activities	-3.94	-6.75
<i>Satiation parameter, <math>\alpha</math> function</i>		
Constant		
Work	-1.26	-21.09
Work-related	-0.41	-4.58
Work at non-fixed location	-0.98	-19.76
Shopping	-0.78	-10.32
Restaurant	-1.06	-112.9
Recreation	-0.88	-30.38
Visiting friends and family	-0.64	-12.76
Health and personal care	-0.85	-22.49
Picking	-0.44	-4.04
At-home in between two home-based tours/trip chains	-0.60	-16.07
Other activities	-0.55	-13.33
Time-of-day (as fraction of 24 hour) interaction with		
Work	-0.31	-7.37
Shopping	0.08	0.53
Dropping	-0.64	-4.23
At-home in between two home-based tours/trip chains	-0.31	-3.22

Following work activity, older people tended to spend longer durations for health and personal activities. Utility of spending longer durations for shopping and recreational activities was higher than utility of spending longer durations for visiting friends and family. Older people tended to spend the shortest durations for dropping off and picking up activities. Time-of-day also seemed to have an influence on time expenditure choices for shopping, health and personal care, other activities and at-home activities in between two home-based tours/trip chains. It was clear that older people tended to spend longer durations at home in between two

home-based tours/trip chains than any other activity if it was chosen in the latter part of the day. In addition, health and personal care activities were longer in duration than shopping activities if it was chosen in the latter part of the day.

### 5.5 Activity Type Choice for Trips Subsequent to the First Trip

Activity type choice model for activities subsequent to the first out-of-home trip of the day is presented in Table 2.6. For older people, activity trip purposes of visiting restaurants, recreation locations and friends and family seemed to have the same constant marginal utility of activity type choice throughout the day. Shopping, dropping off and picking up activities had the same constant utility of activity type choice throughout the day. School and work-related activities had the lowest constant utility of activity type choice. The choice set for activity type choice at any out-of-home location included two types of return home options: return home temporarily; return home for the rest of the day. Choice of return home for the rest of the day defined the end of out-of-home activity scheduling. Separate age specific constant effects identified the choice of such end of out-of-home activity scheduling. Results showed that older people with 75 years of age or older tended to terminate their out-of-home activities earlier than all other age groups. Those who belonged to the 70 to 75 age group terminated their out-of-home activities earlier than those who belonged to the below 70 age group. In summary, older people with higher age tended to terminate their out-of-home activity scheduling earlier than others.

**Table 2.6: Activity type choice model component for activities subsequent to first out-of-home trip of the day**

	Parameter	t-statistics
Alternative Specific Constant (asc) Interactions with Activity number of the day		
Work	0.00	---
Work-related	-0.23	-16.54
Work at non-fixed location	0.00	---
School	-0.21	-2.38
Shopping	-0.07	-12.22
Restaurant	-0.06	-6.18
Recreation	-0.06	-6.10
Visiting friends and family	-0.07	-5.73
Health and personal care	-0.08	-3.86
Dropping	-0.11	-14.20
Picking	-0.09	-14.15
Other activities	0.00	---
Return home temporarily	---	
Return home for rest of the day:		
Age less than 70 years	-0.11	-10.94
Age equal or greater than 70, but less than 75 years	-0.10	-11.02
Age greater than or equal to 75 years	-0.08	-7.60
Time of day (as a fraction of 24 hour) interaction with		
Work	6.77	55.65
Work-related	0.00	---
Work at non-fixed location	0.00	---
School	-1.60	-2.10

Shopping	0.77	19.38
Restaurant	0.07	0.86
Recreation	0.35	4.86
Visiting friends and family	0.16	1.81
Health and personal care	-0.11	-0.78
Dropping	0.00	---
Picking	0.00	---
Other activities	0.00	---
Return home temporarily	6.96	78.56
Return home for rest of the day	8.18	98.19
Travel time (minutes) to return home		
Return home temporarily:		
Auto travel time	0.69	49.10
Transit travel time	0.33	22.17
Return home for rest of the day:		
Auto travel time	0.68	71.07
Transit travel time	0.29	22.89
Non-motorized travel time	0.19	1.82

The model correctly captured that the return home choice probability increased with increasing time-of-day. Time-of-day effects on the choice to return home temporarily were higher than those on the choice to return home for the rest of the day. It was also clear that older people tended to work and shop later in the day as time-of-day effects were higher on work and shopping activity type choices than other out-of-home activity types. Health and personal care, visiting friends and family and restaurant activities seemed to be chosen earlier in the day than other activities. Mode specific travel times also had differential effects on return home choices. In general, travel times by various modes had negative effects, however, auto users showed higher sensitivity to travel time than other mode users.

### 5.6 Activity Location Choice

Activity location choice was modelled considering time-space constraints at any time of the day (Scott and He 2012, Yoon et al. 2012). Consideration of locations in the PPA were dependent on whether visiting such locations would exceed a total round trip travel time of more than 75 percent of the total time budget. For modelling location choice, the chosen location and 10 randomly selected locations from the PPA were considered. Random selection was based on a uniform random number, which has proven to be consistent with discrete choice modelling (McFadden 1978). Estimated model parameters are presented in Table 2.7.

For location choice modelling, traffic analysis zones (TAZ) were considered for choice alternatives and attributes of alternative TAZs in the choice set were used to explain the utility of location choices. Figure 2 presents a map of the TAZ boundaries. A generic location choice model was considered for all activities. It was expected that zones with higher population densities would experience higher visitation rates. However, older people tended to choose zones with lower population density for visiting friends and family. Possibly, older people are more suburbanized and tend to have friends and families in suburban areas where population densities are low. Older people also tended to choose zones with lower population densities and higher employment densities for dropping off and picking up activities. Location choices were not modelled for fixed work locations, but were modelled for work-related activities and work at non-fixed locations. Zones with higher employment densities were attractive for work-related

activities. Likewise, zones containing a higher number of restaurants were more attractive for restaurant type activities than zones containing a lower number of restaurants.

Distance from the central business district (CBD) was also considered as a variable to capture the distribution of land use and their effects on activity location choices of older people in the model. Zones that were far away from the CBD were most attractive for visiting friends and family, emphasizing the fact that older people are suburbanized and tend to socialize in suburban areas. This finding has strong implications for transportation and urban planning. Since transit services are more available in areas near the CBD than in suburban areas, the elderly heavily depend on private automobiles as they have a tendency to travel to locations far away from the CBD for socializing purposes. It is also for this reason that results showed older people to be fully auto dependent. Older people tended to choose locations that were closer to the CBD for work, school and dropping off/picking up activities. Higher number of shopping locations/points increased the attraction of the zone for shopping, recreation, visiting friends and family, health and personal care activities. In terms of travel time, older people were most sensitive to auto and non-motorized travel times.

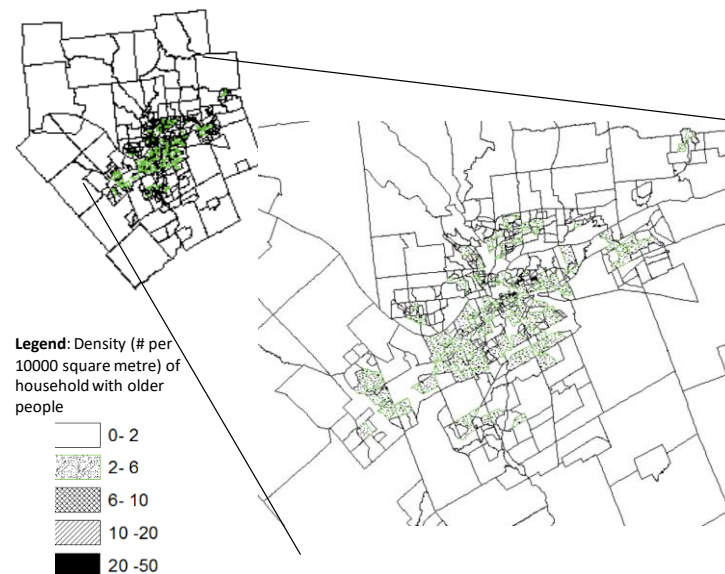


Figure 2: Zone boundaries and sample distribution of households with older people in the study area, the National Capital Region of Canada

**Table 2.7: Activity location choice model component**

	Parameter	t-statistics
Logarithm of population density per sq km		
Visiting friends and family	-0.05	-6.73
Dropping someone/something	-0.03	-2.83
Picking someone/something	-0.03	-2.66
Logarithm of employment density per sq km		
Work-related	0.02	3.70
Dropping someone/something	0.02	2.85
Logarithm of number of restaurants		
Restaurant	0.05	1.16
Logarithm of distance from central business district (CBD)		
Work-related	-0.23	-13.57
School	-0.34	-7.97

Shopping	-0.28	-53.20
Restaurant	-0.23	-13.46
Recreation	-0.25	-42.55
Visiting friends and family	-0.15	-10.05
Health and personal care	-0.21	-30.21
Dropping someone/something	-0.15	-4.72
Picking someone/something	-0.15	-4.64
Other activities	-0.24	-36.40
Logarithm of number of shopping and service locations		
Shopping	0.02	2.12
Recreation	-0.05	-3.20
Visiting friends and family	0.02	0.36
Health and personal care	-0.06	-4.90
Dropping someone	0.10	2.47
Picking someone	0.21	4.39
Logarithm of round-trip travel time (minutes): origin-destination-home		
Auto travel time	-0.70	-98.25
Transit travel time	-0.48	-62.30
Non-motorized travel time	-0.78	-13.92

## 6. Conclusions and Recommendation for Future Research

This paper focused on activity-travel scheduling behaviour of older people in the NCR. Results showed that older people optimize their activity-travel engagement choices on a daily level rather than on an individual activity level. Effects of time-space constraints in the context of dependence on the private automobile were evident in out-of-home activity type, location and time expenditure choices. Spatial accessibility to activity locations significantly influenced daily activity engagement processes, implying that increasing accessibility would increase out-of-home activity. It was found that age and household size in the context of time-of-day and activity number influenced the activity-travel scheduling optimization behaviour. Older people of higher age tended to optimize less than older people with lower age. Males also had higher marginal utility of spending time at home than females. Finally, older people with age greater than or equal to 75 years tended to terminate their out-of-home trips earlier than all other age groups.

The results also spoke to the relevance of the framework for policy purposes. In circumstances where auto travel time was longer than transit, cycling or walking travel times, older people tended to choose to return home than to carry out other activities. This suggests the need for reliable and accessible transit services, or appropriate cycling and walking infrastructure. Such an implementation of mobility services pertaining to the needs of the elderly would encourage older people to be active within their neighbourhoods even without an auto-vehicle. Consequently, the issue of elderly mobility is also complicated by the fact that most trips conducted by older people are in suburban areas of the NCR, which tend to be underserved by transit. Moreover, the elderly tend to make trips during off-peak periods, when transit services are even less frequent.

The main limitation to the econometric framework is that the mode choice model was considered exogenous to the modelling system. The primary reason for this assumption was that older people in the NCR are predominantly users of the private automobile. Integration of the mode choice modelling component within this framework would produce a full activity-based



travel demand model that could capture trip generation, start times, trip distribution and mode choice through the use of a single modelling framework.

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