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Understanding variations in activity-based vehicle allocation decisions for solo and joint tours: A latent segmentation-based random parameter logit modeling approach

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Abstract

This paper examines the tour-level vehicle allocation decisions among individuals during mandatory- and discretionary-activity tours based on travel accompanying arrangements, specifically, solo travel (i.e. traveling alone) and joint travel (i.e. traveling with household/non-household members). Latent segmentation-based random parameter logit (LSRPL) models are developed in this study to explore the factors affecting vehicle allocation behavior within households, including travel characteristics, built environment and accessibility measures. For instance, model results suggest that presence of children in joint mandatory- and discretionary-activity tours increases individuals' probability of getting SUVs from their households' existing vehicle fleet. Also, tour complexity identified by higher number of activity stops, exhibits positive coefficient value for SUV allocation in case of discretionary-activity tours. One of the unique features of this study includes evaluating the effects of individuals' attitudes on vehicle allocation decisions at tour-level. For example, due to a positive attitude towards active transportation, individuals are observed to decrease their likelihood of using vehicles during both solo and joint mandatory-activity tours. The vehicle allocation decisions in the households, however, vary across two segments. Older-higher income individuals in segment one tend to get SUVs from their household vehicle fleet during a joint discretionary-activity tour while living in higher mixed land-use areas, however, younger-lower income individuals in segment two exhibit a negative relationship for SUVs. In addition to the heterogeneity across segments, preference of SUVs during a joint discretionary-activity tour might vary among individuals within the same segment, as indicated by statistically significant standard deviation of 'land-use index' variable.

Keywords: Vehicle allocation; Mandatory-activity tour; Discretionary-activity tour; Solo travel; Joint Travel; Latent segmentation-based random parameter logit model.

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1. Introduction

Activity-based travel models have been gaining popularity for the last few decades as the field has recognized travel demand as the outcome of individuals' daily needs and the activities they undertake to accomplish these needs (Davidson et al., 2007). Activity-based analysis explicitly accommodates spatial, temporal and modal interrelationships by recognizing the motivations underlying the performance of daily activities and travel. Activity-based travel demand models anticipate individuals' movement and travel decisions over an entire day and depict those decisions in a behaviorally representative manner by considering the underlying reasons and constraints. These models evaluate the interdependencies among different dimensions of travel (e.g. activity, time, mode, etc.) by considering the sequence of activities and travel segments (Pinjari et al., 2011). Most activity-based research focuses on daily activity participation and scheduling (Chu, 2005). There is an extensive body of literature on tour (i.e. series of trips, starts and ends at same location), mode choice and destination location choice (Mishra et al., 2013; Ding et al., 2014) as well. However, further investigation is required to develop more behaviorally plausible activity-based models to predict individuals' activity-travel preference decisions. Within a 24-hour period, individuals not only choose their activity type, locations, schedules and modes, but also choose which vehicle to use while going for a tour. The type of vehicle an individual takes from their households' existing vehicle fleet during their tours has direct effects on the transportation network. Since dynamic traffic microsimulation is gaining prevalence, modeling how individuals get vehicles for each tour is becoming an important research agenda. In addition, large-scale land use models are being developed that predict vehicle ownership decisions for households. Developing vehicle allocation models could further link land use models to activity-based travel models within large-scale integrated urban models. Research that addresses the allocation of vehicles to individuals within a household for various activity-based trip sequences is limited. It is not evident in the literature what differences exist among different groups of people while assigning vehicles from their existing vehicle fleet in multi-car households for specific travel arrangement situations. This study attempts to fill these gaps by developing vehicle allocation models for specific tour and travel accompanying arrangements using information from a travel-activity survey conducted in Halifax, Canada.

Modeling vehicle allocation is becoming an essential component of activity-based travel models, specifically in relation to data needs for dynamic traffic assignment and emission analysis. A critical linkage between activity scheduling and vehicle emission estimation is vehicle utilization for specific travel activities (Hao, 2009). However, limited research explores how different types of vehicles in multi-car households are allocated among the members based on their activity purpose at the tour level. In a dynamic microsimulation framework, vehicle allocation decision at tour-level is crucial, as it influences the estimation of emission and energy consumption. While specific emission rates exist for specific vehicle types, most of the emission models (Chamberlin et al., 2011) assume a fixed distribution of vehicle type to estimate vehicle emission and energy consumption across road networks. Therefore, to better forecast daily traffic emission and energy consumption, it is essential to know how households' vehicle fleets are being utilized, particularly how different types of vehicles are assigned to different individuals in a household.

This study contributes to the literature by exploring the determinants that affect vehicle allocation decisions among different types of individuals in multi-car households for mandatory- and discretionary-activity tours while traveling alone and traveling with household/non-household members. One of the unique contributions of this paper is to investigate the latent heterogeneity across the population regarding households' vehicle allocation decisions. Latent segmentation-based random parameter logit (LSRPL) models are developed in this study that incorporate two layers of heterogeneity across population. First, the model probabilistically allocates the individuals into different latent segments to capture the heterogeneity across individuals. Then random parameters are introduced within the LSRPL modeling framework that captures preference variations of individuals within the segments. By accommodating two layers of heterogeneity, the models developed in this study reveal vehicle trade-offs among individuals with different characteristics, and at the same time evaluate diversity in the behavior of individuals with similar characteristics.

2. Literature Review

A substantial amount of literature exists on activity-based models (ABM). ABMs are generally modeled as the choice of activity types and schedule based on mandatory, maintenance and discretionary activities. Literature suggests that socio-demographic attributes have significant effects on individuals' activity participation behavior. For example, Yamamoto and Kitamura (1999) found behavioral variations between in-home and out-of-home discretionary activity participation and time allocation during working and non-working days in terms of several socio-demographic determinants. Bhat (2005) also confirmed significant effects of both household and individual socio-demographic characteristics on individuals' discretionary activity participation. In the case of maintenance activities, researchers also found considerable influence of socio-demographic attributes on individuals' activity participation (Srinivasan et al., 2005). Some studies explored that along with socio-demographic attributes, land-use and accessibility factors also affect the maintenance activity participation behavior substantially (Chu, 2017; Schwanen et al., 2007). In addition, tour-based ABMs that evaluate individuals' participation and time allocation at the tour level are also common practice in the activity-based travel research field (You et al., 2013; Garikapati et al., 2014).

Due to the interdependencies among activity type choice, scheduling and modes to participate in an activity, tour-based mode choice models started to gain popularity in the activity-based research paradigm. Generally, tour-based mode choice models focus on individuals' mode choice decisions based on tour complexity, represented by the number of activity stops within a tour. The presence of a higher number of activity stops within a tour increases individuals' probability of choosing private transportation, such as auto, rather than public transit (Hensher and Reyes, 2000; Wallace et al., 2000). Also, during a complex tour, people are more likely to take a non-driving mode for non-work tours and a driving mode for work tours (Yun et al., 2014). Tour-based mode choice models are often modeled with the activity type choice and scheduling. For instance, while modeling individuals' activities and travel decisions simultaneously, Ho and Mulley (2013) identified that individuals' age, activity purpose and household structure are the most important factors for deciding out-of-home activities and mode choice, regardless of day of the week. Ding et al. (2014) found that built environment attributes have variable effects on mode choice during work tours and non-work tours. Moreover, Hess et al. (2007) and Day (2008) estimated individuals' departure time and mode choice models and observed a significant influence of travel characteristics on individuals' departure time and mode choice decisions. However, there is a gap in understanding how vehicles are assigned to the individuals in the households upon choosing auto as their mode for travel.

In an integrated urban model, vehicle ownership is a critical component that demonstrates households' decisions of ownership level and transaction events. An extensive body of literature on vehicle ownership choices exists in case of modeling vehicle ownership level (Potoglou and Kanaroglou, 2008), vehicle transaction (Mohammadian and Rashidi, 2014), vehicle type choice (Choo and Mokhtarian, 2004), etc. A recent growing interest in vehicle ownership phenomena is to explore how vehicles are allocated to the individuals in a household at the tour level. How different types of vehicles in the households are utilized to perform daily activities and tours is not clear in the existing studies. It is necessary to be informed what vehicles are taken by individuals during their tours while entering the traffic network since this could contribute in dynamic traffic assignment-based models or disaggregate traffic simulation models where vehicles can be tracked. Hence, traffic congestion, vehicular emission and energy consumption can be measured based on each vehicle type in the network. A few studies exist on the vehicle allocation choice behavior. For instance, Petersen and Vovsha (2005) estimated a vehicle choice preference model for travel needs at the tour level, where they showed that vehicle allocation decisions are dependent on mode choice, travel arrangements and activity schedule adjustments. They found significant socio-demographic effects on the vehicle preferences of households, for example, men are less likely to use larger cars than women for joint travel and escorting. A tour-level vehicle type choice model, developed in Konduri et al. (2010), confirmed that older age, increasing tour length and tour complexity increase individuals' probability of preferring larger cars. Anggraini et al. (2008) investigated vehicle assignment behavior in car-deficient households for work tours. They found that men usually get the car rather than women while traveling to workplaces. Utilizing the same framework, Anggraini et al. (2012) later estimated a non-work tour-based car allocation, which revealed that, even for the non-work tour, men have a greater probability to use the car than women. An unlabeled binary choice model developed by Lim (2016) also confirmed significant effects of various tour and socio-demographic attributes on individuals' vehicle type choice for social-recreational tours. He found that bigger party size and the presence of at least one child in the household increases the likelihood of preferring larger cars during social-recreational tours. Furthermore, Wen and Koppelman (2000) argued that the allocation of vehicles for maintenance activities in a car-deficient household significantly depends on the choice of activities. The study highlighted that employment and performing maintenance activities tend to increase both males and females' probability of getting a car.

In summary, although there are few studies on vehicle allocation within households, a clear gap exists in understanding the behavioral differences of vehicle allocation among individuals in a multi-car household for mandatory- and discretionary-activity tours. It is also not evident, in terms of determinants, how members of the households get vehicles from their existing vehicle fleet for different travel accompanying arrangements, specifically traveling alone (i.e. solo travel) and traveling with household/non-household members (i.e. joint travel), and whether any differences exist while allocating vehicles between different types of individuals. This study attempts to fill these gaps by developing vehicle allocation models for specific tours and travel accompanying arrangements. One of the unique contributions of this study is to examine the influence of attitudinal factors on vehicle allocation decisions, which is limited in the existing literature. Four activity-based vehicle allocation models at tour-level are developed in this paper based on individuals' solo mandatory-activity tour, joint mandatory-activity tour, solo discretionary-activity tour and joint discretionary-activity tour. The study assumes that vehicles are allocated from the vehicle fleet a household owns for the purpose of individuals' activity needs, as reflected in the identified tours. The study develops Latent Segmentation-based Random Parameter Logit (LSRPL) models that explore the factors affecting households' vehicle allocation decisions for the individuals belonging to distinct latent groups. These factors include travel characteristics, attitudinal factors, built environment and accessibility measures.

3. Data

3.1 Data source

The datasets used in this study are obtained through a travel-activity survey known as the 2016 Nova Scotia Travel Activity (NovaTRAC) Survey, which was conducted in Halifax, Canada. The 2016 NovaTRAC is a cross-sectional survey that collected information on the household and its members, household vehicles, and a 24-hour travel activity log. The survey resulted in 647 total individual responses. Household vehicle information included number and types of vehicles (i.e. make-model-year of a vehicle) available in the households. Information related with the residential location, type, ownership status, household size, etc. were included in household information. In household members' information, members' age, education, employment, annual income, attitudes and lifestyle preferences, etc. were included. Lastly, a 24-hour travel activity log included household members' trip locations, time, purpose, mode, vehicle used, accompanying person, etc. Additional data sources used in this study include the 2011 Canadian Census, land-use information from Halifax Regional Municipality (HRM), and location information for activity points and transportation services from Desktop Mapping and Technologies Inc. (DMTI).

3.2 Data preparation

The NovaTRAC survey suggests that 14.68% of the total respondents belong to zero-car households, 40.34% respondents are from one-car households, and 44.98% respondents are from multi-car households. Following the choice of auto mode to use during daily tours, one-car household members usually have no other alternatives but to take their only available vehicle. However, in multi-car households, individuals' choice of vehicles from the existing household fleet might vary depending on their characteristics, attitudes, travel attributes, etc. while performing different tours in a day. Hence, this study estimates the vehicle allocation models for specific activity purposes in multi-car households in terms of travel accompanying arrangements, namely traveling alone and traveling with household/non-household members. Tour-level data is processed from the trip-level data of the NovaTRAC survey using a routine written in the PHP programming language. Formation of tour-level data from trip information includes several steps. First, all the home-based tours (HBTs, starts and ends at home) by the respondents are identified. Next, respondents' activities are categorized into following three groups:

a) *Mandatory activities*: work/job and all other activities at work location, attending class and all other activities at school;
b) *Maintenance activities*: escorting, routine shopping, household and work-related errands, personal business,and health care;
c) *Discretionary activities*: eating out, civic or religious activities, recreation/entertainment, and visiting friends/family.

Note that all maintenance activities are further assumed to be considered within the 'discretionary activity' category in this study. Presumably, maintenance activities are more flexible than the mandatory activities, and individuals might be able to use discretion to reschedule their maintenance activities. After activity categorization, a primary activity is identified for each HBT. The primary activities are defined based on activity priority and dwell time at activity destinations (i.e. time spent getting to and at activity). Mandatory activities are given the highest priority in a tour. A tour is characterized as a 'mandatory-activity tour' in the presence of at least one mandatory activity within that tour. In case of multiple mandatory activities within a tour, the activity with the higher dwell time is given the highest priority. All other activities in a mandatory-activity tour are included in intermediate stops. Furthermore, if a tour consists of only discretionary activity stops, the activity with the highest dwell time is assigned as the primary activity, and the tour is designated as a 'discretionary-activity tour'. Other discretionary activities are assigned as intermediate stops within the tour. In addition, since tours are specified based on their primary activities, travel arrangement and vehicle used to get to the primary activity destination are specified as the corresponding tour's travel arrangement and vehicle used. Hence, four separate datasets for vehicle allocation models at tour-level are prepared based on the type of tour and travel accompanying arrangements:

a) *Solo mandatory-activity tour*: traveling alone to the mandatory-activity destination.
b) *Joint mandatory-activity tour*: traveling with household/non-household members to the mandatory-activity destination.
c) *Solo discretionary-activity tour*: traveling alone to the discretionary-activity destination.
d) *Joint discretionary-activity tour*: traveling with household/non-household members to the discretionary-activity destination.

In this study, vehicles are categorized depending on their body types in alignment with the earlier vehicle ownership model (Khan and Habib, 2016) and integrated land use model that is being developed in Halifax, Canada (Fatmi and Habib, 2018). Since the types of vehicles available in a multi-car household vary across households, variable choice sets are used in this study to evaluate vehicle allocation decisions in the households for different types of tours and travel accompanying arrangements. All individuals are assumed to choose from a set of following five types of vehicles, albeit some of the vehicles might be unavailable to them:

a) *Subcompact vehicles*: Ford Fiesta, Honda Fit, Toyota Yaris, etc.
b) *Compact vehicles*: Honda Civic, Hyundai Accent, Kia Forte, etc.
c) *Midsize vehicles*: Honda Accord, Chrysler 300, Ford Taurus, etc.
d) *SUV (Sport Utility Vehicle)*: Ford Escape, Honda CR-V, Toyota RAV4, etc.
e) *Vans (van/minivan/truck)*: GMC Savana, Ford E150, Chevrolet Silverado 1500, etc.

Individuals' socio-demographic and travel characteristics are extracted from the NovaTRAC survey. In addition, to evaluate the effects of individuals' attitudes on vehicle allocation, initially this study attempted to test hypotheses regarding all attitudinal statements. However, a correlation test showed that the attitudinal statements are highly correlated. To address this issue, the Principal Component Analysis (PCA) with selected attitudinal statements is conducted. Varimax orthogonal rotation method is used to extract the components (Corner 2009). Two components are extracted, driving attitude component and AT (active transportation) attitude component. Table 1 shows the component loadings on each attitudinal statement variables for all four models.

Table 1. Principal component analysis of the vehicle allocation models.

Statement variables	Solo Mandatory-Activity Tour		Joint Mandatory-Activity Tour		Solo Discretionary-Activity Tour		Joint Discretionary-Activity Tour	
	Driving attitude component	AT attitude component	Driving attitude component	AT attitude component	Driving attitude component	AT attitude component	Driving attitude component	AT attitude component
Enjoy bicycle riding	-0.1187	0.8019	-0.1862	0.8160	-0.0590	0.7394	-0.2202	0.7546
Prefer walking to driving	-0.2257	0.5843	-0.3788	0.3525	-0.0626	0.6620	-0.2275	0.5233
Take pride owning a car	0.6509	-0.0622	0.3666	-0.4268	0.6647	-0.0930	0.2862	-0.3895
Driving gives freedom	0.7151	-0.1079	0.8291	-0.1664	0.7421	-0.0803	0.9044	-0.0712
% Variance Explained	*38.94%*	*32.93%*	*33.54%*	*34.55%*	*35.72%*	*32.12%*	*29.39%*	*40.53%*

Built environment variables, for instance, number of people and dwellings in the neighborhood are collected from the 2011 Canadian Census and the HRM Geodatabase at the dissemination area (DA) level. Dissemination areas are identified using respondents' home locations and HRM map in ArcGIS. Land-use information is taken from the land-use database of HRM at the DA level. Furthermore, accessibility measures are calculated based on respondents' home locations and different activity points' locations by using the Network Analyst Tool of ArcGIS. Location information of the activity points, such as location of central business district, schools, food stores, entertainment facilities, etc., is collected from the DMTI database. Finally, utilizing the common dissemination area ID, all the databases are joined with the tour-based datasets to prepare four complete vehicle allocation datasets.

4. Modeling approach

This study evaluates the preference heterogeneity among different types of individuals for households' vehicle allocation decisions in case of repeated mandatory- and discretionary-activity tours. A latent segmentation-based logit (LSL) modeling approach can accommodate the heterogeneity by allocating individuals into different segments following a discrete distribution (Shen, 2009). Generally, the segments are defined based on individuals' characteristics, and behavioral homogeneity is assumed within each segment. However, there is a strong possibility that all individuals with similar characteristics may not behave the same and may have variations in their preferences. As a result, biased estimations might occur due to the restrictive assumption of homogeneity within segments, and the model might be inadequate to describe preference of individuals from different segments. Therefore, to accommodate the diversity within segments, a continuous distribution of random parameters is integrated over the segments in the LSL framework. Thus, a latent segmentation-based random parameter logit (LSRPL) model is developed in this study that anticipates two layers of unobserved heterogeneity, first a) by allowing a discrete distribution of parameters that implicitly sorts individuals into different segments, then b) by allowing random parameters to vary across individuals within the same segment following a continuous distribution.

In the LSRPL modeling framework, heterogeneity across segments is captured by latent segment formulation. Allocation of individuals into segment *s* is unknown, hence the term 'latent segment'. A segment allocation model is developed within the latent segment formulation that permits the LSRPL model to probabilistically allocate individuals into discrete latent segments. Flexibility of the segment allocation model arises when segment allocation probabilities are determined by using an individual's characteristics (Hess et al. 2011). This study develops flexible segment allocation models that are defined by individuals' socio-demographic characteristics. If Y_j is the characteristics of an individual *j* that is used to define the segments, then the probability of an individual to be allocated to segment *s* can be written as equation 1:

$$\theta_{js}\left(Y_j,\varphi\right)=\frac{exp\left(\nu_s+\varphi_s'Y_j\right)}{\sum_{s=1}^{S}exp\left(\nu_s+\varphi_s'Y_j\right)} \tag{1}$$

Here, υ_s and φ'_s are the latent segment membership constant and parameter vector, respectively. To identify the model, one of the latent segments is considered as the reference segment by considering υ_s and φ'_s fixed for that segment. Let, $\beta_j|s$ is the segment-specific parameter vector for individuals *j* in the segment *s*. To allow heterogeneity within segments, continuous variation of random parameters is allowed in each segment. Heterogeneity within the segments can be described as equation 2:

$$\beta_j \mid s = \beta_s + \sigma_{j|s}$$
$$\sigma_{j|s} \sim E\left[\sigma_{j|s} \mid X_{jt,i}\right] = 0, \qquad Variance\left[\sigma_{j|s} \mid X_{jt,i}\right] = \delta_s \tag{2}$$

Assuming that an individual *j* gets vehicles from household's existing vehicle fleet I_j, during an activity-tour *t*, the vehicle allocation choice probability of an individual *j* belongs to segment *s* is given by equation 3:

$$g\left[C_{jt,i} \mid \left(\beta_s + \sigma_{j|s}\right), X_{jt,i}\right] = \frac{exp\left[\sum_{i=1}^{I_j} C_{jt,i}\left(\beta_s + \sigma_{j|s}\right)' X_{jt,i}\right]}{\sum_{i=1}^{I_j} exp\left[\sum_{i=1}^{I_j} C_{jt,i}\left(\beta_s + \sigma_{j|s}\right)' X_{jt,i}\right]}, \qquad i = 1, 2, ..., I_j \tag{3}$$

Here, $X_{jt,i}$ is the observed vector attributes of an individual *j* during an activity-tour *t* while choosing vehicle *i* from the household's existing fleet. $C_{jt,i}$ is the vehicle allocation choice representing *1* when a vehicle *i* is assigned to an individual *j* from his household's own existing vehicle fleet I_j during an activity-tour *t*, and *0* for all others. Furthermore, the unconditional probability can be expressed as equation 4:

$$P\left(C_{jt,i} \mid X_{jt,i}, \beta_1, ..., \beta_S, \varphi, Y_j, \delta_1, ..., \delta_S\right) = \sum_{s=1}^{S} \theta_{js}\left(Y_j, \varphi\right) \int_{\sigma_{j|s}} \prod_{t=1}^{T_j} g\left[C_{jt,i} \mid \left(\beta_s + \sigma_{j|s}\right), X_{jt,i}\right] G\left(\sigma_{j|s} \mid \delta_s\right) d\sigma_{j|s} \tag{4}$$

Where, T_j represents number of tours performed by individuals *j* in a day. For within-segment heterogeneity, this study assumes a normally distributed density function (specified by *G* in equation 4) with mean *0* and covariance *δ*. The log-likelihood function based on above probability expression can be written as equation 5:

$$LL_u = \sum_{j=1}^{J} \log\left[P\left(C_{jt,i} \mid X_{jt,i}, \beta_1, ..., \beta_S, \varphi, Y_j, \delta_1, ..., \delta_S\right)\right] \tag{5}$$

Since equation 5 involves a multivariate integral that does not have any closed form, use of simulation method is required to estimate the model (. Hence, this study utilizes a maximum simulated likelihood estimation to evaluate the parameters. The contribution of each individual to the simulated likelihood can be given by the following equation 6:

$$L = \sum_{s=1}^{S} \theta_{js}\left(Y_j, \varphi\right) \frac{1}{Q} \sum_{q=1}^{Q} \prod_{t=1}^{T_i} g\left[C_{jt,i} \mid \left(\beta_s + \sigma^q{}_{j|s}\right), X_{jt,i}\right] \tag{6}$$

Here, $\sigma^q{}_{j|s}$ is the *q*-th random draw of the random vector $\sigma_{j|s}$, which is repeated total *Q* times. Finally, the simulated log-likelihood function (*SL*), described by equation 7, can be obtained by taking the logarithm of equation 6

$$SL = \sum_{j=1}^{J} \log\left[\sum_{s=1}^{S} \theta_{js}\left(Y_j, \varphi\right) \frac{1}{Q} \sum_{q=1}^{Q} \prod_{t=1}^{T_i} g\left[C_{jt,i} \mid \left(\beta_s + \sigma^q{}_{j|s}\right), X_{jt,i}\right]\right] \tag{7}$$

The Halton sequence is used in this study as it requires a substantially lower number of draws. The models converge and stable covariates are found at 200 Halton draws. Each model is evaluated on the basis of model fit results of log-likelihood value at convergence and Bayesian Information Criteria (BIC) measures.

5. Discussion of results

5.1 Independent variables considered

This study examines the effects of individuals' various socio-demographic characteristics, travel characteristics, attitudinal factors, built environment and accessibility measures on vehicle allocation decisions for different types of tours and travel arrangements.

Individuals' socio-demographic characteristics retained in final models include their age, gender, household size, annual income, employment status, and current home, among others. Flexible latent segmentation-based random parameter logit models can be developed by utilizing individuals' characteristics to define segment allocation probability. Hence, this study uses several socio-demographic characteristics, for example, age, annual income, employment status and current home, to develop the segment allocation models. Critical travel characteristics, such as tour duration, number of activity stops within each tour, travel companions etc. are also examined during model specification. One of the unique contributions of this study is to explore the effects of individuals' attitudes on households' vehicle allocation decisions. Previous studies found that attitudes have substantial effects on individuals' vehicle choices (Choo and Mokhtarian, 2004). Therefore, using two PCA-derived components, a driving attitude component and an AT attitude component (Table 1), and the corresponding attitudinal statements of the survey, this study obtains two attitudinal variables, namely 'positive attitude towards driving' and 'positive attitude towards active transportation' to explore vehicle allocation decisions during mandatory- and discretionary-activity tours. In addition, various built environment and accessibility measures are used during final model specifications to understand how individuals' residential location influences vehicle allocation decisions during different types of tours. A detailed description of the variables retained in the final models along with their summary statistics are presented in Table 2 and 3.

Table 2. Mandatory-activity tour descriptive statistics.

Distribution of dependent variables		
Available vehicle type in multi-car households	Solo mandatory-activity tour (n = 295)	Joint mandatory-activity tour (n = 238)
Subcompact vehicle	14.63%	21.90%
Compact vehicle	27.21%	24.82%
Midsize vehicle	26.87%	13.87%
SUV (sport utility vehicle)	22.79%	32.12%
Van	8.50%	7.30%

Distribution of independent variables					
Variables	Description	Solo mandatory-activity tour		Joint mandatory-activity tour	
		Mean/ Proportion	Standard Deviation	Mean/ Proportion	Standard Deviation
Socio-demographic characteristics					
Age	Age of individual	40.364	16.052	38.920	14.514
Female partner/spouse	Dummy, if individual is a female partner/spouse = 1, 0 otherwise	52.78%	-	55.69%	-
Annual income > $75,000 CAD	Dummy, if individual's annual income is more than $75,000 CAD = 1, 0 otherwise	63.61%	-	58.83%	-
Full-time employment	Dummy, if individual is full-time employed = 1, 0 otherwise	62.20%	-	-	-
Part-time employment	Dummy, if individual is part-time employed = 1, 0 otherwise	-	-	15.33%	-
Current home_Single detached house	Dummy, if individual lives in a single detached house = 1, 0 otherwise	57.48%	-	57.15%	-
Household size	Number of people in the household	2.490	1.260	2.774	1.243
Travel characteristics					
Tour duration	Total time spent within a mandatory-activity tour (minutes)	523.201	173.010	514.949	194.665
Number of activity stops	Number of activity stops within a mandatory-activity tour	1.221	1.674	1.409	1.607
Number of tours	Number of tours performed in a day	1.323	0.646	1.387	0.621
Traveling with partner/spouse	Dummy, if individual travel with partner/spouse = 1, 0 otherwise	-	-	45.18%	-
Traveling with children	Dummy, if individual travel with children = 1, 0 otherwise	-	-	25.56%	-
Attitudinal variables					
Positive attitude towards driving	Individual's positive attitude towards driving (PCA-derived)	2.061	1.372	1.050	1.090
Positive attitude towards AT	Individual's positive attitude towards active transportation (PCA-derived)	2.640	1.532	1.146	1.281
Built environment and accessibility measures					
Land-use index	Land-use index of the neighborhood	0.510	0.150	0.487	0.143
Dwelling density	Dwelling per square kilometers area in the neighborhood	17	25	20	27

Distance from home to CBD	Individual's home to central business district (CBD) distance (kilometers)	38.677	62.277	29.599	46.179
Distance from home to nearest school	Individual's home to nearest school distance (kilometers)	1.299	1.908	1.330	1.660

Table 3. Discretionary-activity tour descriptive statistics

Distribution of dependent variables		
Available vehicle type in multi-car households	Solo discretionary-activity tour (n = 285)	Joint discretionary-activity tour (n = 229)
Subcompact vehicle	22.49%	21.49%
Compact vehicle	29.41%	23.68%
Midsize vehicle	21.11%	13.35%
SUV (sport utility vehicle)	18.69%	28.95%
Van	8.30%	10.53%

Distribution of independent variables					
Variables	Description	Solo discretionary-activity tour		Joint discretionary-activity tour	
		Mean/ Proportion	Standard Deviation	Mean/ Proportion	Standard Deviation
Socio-demographic characteristics					
Age	Age of individual	42.806	16.414	41.711	14.990
Male partner/spouse	Dummy, if individual is a male partner/spouse = 1, 0 otherwise	50.45%	-	43.77%	-
Annual income > $75,000 CAD	Dummy, if individual's annual income is more than $75,000 CAD = 1, 0 otherwise	41.87%	-	44.12%	-
Full-time employment	Dummy, if individual is full-time employed = 1, 0 otherwise	44.29%	-	59.74%	-
Travel characteristics					
Tour duration	Total time spent within a discretionary-activity tour (minutes)	338.747	243.950	435.106	246.021
Number of activity stops	Number of activity stops within a discretionary-activity tour	1.111	1.420	1.162	1.619
Traveling with partner/spouse	Dummy, if individual travel with partner/spouse = 1, 0 otherwise	-	-	37.72%	-
Traveling with children	Dummy, if individual travel with children = 1, 0 otherwise	-	-	30.26%	-
Attitudinal variables					
Positive attitude towards driving	Individual's positive attitude towards driving (PCA-derived)	2.780	1.141	1.255	1.119
Positive attitude towards AT	Individual's positive attitude towards active transportation (PCA-derived)	2.718	1.362	1.888	1.485
Built environment and accessibility measures					
Land-use index	Land-use index of the neighborhood	0.518	0.157	0.486	0.162
Dwelling density	Dwelling per square kilometers area in the neighborhood	18	39	15	25
Distance from home to nearest foodstore	Individual's home to nearest foodstore distance (kilometers)	1.493	2.630	1.221	1.794
Distance from home to nearest shopping mall	Individual's home to nearest shopping mall distance (kilometers)	9.351	15.562	5.102	11.238
Distance from home to nearest entertainment facility (cinema)	Individual's home to nearest entertainment facility (cinema) distance (kilometers)	10.223	17.136	7.735	16.296

5.2 Model results

5.2.1 Goodness-of-fit measures

In this study, an appropriate number of segments is determined based on the Bayesian Information Criteria (BIC) measures. According to literature, models with smaller BIC value are considered as better models while comparing (Burnham and Anderson 2004). Model results suggest that BIC measures for all four models that consist of two segments are lower (Table 4). Therefore, all the final models are assumed to have two segments.

Table 4. Model fits for number of segment determination

Goodness-of-fit	Solo Mandatory-Activity Tour		Joint Mandatory-Activity Tour		Solo Discretionary-Activity Tour		Joint Discretionary-Activity Tour	
	No. of segments 2	No. of segments 3	No. of segments 2	No. of segments 3	No. of segments 2	No. of segments 3	No. of segments 2	No. of segments 3
Log-likelihood (convergence)	-150.67	-167.08	-130.16	-165.78	-134.79	-168.98	-119.45	-142.32
BIC	2.76	3.73	4.81	6.23	2.65	3.74	2.66	3.66

Below is a brief description of the vehicle allocation models developed in this study.

5.2.2 Vehicle allocation models for mandatory-activity tours

Latent Segment Allocation Component Characterization

For both solo and joint mandatory-activity tour vehicle allocation models, individuals' socio-demographic characteristics are used to define the latent segment allocation components. Segment two is considered as the reference segment during both model estimation. In case of the vehicle allocation model for solo mandatory-activity tours (Table 5), older full-time employed individuals who earn more than $75,000 CAD annually and live in single-detached houses exhibit positive coefficient values in segment one. This indicates such individuals' higher likelihood to be included in segment one. Latent segment allocation model for joint mandatory-activity tour (Table 6) suggests positive signs for variables representing age, annual income above $75,000 CAD and living in a single detached house, and a negative sign for part-time employment in segment one. Presumably, segment one in both models is identified as the segment of 'older-higher income individuals' for ease of discussion. In contrast, segment two is assumed as the segment of 'younger-lower income individuals'. Table 5 and 6 exhibit the results of vehicle allocation models for mandatory-activity tours.

Solo Mandatory-Activity Tour Model

The majority of the variables retained in the final model (Table 5) suggest that individuals have a higher probability to get smaller vehicles (i.e. subcompact and compact vehicles) while performing solo mandatory activity-tours. For example, female partner/spouse in the households show positive signs for subcompact and compact vehicles (coefficient values 11.162 and 9.522, respectively) in segment one that consists of older-higher income individuals. Higher coefficient value for subcompact vehicles (11.162) in the older-higher income segment indicates such female partner/spouse's higher probability of getting subcompact vehicles over compact vehicles from their household's existing vehicle fleet during a solo mandatory-activity tour. Female partners/spouses in segment two (i.e. younger-lower income segment) also exhibits a higher likelihood to choose subcompact vehicles from their existing vehicle fleet. However, in both segments, statistically significant standard deviations demonstrate some female partners/spouses' preference variations for subcompact vehicles. With the increase of household size, larger vehicles like SUVs are more likely to be allocated to the older-higher income individuals of segment one. In contrast, younger-lower income individuals who belong to segment two exhibit an opposite relationship. As the number of people in the household increases, comparatively smaller vehicles (i.e. compact vehicles) are highly likely to be assigned to younger-lower income individuals in segment two from their household's existing vehicle fleet. Standard deviations for compact vehicles in both segments suggest that household size has heterogeneous effects on some individuals' compact vehicle preference during a solo mandatory-activity tour.

In case of travel characteristics, complex solo mandatory-activity tour (i.e. presence of higher number of activity stops within the tour) increases the probability of allocating subcompact vehicles over SUVs to the individuals in both segments. However, there might be some individuals in each segment who would behave differently by choosing SUVs, as indicated by the standard deviations of 'number of activity stops'. As expected, older-higher income individuals with a positive attitude towards driving show positive coefficient values for compact vehicles, SUVs and vans, although the higher coefficient value for SUVs suggests a propensity toward preferring SUVs in the older-higher income segment during a solo mandatory-activity tour. On the other hand, the variable exhibits a positive sign for compact vehicles in the younger-lower income segment. Interestingly, the variable representing a positive attitude towards AT demonstrates negative relationships with all vehicle types irrespective of segments, perhaps indicating such individuals' disinclination towards driving.

Table 5. Results of vehicle allocation model for solo mandatory-activity tour.

Results of the latent segment allocation component		
	Segment 1	Segment 2
Segment Membership Probabilities	0.578	0.422
Constant	1.2171*	-
Annual income > $75,000 CAD	2.2839**	-
Age	0.0189***	-
Full-time employment	2.7079**	-
Current home_Single detached house	0.1702**	-

Parameter estimation results										
Variables	Available vehicle type in multi-car households									
	Subcompact		Compact		Midsize		SUV		Van	
	Segment 1	Segment 2	Segment 1	Segment 2	Segment 1	Segment 2	Segment 1	Segment 2	Segment 1	Segment 2
Constant	-0.6631*	0.8913**	1.1347**	-12.9918*	Reference	Reference	-4.2347**	-17.2437*	-12.3124*	-16.3829**
Socio-demographic characteristics										
Female partner/spouse	11.1615*	6.4798	9.5221**	-12.4035*	-	-	-0.8361**	-7.5599**	-1.0600**	-0.1064*
Household size	-	-	-1.6469*	4.5859*	-	-	5.7539*	-3.8643*	-	-
Travel characteristics										
Tour duration	-	-	0.0232	0.0026	-0.0012**	-0.0088**	-	-	-0.0071**	-0.0335*
Number of activity stops	3.7174	4.8195**	-	-	-	-	-0.6478**	-0.2193**	-	-
Number of tours	-	-	-0.2322**	4.7765**	-	-	-	-	0.2743***	-2.6768**
Attitudinal variables										
Positive attitude towards driving	-	-	3.4449*	2.7981**	-	-	4.2175**	-4.1844*	2.6501**	-3.1649
Positive attitude towards AT	-7.2376**	-3.2514**	-1.7970*	-5.8339*	-8.4599**	-1.2221*	-	-	-0.1247	-7.0863*
Built environment and accessibility measures										
Land-use index	3.3530*	0.6658**	-	-	-8.6147**	-8.0823**	-5.3416**	-9.605***	-	-
Dwelling density	0.0034***	0.0081**	-0.0027**	-0.0084*	-	-	-0.0178**	-0.0075	-	-
Distance from home to CBD	-0.1039*	0.0521*	-	-	0.0346**	-0.1850**	0.5763	-0.5947	-	-
Distance from home to nearest school	-	-	-0.0145	0.0120**	0.0063**	-0.0087**	-	-	-0.0077*	-0.0084**
Standard deviation of random parameters										
Female partner/spouse	0.0413*	0.0745*	-	-	-	-	-	-	-	-
Household size	-	-	0.0556***	0.0201*	-	-	-	-	-	-
Number of activity stops	-	-	-	-	-	-	0. 0411**	0.0758**	-	-
Positive attitude towards AT	-	-	-	-	-	-	-	-	0.1216*	0.0292**
Distance from home to nearest school	-	-	-	-	0.1650**	0.7620***	-	-	-	-

*Note: ***1% confidence level; **5% confidence level; *10% confidence level*

Furthermore, positive coefficient values of land-use index and dwelling density for subcompact vehicles in both segments indicate that smaller vehicles are more likely to be preferred by individuals during a solo mandatory-activity tour who reside in urban areas (i.e. higher dwelling density and mixed land-use areas). Suburban area dwellers, who live farther away from the CBD, exhibit heterogeneity across segments during solo mandatory-activity tours. The probability of larger vehicle (i.e. SUVs, midsize vehicles) allocation is higher in segment one that includes older-higher income individuals, whereas, younger-lower income individuals in segment two tend to get smaller subcompact vehicles during a solo mandatory-activity tour. In addition, heterogeneous effects across segments are observed in case of the distance from home to nearest school. Living farther away from a school, individuals' probability of getting midsize vehicles increases in the older-higher income segment but decreases in younger-lower income segment. As the distance from home to nearest school increases, compact vehicles are more likely to be allocated to the younger-lower income individuals. Interestingly, standard deviations of the variable in the case of midsize vehicles are found higher than the mean (i.e. segment one 0.0063 mean, 0.1650 standard deviation; segment two -0.0087 mean, 0.7620 standard deviation), which suggests significant behavioral variations in each segment while choosing midsize vehicles from the household's existing vehicle fleet.

Joint Mandatory-Activity Tour Model

Table 6 presents the vehicle allocation model results for joint mandatory-activity tours. While performing a joint mandatory-activity tour with household/non-household members, female partner/spouse in the households has a higher chance of getting larger vehicles, especially SUVs, from household vehicle fleet irrespective of segments. In case of solo mandatory-activity tour, this result was found opposite. This intuitively suggests female partner/spouse's association with children's school trips in their mandatory-activity tour. However, compact vehicles might also be preferred by some female partners/spouses within both segments as indicated by the statistically significant standard deviations. As expected, individuals belonging to larger households are also positively related with the allocation of larger vehicles in both segments for joint mandatory-activity tour, as suggested by the positive coefficient values for SUVs in segment one and two. Interestingly, heterogeneity within segments is observed for individuals in larger households in case of getting SUVs during a joint mandatory-activity tour, indicated by the significant standard deviation.

Model estimation demonstrates expected results in case of traveling with household members during a joint mandatory-activity tour. For example, presence of children within the tour increases individuals' probability of getting SUVs in both older-higher income and younger-lower income segment. This finding perhaps implies travelers' concern for safety and comfort of the accompanying child while traveling to perform mandatory activities. Tour complexity, represented by the higher number of activity stops within the tour, also increases probability of SUV allocation in segment one that consists of older-higher income people. In contrast, individuals belonging to the younger-lower income segment tend to prefer compact vehicles during their joint mandatory-activity tour. In addition to the variations across segments, statistically significant standard deviations demonstrate heterogeneity in each segment for compact vehicle allocation to individuals during complex joint mandatory-activity tours. Furthermore, during a joint mandatory-activity tour, individuals with a positive attitude towards driving exhibit higher probability to choose SUVs in older-higher income segment and midsize vehicles in younger-lower income segment, which during solo tours were midsize vehicles in older-higher income segment and compact vehicles in younger-lower income segment. This essentially suggests that presence of another person(s) during a tour increases probability to get larger vehicles from existing vehicle fleet than driving alone. However, standard deviations in case of 'positive attitude towards driving' at 5% significance level for midsize vehicles confirm individuals' heterogeneous nature within segments. As expected, variable representing individuals' positive attitude towards active transportation exhibit negative coefficient values for the choice of vehicles.

Positive relationships between urban area dwellers and larger vehicle allocation are observed for joint mandatory-activity tours. For example, individuals belonging to older-higher income and younger-lower income segments are more likely to get SUVs and vans while living in the higher dwelling density neighborhoods. Also, midsize vehicles tend to be assigned to the individuals who live in higher mixed land-use areas. Perhaps, individuals travel higher distances with household/non-household members to perform their mandatory activities despite living in urban areas, hence, require high performance and larger vehicles from their existing vehicle fleet. As expected, older-higher income individuals living in suburban areas (i.e. higher distance from home to CBD) have higher propensity to choose SUVs from their households' vehicle fleet during joint mandatory-activity tours. However, with the distance from home to CBD, probability of SUV allocation decreases in the segment of younger-lower income individuals. Rather, they exhibit a higher preference for compact vehicles.

Table 6. Results of vehicle allocation model for joint mandatory-activity tour.

Results of the latent segment allocation component		
	Segment 1	Segment 2
Segment allocation probabilities	0.487	0.513
Constant	-0.0455*	-
Annual income > $75,000 CAD	0.1533**	-
Age	0.0075**	-
Part-time employment	-0.1893**	-
Current home_Single detached house	0.0549**	-

Parameter estimation results										
Variables	Available vehicle type in multi-car households									
	Subcompact		Compact		Midsize		SUV		Van	
	Segment 1	Segment 2	Segment 1	Segment 2	Segment 1	Segment 2	Segment 1	Segment 2	Segment 1	Segment 2
Constant	2.3656*	2.5520*	-0.1816*	-0.2606**	Reference	Reference	0.8322***	0.5839*	5.1593*	4.9926**
Socio-demographic characteristics										
Female partner/spouse	-1.7555**	-1.7274*	-1.5952**	-1.6862*	-	-	0.4381***	0.6947*	-2.6664**	-2.5602**
Household size	-	-	-0.9417*	-0.3364**	-	-	1.8608*	0.8629*	-	-
Travel characteristics										
Traveling with partner/spouse	-2.2457**	-2.2187*	-	-	-	-	-	-	-2.9142*	-2.8366***
Traveling with children	-2.9359***	-2.8645*	-	-	-	-	0.2315*	0.4335**	-1.215***	-0.8608**
Tour duration	-	-	-0.0012**	-0.0030**	0.0030	0.0028	-	-	-0.0044**	-0.0135**
Number of activity stops	-0.2965**	-0.5920**	-0.3828**	0.4391**	-	-	1.2422**	-0.3446*	-	-
Attitudinal variables										
Positive attitude towards driving	-	-	-	-	-0.0921	0.5380*	0.4628*	-0.0649	-	-
Positive attitude towards AT	-	-	-0.5451**	-1.1269**	-0.2129**	-0.3524**	-	-	-	-
Built environment and accessibility measures										
Land-use index	-	-	-0.2679	-0.3767*	2.1000**	1.7066**	-	-	-	-
Dwelling density	-	-	-	-	-0.7728**	-0.0415**	0.0015**	0.0014**	0.0047*	0.0021
Distance from home to CBD	-	-	-0.0056**	0.0766*	-	-	0.0364*	-0.0278**	-	-
Standard deviation of random parameters										
Female partner/spouse	-	-	0.0046*	0.0056**	-	-	-	-	-	-
Household size	-	-	-	-	-	-	0.0273**	0.0114*	-	-
Number of activity stops	-	-	0.1092**	0.0624*	-	-	-	-	-	-
Positive attitude towards driving	-	-	-	-	0.0284**	0.0127**	-	-	-	-

*Note: ***1% significance level; **5% significance level; *10% significance level*

5.2.3 Vehicle allocation models for discretionary-activity tours

Latent Segment Allocation Component Characterization

Table 7 and 8 exhibit the results of vehicle allocation models for discretionary-activity tours. Like mandatory-activity tour models, segment two is assumed as the reference segment for discretionary-activity tour vehicle allocation models. For solo tours (Table 7), results suggest positive coefficient values for the variables representing age, full-time employment and annual income more than $75,000 CAD in segment one. This indicates that older full-time employed individuals earning more than $75,000 CAD annually have higher propensity to belong in segment one. In contrast, segment two can be characterized by younger individuals who are not employed full-time and who earn less than $75,000 CAD annually. The segment allocation model for joint discretionary-activity tour exhibits the same probabilities as solo tour (Table 8). Therefore, similar to mandatory-activity models, segment one can be defined as the segment of ‘older-higher income individuals’, whereas segment two as ‘younger-lower income individuals’ for discussing vehicle allocation model results of discretionary-activity tours.

Solo Discretionary-Activity Tour Model

Model results in Table 7 suggest that a male partner/spouse in the household who belongs to segment one (i.e. older-higher income) is more likely to get an SUV or van, and less likely to get a midsize vehicle from their existing vehicle fleet during a solo discretionary-activity tour. On the other hand, segment two, which consists of younger-lower income individuals, exhibit higher propensity to choose midsize vehicles. This might indicate such individuals’ possibility of being the household head who performs major shopping or grocery responsibilities despite traveling alone. Therefore, allocation of larger vehicles (i.e. midsize vehicles, SUVs or vans) to a male partner/spouse is plausible. Due to longer tour durations, the likelihood of assigning midsize vehicles to older-higher income individuals and compact vehicles to younger-lower income individuals are found higher. However, tour duration shows a higher standard deviation than its mean for compact and midsize vehicles in each segment, indicating that the effects of longer tours vary broadly across individuals with similar characteristics. As expected, more complex tours (i.e. higher number of activity stops) demonstrate higher probabilities of SUV allocation during solo discretionary-activity tours irrespective of the segments individuals belong to.

A higher likelihood of allocating subcompact vehicles from their existing vehicle fleet is observed for individuals across both segments who possess positive attitudes towards active transportation (AT). This finding perhaps suggests the obstacles of using active transportation during regular shopping, groceries, or other major discretionary activities. Standard deviations of the variable for SUVs in both segments demonstrate some individuals’ higher propensity to get such vehicles despite having positive attitudes towards AT. Interestingly, positive attitudes towards driving exhibits individuals’ higher preference towards subcompact and compact vehicles while performing solo discretionary-activity tours. Although, the probability of assigning vans across both segments is lower for individuals with a positive attitude towards driving, standard deviations indicate that heterogeneous effects of the variable exist within each segment in case of van allocation.

Regarding the built environment, higher land-use index exhibits a positive coefficient value for SUVs and a negative coefficient value for compact vehicles in segment one, which is the segment of older-higher income individuals. In contrast, heterogeneous effects of land-use index are observed across segment two that consists of younger-lower income individuals. The variable representing dwelling density shows similar results. Living in the higher dwelling density areas, individuals in older-higher income segment have higher propensity to choose relatively larger vehicles (compact vehicles) than the younger-lower income individuals (subcompact vehicles). With the distance to the nearest shopping mall from home, older-higher income individuals tend to get SUVs, compact and midsize vehicles during a solo discretionary-activity tour, although the higher positive value for midsize vehicles indicate that allocating midsize vehicles from households’ existing vehicle fleet is preferred. In the younger-lower income segment, a higher likelihood of compact vehicle allocation is observed. However, the variable for distance from home to nearest shopping mall shows standard deviations at the 5% significance level for compact vehicles in each segment, which indicates the existence of heterogeneity within both segments.

Table 7. Results of vehicle allocation model for solo discretionary-activity tour.

Results of the latent segment allocation component		
	Segment 1	Segment 2
Segment allocation probabilities	0.515	0.485
Constant	0.7355**	-
Age	0.0650**	-
Full-time employment	1.4400*	-
Annual income > $75,000 CAD	0.6553**	-

Parameter estimation result

Variables	Available vehicle type in multi-car households									
	Subcompact		Compact		Midsize		SUV		Van	
	Segment 1	Segment 2	Segment 1	Segment 2	Segment 1	Segment 2	Segment 1	Segment 2	Segment 1	Segment 2
Constant	2.9028**	2.8448**	1.0157**	0.9953*	-4.1205	4.0381	-3.7972**	-3.7213**	Reference	Reference
Socio-demographic characteristics										
Male partner/spouse	-	-	-	-	-0.8401	0.9530*	1.0260*	-1.0054**	1.4039*	-1.3759**
Travel characteristics										
Tour duration	-	-	-0.0004***	0.0052***	0.0028**	-0.0010	-	-	-0.0030*	-0.0070*
Number of activity stops	-0.0740**	-0.0719***	-	-	-	-	0.1839**	0.1797	-	-
Attitudinal variables										
Positive attitude towards driving	0.7502**	0.7355*	0.5948**	0.5829**	-	-	-	-	-1.1496*	-1.1265*
Positive attitude towards AT	0.2450*	0.2399**	-	-	-	-	-0.0162**	-0.1934**	-0.4912**	-0.4811
Built environment and accessibility measures										
Land-use index	-	-	-5.192***	0.9022*	-	-	2.4902**	-1.8377**	-	-
Dwelling density	-0.3210**	3.1011	5.3130**	-1.2001*	-2.0993*	-3.6823**	-	-	-	-
Distance from home to nearest foodstore	-	-	-0.2080**	2.7000*	0.9592**	-0.1129**	-	-	-	-
Distance from home to nearest shopping mall	-	-	0.1156*	0.0151*	0.3672**	-0.2040*	0.1028	-0.0879**	-	-
Distance from home to nearest entertainment facility (cinema)	-0.2097	0.2382**	-	-	0.4590***	-0.0573**	-	-	-1.3374*	-3.1485**
Standard deviation of random parameters										
Number of activity stops	0.1089**	0.3656*	-	-	-	-	-	-	-	-
Tour duration	-	-	0.2549*	0.0701**	0.3607*	0.2798*	-	-	-	-
Positive attitude towards driving	-	-	-	-	-	-	-	-	0.0678**	0.1537**
Positive attitude towards AT	-	-	-	-	-	-	0.0107**	0.0050***	-	-
Distance from home to nearest shopping mall	-	-	0.0119***	0.0011**	-	-	-	-	-	-

*Note: ***1% confidence level; **5% confidence level; *10% confidence level*

Joint Discretionary-Activity Tour Model

Table 8 shows the final vehicle allocation model results for joint discretionary-activity tours. Results demonstrate that while traveling with household/non-household members in a discretionary-activity tour, SUVs are more likely to be allocated to male partners/spouses irrespective of the segments they belong to. Although individuals from both segments have a lower probability to get compact vehicles, some male partners/spouses might prefer compact vehicles during joint discretionary-activity tours as indicated by the statistically significant standard deviations. If the accompanying person is the partner/spouse during the joint discretionary-activity tour, older-higher income individuals in segment one tend to choose vans, whereas, younger-lower income individuals in segment two have a higher preference for compact vehicles from households' existing vehicle fleets. This intuitively suggests that older-higher income individuals' major household responsibilities might require larger vehicles to complete while traveling with a partner/spouse. As expected, presence of children within the tour increases probability of SUV allocation across segments. Complex joint discretionary activity tours, identified by higher number of activity stops, also exhibit positive relationships with SUV allocation across segments. Higher number of activity stops possibly represent a higher number of travel companions to pick-up or drop-off, which might require larger vehicles from households' existing vehicle fleet to perform complex joint tours. Although individuals' lower preference towards subcompact vehicles is observed across segments for complex joint discretionary-activity tours, standard deviations confirms the existence of heterogeneity within segments for subcompact vehicle allocation.

Irrespective of segment, individuals with a positive attitude towards driving exhibit higher likelihood of getting vans. However, standard deviation is observed that suggests allocation of vans might be different for some individuals within segments. Interestingly, subcompact vehicles tend to be allocated to both older-higher income and younger-lower income individuals who have a positive attitude towards active transportation (AT), perhaps indicating disadvantages of using AT while performing discretionary activities during a joint tour. Furthermore, higher land-use index (i.e. urban areas) exhibits positive coefficient values for SUVs and midsize vehicles in the older-higher income segment, and compact vehicles in the younger-lower income segment. The variable 'land-use index' exhibits significant standard deviations for SUV allocation in both segments. This suggests that individuals who live in urban areas and possess similar characteristics have preference variations while choosing SUVs from their households' existing vehicle fleet. In addition, with the distance from home to the nearest shopping mall, older-higher income individuals tend to choose SUVs. On the other hand, individuals belonging to the younger-lower income segment exhibit a higher tendency to get compact vehicles during a joint discretionary-activity tour.

6. Conclusion

This study presents the findings of a comprehensive investigation on activity-based vehicle allocation decisions at tour-level in multi-car households utilizing individuals' travel-activity information. This study contributes in the current literature by offering insights on the behavioral variations of activity-based vehicle allocation decisions, while traveling alone (i.e. solo travel) and traveling with household/non-household members (i.e. joint travel). Following a latent segmentation-based random parameter logit (LSRPL) modeling approach, four vehicle allocation models are developed in this study for solo mandatory-activity tours, joint mandatory-activity tours, solo discretionary-activity tours and joint discretionary-activity tours. The models capture taste preference heterogeneity across individuals by implicitly sorting them into two discrete latent segments. Results of the segment allocation components of all four vehicle allocation models suggest that segment one can be identified as the segment of older-higher income individuals, whereas, segment two can be identified as the segment of younger-lower income individuals based on their socio-demographic characteristics. In addition, individuals' preference heterogeneity within each segment are also captured during model estimation by introducing random parameters within the modeling framework.

The model results suggest that individuals' travel characteristics, attitudinal variables, built environment and accessibility measures have a considerable influence on vehicle allocation decisions in multi-car households. For instance, during joint mandatory- and discretionary-activity tours, individuals' probability of getting SUVs is found higher in the presence of children within the tours. Also, a higher number of activity stops within discretionary-activity tours exhibits positive coefficient values for SUV allocation. In case of the mandatory-activity tours, individuals' higher preference for subcompact vehicles are observed with the increase in number of activity stops within the tour while traveling alone. Interestingly, positive attitude towards active transportation decreases the probability of getting vehicles from household's available existing vehicle fleet during solo and joint mandatory-activity tours. Nevertheless, in case of discretionary-activity tours, individuals tend to prefer subcompact vehicles despite being positive towards active transportation. Living in higher mixed land-use areas increase individuals' probability of getting subcompact vehicles while traveling alone during a mandatory-activity tour. As expected, mixed land-use area dwellers exhibit higher preference for subcompact vehicles during a solo mandatory-activity tour, however, addition of another person(s) increases such individuals' probability to get relatively larger vehicle (i.e. midsize vehicles) during a joint mandatory-activity tour.

Table 8. Results of vehicle allocation model for joint discretionary-activity tour.

Results of the latent segment allocation component										
	Segment 1	Segment 2								
Segment allocation probabilities	0.591	0.409								
Constant	1.6013**	-								
Age	0.0345**	-								
Full-time employment	0.6951**	-								
Annual income > $75,000 CAD	1.8124**	-								
Parameter estimation results										
Variables	Available vehicle type in multi-car households									
	Subcompact		Compact		Midsize		SUV		Van	
	Segment 1	Segment 2	Segment 1	Segment 2	Segment 1	Segment 2	Segment 1	Segment 2	Segment 1	Segment 2
Constant	-1.6656	-0.3029*	-1.7131*	-0.4822*	-4.7641**	-5.1272**	2.5070**	0.0230**	Reference	Reference
Socio-demographic characteristics										
Male partner/spouse	-	-	-0.0342*	-0.6225**	-	-	4.8756**	5.0049***	-1.7391**	-2.8852*
Travel characteristics										
Traveling with partner/spouse	-	-	-	-	-0.0480	0.0635**	-	-	0.0597**	-0.0090**
Traveling with children	-1.4426**	-0.8865**	-2.9493*	-2.225***	-	-	1.4145**	0.0012*	-	-
Number of activity stops	-5.7825	-2.9478	-	-	-	-	0.5447***	0.2916**	-	-
Attitudinal variables										
Positive attitude towards driving	-	-	-0.0578**	-1.2254**	-	-	-	-	0.6453**	0.2985
Positive attitude towards AT	1.5287**	1.5659*	-	-	-0.5900**	-0.0015	-	-	-	-
Built environment and accessibility measures										
Land-use index	-	-	-0.0540*	0.0190***	2.8632***	-3.1642**	1.6516**	-0.0523*	-	-
Distance from home to nearest shopping mall	-0.2992***	-0.7609*	-0.2953**	0.3883*	-	-	0.2100***	-0.5034*	-	-
Distance from home to nearest entertainment facility (cinema)	-	-	-	-	0.1600*	0.6869*	-0.2490**	0.3282	0.6556*	-0.2879***
Standard deviation of random parameters										
Male partner/spouse	-	-	0.1592*	0.0607***	-	-	-	-	-	-
Number of activity stops	0.1854**	0.0259*	-	-	-	-	-	-	-	-
Positive attitude towards driving	-	-	-	-	-	-	-	-	0.0791**	0.0488**
Land-use index	-	-	-	-	-	-	0.7822**	0.8832*	-	-

*Note: ***1% significance level; **5% significance level; *10% significance level*

The findings of the study suggest that substantial heterogeneity exists not only across different segments, but also among individuals within the same segment. For example, having a positive attitude towards driving exhibits heterogeneous effects across older-higher income and younger-lower income segments in case of SUV and midsize vehicle allocation during joint mandatory-activity tour. Allocation of midsize vehicles also confirms individuals' preference variations within each segment during joint mandatory-activity tour by showing significant standard deviations. Interestingly, no heterogeneous effects are observed for 'positive attitude towards driving' across segments during discretionary-activity tours. Individuals with positive attitude towards driving are more likely to choose subcompact vehicles for solo discretionary-activity tour, and vans for joint discretionary-activity tour across older-higher income and younger-lower income segments. However, taste preference variations are found within each latent segment for the allocation of vans during both solo and joint discretionary-activity tours, as indicated by the significant standard deviations. Although mixed land-use area dwellers show homogeneous behavior during mandatory-activity tours, their preference vary broadly while performing discretionary-activity tours. Belonging to older-higher income segment, they are more likely to prefer larger vehicles (i.e. SUVs, midsize vehicles), whereas, relatively smaller compact vehicles are allocated to the younger-lower income individuals for both solo and joint travel arrangements.

Results presented in this study have important policy implications. For example, people living in mixed land-use areas prefer to use smaller subcompact vehicles than midsize vehicles and SUVs in suburban areas for solo mandatory-activity tours. Hence, creating better designed neighborhoods with diverse land uses and sustainable transportation alternatives might decrease the usage of larger vehicles, thus reducing daily fuel consumption. Also, the model results suggest that a positive attitude towards active transportation decreases the likelihood of vehicle usage for mandatory-activity tours. This information could be used for target marketing to identify such groups to encourage active transportation by offering more active transportation facilities. However, results of this study suggest that significant preference heterogeneity exists across individuals for different tours and travel accompanying arrangements. Therefore, flexibility should exist in policy interventions to achieve better outcomes for all types of travelers.

One of the limitations of this study is to categorize tours in terms of primary activities alone. However, it could be interesting to explore vehicle usage decisions for multiple intermediate activity purposes along the tour in the modeling process. Therefore, the immediate future work is to develop a joint model, which would simultaneously evaluate the tour- and stop-level vehicle allocation and activity engagement decisions within a 24-hour temporal scale. Nevertheless, this research significantly contributes to extend integrated urban systems modeling. The models developed in this study will generate a newer module within the Halifax iTLE (integrated Transportation, Land-use and Energy) model as an extension of the vehicle ownership decision model. It is expected that the resulting module will assist in developing the linkage with long-term vehicle ownership decision module, which can be utilized in dynamic traffic microsimulation for daily energy and emission prediction.

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