Modelling and Microsimulation of Activity Generation, Activity Scheduling and Mobility Assignment

by

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Dedicated to

My Abbu (Father) A.B.M. Moudud Khan
&
My Ammu (Mother) Nazmun Nahar

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Abstract

This thesis develops a novel framework for modelling and microsimulation of activity-based travel demand. It explores alternative micro-behavioural modelling methods for individuals' activity participation, time allocation, shared travel choice, mode choice and vehicle allocation. For example, mixed logit models of shared travel choices are developed that accommodate individuals' social interactions with household and non-household members while travelling to different activity-based tours. A multiple discrete continuous extreme value model is formulated, which addresses individuals' social interactions within the modelling framework to explore the joint decision of activity participation and time allocation. Latent segmentation-based random parameter logit models are developed to evaluate vehicle allocation decisions for different activity-based tours. This thesis also presents the development of a novel activity-based shorter-term decisions simulator (SDS) to predict activity and travel decisions. SDS consists of three sub-modules: activity generation, activity scheduling and mobility assignment, which are developed by implementing different components, namely activity types, frequencies, durations, start times, destination locations, shared travel arrangements, mode choice and vehicle allocation. The model addresses underlying process mechanisms of such components within the microsimulation framework by developing advanced modelling techniques. For instance, activity generation implements a Markov Chain Monte Carlo method to represent the process orientation of generating activity types. Activity scheduling is implemented as a three-stage decision process: activity agenda formation, destination location choice and shared travel choice, and accommodates social interaction-based feedback from shared travel choice component within the computational procedure. Furthermore, mobility assignment is a two-stage dynamic process of mode choice and vehicle allocation that addresses social interactions within empirical and computational procedures. SDS generates baseline information for the year 2006, and simulates activity and travel decisions for a 30-year period of 2007-2036. This thesis presents the validation of the SDS model results, and predicts the evolution of activity-travel information of Halifax population. SDS is implemented within the integrated urban model, iTLE, and provides activity-based feedbacks to households' long-term residential decisions; thus, develops an integrated and behaviourally consistent urban modelling system. The SDS microsimulation model would be helpful to test different emerging travel demand management strategies as well as alternative land use and transportation policy interventions.

List of Abbreviations Used

SDS	Shorter-term Decisions Simulator
LDS	Longer-term Decisions Simulator
TFS	Traffic Flow Simulator
iTLE	Integrated Transportation, Land Use and Energy Model
APE	Absolute Percentage Error
AIC	Akaike Information Criteria
BIC	Bayesian Information Criteria
DA	Dissemination Area
CBD	Central Business District
DMTI	Desktop Mapping Technologies Inc.
NovaTRAC	Nova Scotia Travel Activity Survey
HRM	Halifax Regional Municipality
MDCEV	Multiple Discrete Continuous Extreme Value Model
MXL	Mixed Logit Model
LSRPL	Latent Segmentation-based Random Parameter Logit Model

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Chapter 1

Introduction

1.1 Background and Motivation

The escalating concern in response to urban sprawl, traffic congestion and air quality over the last few decades has transformed the focus of transportation planning from forecasting long-term aggregate mobility requirements to short-term travel demand. This change in focus has encouraged transportation planners and policy makers to promote sustainable transportation opportunities and plan for smart growth of communities. An activity-based travel demand model has the potential to predict the travel behaviour of a region by simulating critical decision processes and interactions among those processes. Microsimulating travel demand is important since it can provide a modelling platform to assess the impacts of alternative transportation and land use policies and changes in socio-demographic trends on short-term travel related decision processes (McNally 2007).

The first-generation travel demand models were developed in the 1950s to tackle the sudden growth of private car usage by investing in new major transportation infrastructure (Goran 2001). These earlier models were developed based on personal trips at the aggregate zonal level, which were capable of evaluating the impacts of major investments on the travel demand of a region (Bhat and Koppelman 1999). Such models commonly included four subsequent steps of operation, hence, often referred as ‘four stage models’. Trip generation, trip distribution, mode choice and trip assignment are the four components of traditional four stage models that forecast the number of trips, location of the trips, modes and routes used for trips at an aggregate regional level. Such aggregated travel forecasts are less sensitive to complex transportation policies related to particular times of a day or network accessibility. Moreover, urbanization, higher auto dependency, energy shortages and increased energy prices posit greater impacts in people's travel behaviour and make it more complex to analyse through traditional methods. A traditional four stage model is not capable of incorporating individuals' underlying behaviour for different travel attributes (Pinjari and Bhat 2011). Hence, second-generation travel demand models were developed following the discrete choice theory that expanded the focus of transportation planning towards analysing the travel needs of a single individual (McNally 2007). However, such discrete choice models disregard the interrelationships among the choice attributes (e.g. time, location, mode) of different trips. Spatial and temporal interrelationships among the trips are also ignored in these models since they consider all the trips of an individual as independent. This results in inadequate behavioural representation and lesser sensitivity towards predicting the effects of behavioural changes. Such phenomena posit challenges while predicting responses to complex policies, for instance, encouraging telecommute, transit ridership, congestion pricing, etc. These limitations of understanding behavioural effects facilitate the advancement towards more high-fidelity level travel demand forecasting models.

Transportation researchers, practitioners and policymakers have experienced a paradigm shift in last three decades towards activity-based travel demand modelling, where 'activity' is assumed as the basis of analysis. Activity-based models have emerged due to the fact that travel decisions are derived from people's daily needs and their desire to participate in activities to accomplish those needs (Davidson et al. 2007). Travel demand models, which are developed following an activity-based modelling approach, can accommodate space-time constraints and the relationships between activities and travel at the disaggregate individual- and household-level (Hägerstrand 1970; Ellegard 1999). Thus, it provides a better understanding of an individual's travel behaviour and becomes sensitive to emerging policy interventions related to travel demand management, land use, and intelligent transportation systems, among others (Shiftan et al. 2003). These models are considered as a significant advancement over traditional trip-based models because of their ability to better predict future travel patterns due to incorporating realistic constraints of time and space and the effects of individual- and household-level attributes within the modelling process. Activity-based travel demand models can predict a multitude of interdependent decisions, such as what type of activity to participate in, how much time to allocate to a particular activity, timing of the activities, what mode to take, what vehicle to choose, where to go, etc. by recognizing individuals' motivations to perform daily activities and associated travel decisions. Such fine-grained travel demand forecasting models allow researchers and policymakers to examine variations in individuals' daily travel behaviour due to alternative policy interventions over a wide range of time and space.

Microsimulation-based modelling techniques are useful to analyse activity-based travel demand that can mimic individuals' complex behaviour by accommodating a sequence of activity and travel segments, multiple spatial-temporal constraints, and interactions among individuals within the simulation framework. In an activity-based travel demand modelling system, activity generation and scheduling are the two most critical components (Miller and Roorda 2003). Activity generation simulates the types and number of activities to participate in a day. The activity scheduling component includes simulating several activity attributes such as activity duration, start time, location, travel companions, etc. In the case of activity generation, it is important to incorporate the interdependency between two consecutive activities. This is because, an individual may not be able to plan all possible activities to participate in at the start of a day. Rather, planning for a subsequent activity is more convenient based on the information the individual could get while participating in a current activity. In addition to that, feedbacks that accommodate for individuals' social interactions with household members (i.e. partners/spouse, children) and non-household members (i.e. parents/other family members and roommates/friends/colleagues) are important to implement within such modelling framework. These interactions may arise while traveling with an accompanying person to perform an activity. To accommodate such feedbacks, it is imperative to investigate the underlying behavioural basis of individuals' decisions to travel with household and/or non-household members. Although the investigation of interactions among household members is well recognized in the existing models, such as ALBATROSS (Arentze and Timmermans 2004), CEMDAP (Pinjari et al. 2006), and TASHA (Roorda 2005), the behavioural basis of choosing a travel companion from individuals' social realm is not well addressed within an activity-based travel demand modelling system. Understanding individuals' behaviour to determine such travel decisions is important due to its role in activity rescheduling, mode choice and households' vehicle assignment processes.

Another important component of a travel demand model is a set of mobility decisions. The growing concerns regarding climate change, vehicular emission and fuel consumption have shifted the focus of travel behaviour research to sustainable travel demand modelling and lead to the introduction of emerging transportation technologies and services (Lavieri et al. 2017). Advanced technologies and newer concepts of travel such as shared mobility, Mobility-as-a-Service (MaaS), autonomous vehicles, etc. are impacting people's daily movement (Matyas and Kamargianni 2019). In this context, it is critical to understand and predict disaggregate-level daily mobility patterns within a travel demand forecasting platform. This could assist in testing various sustainable policy strategies as well as evaluate the impacts of implementing newer travel alternatives in road networks. Activity-based analysis of mobility patterns is more suitable considering such analysis has the capacity to predict disaggregate-level mobility choices by accommodating interdependencies among different activity and travel attributes (Castiglione et al. 2015). In particular, mode choices are analysed at activity-based tour-level, where tours are defined as activity chains that start and end at the same location (Enam and Konduri 2017). However, vehicle allocation, a critical mobility choice decision, is often disregarded when analysing mobility patterns within a travel demand forecasting model. Vehicle allocation decisions are critical as the allocation of a specific type of vehicle from households' existing vehicle fleet has direct effects on the energy consumption and vehicular emission within a traffic network. Advanced traffic microsimulation technique, such as dynamic traffic assignment, has been gaining prevalence over last couple of years, hence, understanding the behavioural process mechanism of vehicle allocation has become vital for tracking specific types of vehicles in a transportation network within the modelling system. Also, in a large-scale urban modelling framework, vehicle allocation decisions link households' long-term vehicle ownership decision with short-term travel decisions, which make an urban model more dynamic in nature. However, a limited number of activity-based travel demand models, such as TASHA (Roorda 2005) and ALBATROSS (Arentze and Timmermans 2004), account for the vehicle allocation process as a part of mobility choice decisions within their modelling framework. These studies mostly implement heuristics to determine vehicle allocation decisions in car-deficient households and assume that all vehicles in the households are identical. The underlying behavioural process is not well represented while implementing such a critical mobility decision. In summary, there are significant gaps in research, particularly in terms of activity-travel process representation, shared travel choice and vehicle allocation mechanism, and linkage between short-term and long-term decision processes.

The goal of this research is to develop a modelling framework that mimics the interactions among different activity and travel attributes and the underlying process mechanism of individuals' different activity-travel decisions within an activity-based travel demand forecasting system. This research presents the development of a prototype activity-based Shorter-term Decisions Simulator (SDS) within an integrated urban model, known as the integrated Transportation Land use and Energy (iTLE) model. iTLE is an agent-based microsimulation model that follows a life history-oriented approach. It focuses on the temporal changes of agents' (i.e. households and individuals) different decisions over the life-course that includes their whole life-time or a segment of the life-time (Chatterjee and Scheiner 2015). The modelling system is modular, and it simulates agents' decisions longitudinally at each simulation time-step along their life-course. iTLE consists of three modules: longer-term decisions simulator (LDS), shorter-term decisions simulator (SDS) and traffic flow simulator (TFS). This thesis focuses on the development of three core sub-modules of SDS, namely activity generation, activity scheduling and mobility assignment.

The underlying process mechanism and interaction between different activity and travel attributes are addressed in this thesis through various micro-behavioural modelling structures and microsimulation modelling techniques. This research presents alternative econometric modelling approaches to analyse different activity and travel decisions, and simulates them within the SDS microsimulation platform. It also provides the predicted spatial and temporal evolution of activity and travel decisions of the Halifax Regional Municipality population.

1.2 Objectives of the Thesis

The broad objective of this thesis is to empirically test alternative approaches of analysing different activity-travel decisions and develop an activity-based travel demand forecasting model, which is agent-based and addresses the underlying process mechanisms and interactions among different activity and travel attributes. The specific objectives of this thesis are following:

1. To develop alternative econometric modelling approaches of analysing different activity and travel choices, including activity participation, time allocation, shared travel choice, mode choice and vehicle allocation.
2. To generate sequential activity participation decisions, and prototype implementation of individuals' short-term activity-travel decision processes within an activity-based travel demand microsimulation model.
3. To forecast disaggregate-level spatio-temporal evolution of a region's activity and travel decisions utilizing the microsimulation model.

1.3 Implications of the Research

The contribution of this research lies in both the modelling and the microsimulation of activity and travel demand. It not only contributes to travel demand modelling and forecasting literature theoretically, but also has practical implications. Theoretically, a social interaction-based approach is adopted in this thesis to explore how different activity and travel decisions evolve over time. Such investigation is critical, considering that individuals' social interactions with household and non-household members can dictate their activity and travel behaviour. The underlying process mechanisms of daily activity and travel choices are addressed in this thesis within the conceptual micro-behavioural and microsimulation modelling frameworks by developing advanced alternative modelling techniques. Such modelling and simulation approaches produce improved empirical outcomes, which contributes to the urban systems modelling literature.

From the perspective of practical implications, this thesis develops a comprehensive activity-based travel demand forecasting system by accommodating social interactions among individuals, and multiple constraints (e.g. spatial, temporal and institutional) within the modelling process. In particular, this thesis microsimulates decision processes of activity generation, activity scheduling and mobility assignment within an activity-based travel demand forecasting model. This research is one of the first attempts to address following phenomena: 1) translating the underlying process mechanisms of individuals' shared travel choices (that address individuals' social interactions) from micro-behavioural models to the computational procedure of a multi-year activity-based travel demand microsimulation model; 2) implementing sequential activity generation process (where forthcoming activity depends on the current activity) within a microsimulation modelling system; and, 3) analysing vehicle allocation decisions by accommodating individuals' social interactions within both micro-behavioural and microsimulation procedure. Also, social interaction-based feedback mechanisms are established within the simulation environment that can provide behaviourally realistic activity-travel choices by rescheduling daily activities. Results of the microsimulation model provide critical insights towards disaggregate individual-level evolution of activity and travel decisions of an urban region over a multi-year period, which includes individuals' pattern of activity participation, activity timing and duration, activity destination location choice, shared travel choice, mode choice and vehicle allocation. Such individual-level information is important to estimate future emission and energy demand, since these results will be useful as the inputs of the traffic flow simulator (TFS) of the iTLE model. This research contributes in developing a decision support tool to test alternative policies related to emerging travel alternatives, intelligent transportation systems, and high occupancy vehicle lanes, among others.

1.4 Thesis Outline

This thesis consists of eight chapters. It is outlined as following: chapter two discusses the existing literatures that includes a review of modelling activity and travel decisions, followed by a brief discussion on the existing activity-based travel demand microsimulation models. From the reviews of existing literature, some research gaps are identified to determine the research questions for this thesis. After that, it describes the modelling framework of a prototype activity-based travel demand microsimulation model, which this research proposes to develop. Following this, data used to develop the proposed prototype model for Halifax is discussed. Then the chapter ends with a concluding remark.

The next three chapters (chapter three, four and five) describe alternative econometric modelling methods and estimation results of different activity and travel attributes. Chapter three and chapter four present a discussion on the methods and parameter estimation results of shared travel choice, mode choice, and joint decisions of activity participation and time allocation. Chapter five presents the advanced econometric modelling methods and estimation results of the vehicle allocation decisions at activity-based tour-level.

Chapter six and chapter seven present the development of the activity-based SDS microsimulation model. Chapter six describes the microsimulation procedures and results of activity generation and activity scheduling sub-modules of the SDS model. A detailed procedure to implement different activity-based components, such as activity types, frequencies, durations, start times, destination locations and shared travel choices within the SDS microsimulation model are discussed in this chapter. Finally, it provides the microsimulation results of the components implemented within the SDS model. Chapter seven presents the microsimulation of mobility assignment sub-module of the SDS model. It discusses the implementation of underlying process mechanisms and simulation results of the mode choice and vehicle allocation decisions within the SDS modelling system.

The final chapter, chapter eight, summarizes the findings and contributions of this thesis. It also presents some policy implications and future directions to advance the current research on activity-based travel demand modelling.

Chapter 2
Conceptual Framework

2.1 Literature Review

This thesis attempts to fill the gaps in existing literature by presenting alternative econometric-based micro-behavioural modelling methods of various activity and travel decisions, and by developing an activity-based travel demand microsimulation model. It develops the travel demand model within an integrated urban modelling system, known as integrated Transportation, Land Use and Energy (iTLE) model, to simulate individuals' short-term activity-travel behaviour and to forecast the evolution of travel demand in a region. Integrated urban models are generally exhaustive in nature that can predict different household- and individual-level decisions over the years, and have the ability to evaluate complex land use and transportation policies. A typical urban modelling system include land use and travel demand modelling components. Such components can simulate households/individuals' long-term decisions (e.g. residential relocation), medium-term decisions (e.g. vehicle transaction), and short-term decisions (e.g. participating in an activity) over a certain number of years. A critical aspect of an integrated urban model is its potential to evaluate interactions between land use models and travel demand models. This provides behavioural consistency of individuals and households as well as a better integration of short-term and long-term processes within an urban modelling system (Adnan et al. 2016). One of the criticisms of existing urban models is their lack of behavioural representation of the multi-domain interactions among long-term, medium-term and short-term decisions. The majority of urban models are integrated based on their travel demand and traffic assignment components (Auld et al. 2013). Further integration efforts by coupling land use and travel demand models is warranted to develop a fully integrated urban model that has the capacity to enhance the effective evaluation of the impacts of individuals' short-term decisions on long/medium-term decisions (Pendyala et al. 2012). Although, attempts have been made to integrate individuals' short-term decisions and households' long-term and medium-term decisions, the majority of models are loosely coupled through a feedback mechanism. For example, UrbanSim (Waddell 2002) and SimMobility (Adnan et al. 2016) utilize logsum measures to establish interdependency among land use and transportation modelling components. The logsum values are mostly measured based on travel characteristics only (e.g. travel time, distance and cost). Such integrations are often criticized as loosely coupled mechanisms. On the other hand, Shiftan (2008) argues that coupling between long-term and short-term modelling components should include logsum measures from activity-based modelling components, which can capture the overall short-term utility of each long-term decision. Also, few researchers emphasized on implementing feedback mechanisms within the modelling frameworks of activity engagement decisions, such as activity participation, activity scheduling, and activity travel arrangements (Sener and Bhat 2007). Therefore, this research aims to explore multiple domain of interactions and feedback mechanisms within short-term activity-based travel demand decision process modelling. The multi-faceted integration mechanisms within travel demand models and land use models is important to develop an urban modelling system responsive towards effective evaluation of complex land use and transportation policies.

In the past few decades, researchers have put great efforts in advancing the development of activity-based travel demand models that simulate the evolution of individuals' activity and travel decisions over the years. Such models' potential to improve the efficiency of evaluating emerging and complex transportation, land use and environmental policies by integrating activity and travel decisions with residential location and vehicle ownership decisions in an integrated urban modelling platform has resulted in the development of different types of large-scale travel demand models, such as TASHA (Roorda 2005), ALBATROSS (Arentze and Timmermans 2004), CEMDAP (Pinjari et al. 2006), and ADAPTS (Auld 2011), among others. Although notable advancements have been made in developing short-term travel demand models, one of the criticisms of many of the existing models is the lack of realistic behavioural representation. To build a behaviourally realistic travel demand modelling system, a possible approach could be to accommodate for individuals' social influences within the activity-based modelling framework. Humans, as social beings, endure social influences to complement their daily activity and travel decisions. Social influences stem from the desire to interact with people (i.e. partner/spouse, children, parents, other family members, roommates, friends, colleagues, etc.) within an individual's social realm. Adopting such influence within an activity-based modelling framework can explain individuals' daily activity-travel patterns in a more reasonable way (Ettema et al. 2011). Further efforts are required to understand individuals' behaviour of choosing their travel companion while performing an activity, which can influence daily mobility choices. Accommodating such interactions within a travel demand modelling system assists in computing behaviourally plausible modal accessibility to provide feedback to long-term and medium-term decision components of an urban model, so that, a fully integrated and behaviourally improved urban modelling system can be developed. A brief discussion on modelling different activity and travel decisions, and microsimulation of activity-based travel demand is presented below.

2.1.1 Modelling Activity and Travel Decisions

A growing body of research has emerged regarding individuals' daily activity and travel decisions in the past few decades. The majority of the research focuses on developing activity generation and scheduling models, where individuals' different activity-travel decisions, such as activity types/purposes, timings and durations are modelled (McNally 2007). Initially, the activity generation and scheduling models were developed separately, where the majority models considered 'time' as a discrete entity (Bhat 1998a; Bhat 1998b; Bradley et al. 1998; Bowman and Ben-Akiva et al. 2001; Scott and Kanaroglou 2002), although there have been some studies that conceptualize 'time' as a continuous activity component (De Palma and Rochat 1996; Wang 1996; Kitamura et al. 1997; Yamamoto and Kitamura 1999). For example, Kitamura et al. (1997) developed an activity and travel decisions model that explored individuals' behaviour to participate into different activities following a multinomial logit model and duration of different activities utilizing a hazard-based model. Yamamoto and Kitamura (1999) developed a tobit model to investigate individuals' participation and time allocation behaviour into discretionary activities. Bowman and Ben-Akiva (2001) evaluated individuals' daily activity-travel pattern utilizing a logit modelling technique where they considered the arrival-departure time of different activities as discrete choice alternatives to represent individuals' activity participation and time allocation behaviour. Jong et al. (2003) formulated a mixed multinomial logit model to estimate individuals' activity time allocation behaviour by categorizing them into different time-of-day segments. Later, researchers started to investigate different activity-travel elements together in a single modelling framework due to their dependencies on each other. Ettema (2005) utilized a simultaneous system of tobit modelling structure to model individuals' maintenance activity participation and time allocation behaviour. Pendyala and Bhat (2004) developed a joint model that accounts for both discrete and continuous choices of different activity and travel attributes that evaluates activity timing and duration decisions for workers and non-workers. Srinivasan and Bhat (2005) formulated a joint logit-hazard modelling technique to evaluate individuals' behaviour for shopping activity participation and duration. One of the criticisms of such modelling techniques was that they could not model participation and time allocation into multiple types of activities in a single framework. To overcome this limitation, Bhat (2008) formulated a joint modelling technique, multiple discrete continuous extreme value model, which accounts for both multiple discrete alternatives of activities and continuous components of the activities. Utilizing such modelling approach, individuals' joint decisions of different activity attributes, such as multiple activity participation, timing and/or duration decisions can be explored. Few studies have utilized such modelling technique to explore individuals' activity participation and time allocation behaviour, such as Eluru et al. (2010), Paleti et al. (2010), You et al. (2013), and Garikapati et al. (2015), among others.

Activity-based tour mode choice models are increasingly being developed in the activity-based research field as individuals' activity participation, scheduling and modes to participate in the activities are dependent on each other. The mode choice decisions vary across the type of primary activities based on which tours are formed. A study by Yun et al. (2014) suggests that during a complex tour (i.e. tours with higher number of activity stops), individuals participating in non-work activities have a higher probability to choose non-driving modes, whereas, driving modes are chosen for work tours in terms of household and individual socio-demographic attributes. These findings are supported by other studies (Hensher and Reyes 2000; Wallace et al. 2000), where researchers explored that complex tours increase individuals' probability of preferring private transportation rather than public transportation. A co-evolutionary approach that combines a set of multinomial logit models developed in Krygsman et al. (2007), captured the interdependencies between work mode and activity type choice. They found that people are more likely to use modes with frequent stops (e.g. transit) for a simple tour, and simple modes (e.g. auto/bike) for complex tours. Their study also concluded that male and high-income individuals with a higher number of cars in the household tend to choose cars for a work tour. Focusing on shopping activity participation, Limanond et al. (2005) estimated a nested logit framework that evaluates behavioural variations of shopping tour mode choice on weekends and weekdays. The study revealed that mode choice for shopping activities largely depends on the number of vehicles available in the household. Using the same logit modelling framework, Ho and Mulley (2013) identified the considerable effects of an individuals' age, activity purpose and household structure on deciding out-of-home activities and mode choice decisions, whether they are undertaken on weekends or weekdays. A hybrid tour-based mode choice model was developed by Miller et al. (2005) that utilized data from the Toronto Tomorrow Survey (TTS). They found significant impacts of travel time, cost, waiting time, etc. on individuals' mode choice during different work and discretionary tours. Using the same survey data, Day (2008) evaluated the relationship between work trip timing and mode choice. The study revealed that older individuals with higher incomes and higher car ownerships are more likely to choose auto mode, and late home departure and arrival time periods.

Since travel decisions are derived from individuals' daily needs and their desires to participate in activities to accomplish those needs, people often confront several in-home and out-of-home interactions within their social realm while carrying out their daily activities. Individuals' activities and associated travel patterns are conditional on several social constraints that make a person dependent on different rules and interactions (Hägerstrand 1970). In the context of activity-travel behaviour, individuals' social influence can be represented through the utility derived from their shared travel arrangements that account for both self-needs and the needs-of-others. Accommodating social interactions within an activity-based modelling framework provides more accurate and reliable activity and travel forecasts (Lai et al. 2019); thus, explaining individuals' daily activity-travel pattern in a more behaviourally realistic way (Ettema et al. 2011). Social interactions significantly influence individuals' decision-making processes (Walker et al. 2011). The majority of existing studies mainly focused on the interactions between household members. For instance, Golob and MacNally (1997), Gliebe and Koppelman (2002), Borgers et al. (2001), Schwanen et al. (2007), Ettema et al. (2004) and Zhang et al. (2004) investigated individuals' time allocation behaviour into different activities by addressing their interactions with household members. Wen and Koppelman (2000) investigated individuals' participation in different activities by accounting for their interactions with different household members within the decision-making process. Scott and Kanaroglou (2002) developed an activity-based travel modelling approach where they modelled daily number of non-work activities by incorporating interactions between partners/spouses in the households. Bradley and Vovsha (2005) developed an activity generation model for household members that explored individuals' behaviour to participate in an activity by accommodating for their interactions with household members. Sener and Bhat (2007) investigated children's discretionary activity participation and time allocation behaviour by considering their travel with parents in the households. Auld et al. (2009) also developed a heuristic activity scheduling process to handle parents' decision to accompany children to school and discretionary activities. Miller and Roorda (2003) evaluated activity-based travel choices by accommodating interactions among household members by developing econometric and heuristics models. However, when performing an activity, how individuals choose their shared travel arrangements by socially interacting with household and non-household members, is not evident. Although, Srinivasan and Bhat (2008) explored individuals' activity and travel choices in the presence of different household and non-household members, the study did not explore effects of any socio-demographic, neighbourhood and travel characteristics on companion choice. Additionally, coupling of shared travel decisions with activity engagement decisions through a social interaction-based feedback mechanism has received limited attention in the activity-based research paradigm.

Vehicle ownership is a critical component in an integrated urban modelling system that demonstrates households' medium-term decisions of ownership level and transaction events. An extensive body of literature on vehicle ownership choices exists in the case of modelling vehicle ownership levels (Potoglou and Kanaroglou 2008), vehicle transactions

(Mohammadian and Rashidi 2007), vehicle type choices (Choo and Mokhtarian 2004), etc. A recent growing interest in vehicle ownership phenomena is to explore how vehicles are allocated in the households by accommodating for various social interactions of the individuals. How different types of vehicles in the households are utilized to perform daily activities and tours is not clear in existing studies. It is necessary to be informed that upon choosing auto as the primary mode of travel, what vehicles are allocated to individuals from a household's existing vehicle fleet while entering into the traffic network since this could contribute to dynamic traffic assignment-based models or disaggregate traffic microsimulation 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. Petersen and Vovsha (2005) was one of the earliest studies that argued the importance of vehicle choice behaviour in the households during different activities and tours. They found that the types of vehicle to be allocated is not random, instead it depends on various household and personal characteristics. They developed a vehicle usage model that estimates the usage of different types of vehicles in a household. Anggraini et al. (2008) investigated vehicle assignment behaviour in car-deficient households for work tours. They found that men usually get the household car over women when 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 a non-work tour, men have a greater probability to use the car over women. An unlabelled 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. The study found that a 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. However, the empirical scope of the study was restricted to two-adult households with two vehicles. Furthermore, Wen and Koppelman (2000) argued that the allocation of vehicles for maintenance activities in a car-deficient household primarily depends on the types of maintenance activities. The study highlighted that employment and responsibility to perform maintenance activities tend to increase both male- and females' probability of getting a car.

2.1.2 Microsimulation of Activity-based Travel Demand Models

Remarkable advancements have been made by researchers over the past four decades in developing activity-based travel demand models. Starting from the PESASP model (Lenntrop 1976) to the recent ADAPTS model (Auld and Mohammadian 2009), a number of activity-based travel demand models are developed due to their behavioural basis and conceptual advancements over traditional trip-based four stage model. This section reviews some notable modelling systems that have been developed following an activity-based approach. The development of activity-based travel demand forecasting models can be categorized into four broad categories: 1) constraint-based models, 2) utility maximization models, 3) computational process models and 4) hybrid agent-based models. A brief discussion on each category is provided below.

The earliest activity-based travel demand models were developed utilizing the constraint-based approach. The primary objective of constraint-based models was to evaluate whether or not a given activity agenda is possible within a particular spatial and temporal context

(Lenntorp 1976). Utilizing combinatorial algorithms, these models first generate activity programs, then check if the generated program fits into a specific space-time context. Such feasibility is tested based on several spatial and temporal criteria, such as, location of the activities, start and end time of two consecutive activities, activity priority, and minimum activity duration, among others. Hence, constraint-based models are useful in the case of recognizing an infeasible activity schedule within variable space-time settings. Some of the prominent examples of constraint-based models existing literature are PESASP (Lenntorp 1976), CARLA (Jones et al. 1983), BSP (Huigen 1986), MAGIC (Dijst and Vidakovic 1997), and GISICAS (Kwan 1997), among others. Although constraint-based models efficiently identify infeasible activities within an activity agenda, they lack the ability to predict activity-travel patterns of households and individuals. Also, uncertainty within the choice behaviour are explicitly overlooked in constraint-based models. Therefore, a second stream of models, utility maximization-based econometric models, has emerged.

Utility maximization-based models are developed on the theory that a person makes his/her activity-travel decisions based on the maximum utility he/she gets from the choices he/she has. Such modelling systems consist of a series of discrete choice models, hazard-based duration models and ordered response models that can predict multiple components of daily activity-travel decisions. PCATS (Kitamura and Fujii 1998), CEMDAP (Pinjari et al. 2006), DaySim (Bradley et al. 2010) and FAMOS (Pendyala et al. 2005) are some notable examples of utility maximization-based models. PCATS is one of the earliest utility maximization-based models that utilizes two nested logit models to predict activity type, duration, location, and transport mode choice in an ordered way. The model anticipates the space-time prism constraints (i.e. set of all spatial and temporal points that can be reached by an individual given a maximum possible speed from a starting point) that depict the feasible area for performing corresponding activities and travel. A nested logit model is utilized to predict activity type choice and duration, and a second nested logit model is estimated for destination location and mode choice decisions in the PCATS model. CEMDAP is another notable modelling system that uses a comprehensive set of utility maximization-based econometric models. It has two major modules: activity generation-allocation module and activity scheduling module. The first module generates activity types, activity start and end time, children's school mode and travel companion (father/mother) during different activities. The second module focuses on estimating commute mode, number of tours, number of stops, activity duration, travel time, and destination location. To represent individuals' behaviour, several micro-behavioural models such as regression, binary logit, multinomial logit, hazard-duration, ordered probit, and spatial location choice models are developed. One of the unique contributions of CEMDAP is that it considers 'time' as a continuous entity, which was generated as a discrete component in previous activity-based travel models. Similar to CEMDAP, FAMOS also recognizes time as a continuous entity while predicting activity-travel pattern. It explicitly considers space-time constraints and generates activities, durations, destination locations, start times and sequence of activity and travel. A unique feature of the FAMOS model is it models the space-time constraints and simulates activity-travel patterns utilizing the space-time prisms as described in Hägerstrand (1970). FAMOS develops different econometric micro-behavioural models to determine the activity-travel pattern. It develops a two-tier nested logit model, where activity types are generated at the top tier and destination-mode choice is determined at the next tier. After that, duration of an activity at the destination is determined utilizing a binary logit model and hazard-based duration model. Finally, FAMOS evaluates travel times and start times on the basis of destinations and activity durations. DaySim is another notable activity-based travel demand model, which is an integral part of the Sacramento Regional Activity-based Travel Simulation (SACSIM) model (Bradley et al. 2010). DaySim is an econometric microsimulation system that predicts a person's activity and travel schedule for a full day within the study area. Each of the activity-travel choice models in DaySim is developed using either multinomial logit or nested logit modelling framework. The system is divided into two modules, activity-travel generation models and scheduling models. Activity-travel generation models are developed following a multinomial logit modelling structure that predicts a list of all activities, tours, and trips generated for each individual. Following this, the scheduling model estimates a multinomial logit model to predict time-of-day, and nested logit models to predict location and mode of the generated activities and travel. One of the limitations of DaySim model is it does not address individuals' interactions within its modelling framework. As evident in above discussion, utility maximization models are solely based on the assumption of rational utility maximization. They recognize all decision makers as rational utility maximisers, which is a less realistic assumption, hence, may not depict actual activity-travel choices. Therefore, to delineate activity-travel decision mechanisms, researchers formulated rule-based computational process models that attenuates the strict and behaviourally less realistic assumptions of utility maximization models.

Based on the notion that individuals' decision-making processes can be represented by some reason-based condition-action rules (Newell and Simon 1972), computational process models have emerged in the activity-based modelling paradigm. These models consist of a comprehensive set of rules that attempt to mimic individuals' behavioural processes while creating an activity schedule. CARLA (Clarke 1985) is one of the earliest computational process models that utilizes observed activity program (activities to be scheduled, durations and times) to generate all feasible activity patterns. CARLA is sometimes considered as a constraint-based model due to its usage of combinatorial algorithms and some constraints to generate feasible-infeasible activity pattern. However, unlike constraint-based models, the feasibility of an activity pattern in CARLA is dependent on a number of pre-defined heuristics rules that are created primarily based on temporal constraints. SCHEDULER is another earlier example of a computational process model that was proposed by Garling et al. (1989). The model focuses particularly on the activity scheduling process. Within the modelling framework, daily activities are generated using the nearest-neighbour heuristics method and possible activity-travel patterns are generated utilizing heuristics search methods. Finally, possible patterns are tested with respect to prior commitments, constraints and activity priority, forming an elaborate activity schedule where mode choice, activity durations, travel times and waiting times are determined. AMOS (Kitamura et al. 1996) is another example of computational process model. Within the modelling framework, rules are established from a set of associated constraints. Based on the rules and an initially observed activity-travel pattern, individuals' activity and travel decisions (i.e. activity re-sequencing and re-linking, departure and arrival time adjustments, mode choice, destination location assignment, etc.) are predicted with the changing activity-travel environment. Perhaps, the most exhaustive rule-based activity-travel simulation model to date is ALBATROSS (Arentze and Timmermans 2004). The simulation process in ALBATROSS involves activity program generation, activity scheduling, location choice, transport mode choice, and accompanying person choice. The model accommodates multiple household, institutional and spatial-temporal constraints to forecast several components of individuals' activity-travel decisions. Activity and travel choices are simulated dynamically during the scheduling process by following a decision tree method that represents heuristics decision-making. However, there are certain limitations of the computational process models. One of the major criticisms is that the system is based on fixed and deterministic rules of individuals, hence, it cannot anticipate behavioural complexity and uncertainty of human behaviour. Even though such models have the ability to create and update activity schedules, they are unable to anticipate all underlying decision processes due to the complex nature of individuals' daily schedules. To overcome such issues, agent-based hybrid models are developed by the researchers.

Hybrid models are developed by adopting both the econometric (i.e. utility maximization) and rule-based modelling approach. Flexibility in managing a number of behavioural, spatial and temporal issues has made this approach popular in activity-based travel demand modelling research. One of the most notable hybrid models is TASHA (Miller and Roorda 2003). This model has three major components: activity generation, scheduling and mode choice. TASHA generates and schedules a broad type of activities, such as work, school, and shopping, among others. These activity episodes and their corresponding characteristics, such as frequency, start time, and duration are generated using random draws from the observed distribution. The activity scheduling component organizes the activities based on pre-defined priority and precedence, and conflict resolution heuristics. Mode choice follows a random utility-based discrete choice modelling technique. The basis of TASHA is the concept of 'project', which is a collection of activities with a common goal. Each project generates a set of candidate activities to schedule, called 'project agenda'. Based on some priority- and precedence-based rules, such activities are inserted to activity scheduler from project agenda. In TASHA, activities are generated randomly, hence it requires the implementation of conflict resolution strategies. The following strategies are implemented in TASHA to resolve conflicts: activity shortening, activity shifting and activity splitting. If none of the strategies work for a conflict, the new generated activity is dropped form the schedule. ADAPTS (Auld and Mohammadian 2009) is the most recent agent-based model that simulates dynamics of activity planning and behaviour. The model consists of three components: activity generation, planning and scheduling. The activity generation component first generates the type of activities for each individual. After that, the activity planning process develops an activity attribute flexibility model that determines the perceived flexibilities of the activity attributes (i.e. whether the attributes are flexible or inflexible). Activity attributes include start time, duration, party composition, location and mode choice. Following this, activity attribute order (i.e. in what order attributes are planned) is determined through a planning order model. An activity scheduling component adds activities to the planned schedule of the individuals and households, as well as resolves scheduling conflicts. ADAPTS resolves conflicts within its modelling framework by modifying and deleting originally planned and conflicting activities. ADAPTS utilizes several econometric methods. For instance, the destination choice component utilizes a multinomial logit modelling technique and the activity planning component follows multivariate and ordered probit modelling techniques.

In recognition of the discussion on existing models, activity generation, activity scheduling and mobility choices are some critical elements of an activity-based travel demand model. Attributes that are implemented within these elements generally include generation of activity types and frequencies; simulation of activity durations, start times, destination locations; and determining modes for different activity purposes. Interestingly, although a few models consider interactions among household members while scheduling activities, none of them implemented a shared travel choice decision component that addresses underlying behavioural process of interacting with household and non-household members; thus, provide more behaviourally plausible feedback to reschedule activities. In addition, very few models address the process mechanisms of mode choice and vehicle allocation; in fact, implementation of vehicle allocation component is rare. Following Table 2-1 exhibits a comparison among the notable existing travel demand models regarding their different elements.

Table 2-1 Components of Notable Activity-based Travel Demand Models

System	Components					
	Activity Generation	Activity Scheduling			Mobility Assignment	
	Type and frequency	*Duration and start time*	*Destination location choice*	*Shared travel choice*	*Mode choice*	*Vehicle allocation*
ALBATROSS (Arentze and Timmermans, 2004)	Heuristics	Heuristics	Heuristics	Heuristics	Heuristics	Heuristics; car deficient households; identical cars
TASHA (Miller and Roorda, 2003)	Heuristics	Heuristics	Micro-behavioural model	X	Micro-behavioural model	X
ADAPTS (Auld and Mohammadian, 2009)	Hazard-based model	Heuristics	Micro-behavioural model	X	Micro-behavioural model	X
CEMDAP (Pinjari et al., 2006)	Micro-behavioural model	Micro-behavioural model	Micro-behavioural model	Micro-behavioural model (escort responsibilities to the parents)	Micro-behavioural model	X
DaySim (Bradley et al. 2010)	Micro-behavioural model	Micro-behavioural model	Micro-behavioural model	X	Micro-behavioural model	X
FAMOS (Pendyala et al. 2005)	Micro-behavioural model	Hazard-based model; Micro-behavioural model; Heuristics	Micro-behavioural model	X	Micro-behavioural model	X

2.2 Research Gaps

In summary, there is abundant research on exploring different activity-travel attributes within activity-based travel demand modelling framework. The majority of the research is focused on modelling activity generation and activity scheduling components. Among them, earlier studies primarily concentrated on estimating various activity attributes separately, however, joint modelling of the attributes has emerged due to their interdependencies. In particular, the estimation of multiple activity type choice and time allocation in a single modelling framework, where 'time' is a continuous entity, is important because it enhances the potential of a travel demand model to examine several policy interventions that are sensitive to specific time of a day. In addition, it is critical to examine how mode choice behaviour influences individuals' daily activity engagement since such decisions explore modal accessibility in the transportation network. Feedbacks from mode choice to the activity engagement decisions, which carry information of the decisions made on mode choices in the form of modal accessibility, is not well addressed in previous studies. An alternative modelling framework is required that can accommodate for the coupling of activity engagement and mode choice decisions within the modelling process, and explore how modal accessibility due to availability of different travel options affects the activity engagement decisions in a 24-hour timescale.

A critical aspect of an activity-based travel demand model is addressing the underlying behavioural mechanism of individuals' interactions with one another within their social realm. Existing studies mostly represent individuals' interactions with household members, such as partner/spouse and children, either by heuristically joining their activities or by developing micro-behavioural models that estimate the decision on whether or not to accompany one another (Pinjari et al. 2006). However, the behavioural basis of choosing a travel companion by accommodating a person's social interactions with household and non-household members (i.e. parents/other family members, roommates, friends, colleagues, etc.) is limited. In addition, such interactions contribute to rescheduling daily activity and travel decisions; hence, they need to be addressed within an activity-based travel demand modelling framework by being coupled with daily activity engagement decisions (Auld 2011). To estimate appropriate travel behaviour, it is imperative to investigate how social utilities (derived from individuals' shared travel choice models that accommodate individuals' social interactions with household and non-household members within the modelling framework) affect individuals' daily activity engagement decisions.

Such behavioural process within an activity-based travel demand model is crucial because it enhances the prediction capability of the model (Scott and Kanaroglou 2002). Also, social utility accommodates both travellers' and their companions' needs, hence, it is critical to understand how such utility shapes a person's activity pattern within a 24-hour temporal scale. To investigate this interrelationship, activity-based social utility needs to be estimated that takes information from individuals' desire to travel alone or to travel with household/non-household members and provides feedback to daily activity engagement behaviour.

Modelling vehicle allocation has become 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 the allocation of vehicles for specific travel activities (Hao 2009). However, limited research explores how different types of vehicles in multi-car households are allocated based on activity purpose at the tour-level. In particular, how individuals' interactions with household and non-household members (e.g. partner/spouse, children, parents/other family members, roommates/friends/colleagues) affect the allocation of vehicles to different activity-based tours have not occurred yet. In a dynamic microsimulation framework, explicit recognition of vehicle allocation decisions is required as it has direct influence on the estimation of emission and energy consumption. While specific emission rates exist for specific vehicle types, most of the emission models assume a fixed distribution of vehicle type to estimate vehicle emission and energy consumption across road networks (Chamberlin et al. 2011). Therefore, to better forecast daily traffic emission and energy consumption, it is essential to know how households' vehicle fleets are being utilized, particularly how the different types of vehicles are assigned to different activities and tours in a household. Although there are few studies on households' vehicle allocation process, a clear gap exists in understanding the behavioural differences of vehicle allocation among individuals in a multi-car household for different types of activities. One of the limitations found in the vehicle allocation literature is, there is no explicit recognition of individuals' interactions with household and non-household members. How presence of a household/non-household member during an activity-based tour affect vehicle allocation decisions is not evident. Also, how members of the household get vehicles from their existing vehicle fleet while traveling alone (i.e. solo travel) and traveling with household/non-household members (i.e. joint travel), and whether any differences exist when allocating vehicles between different types of individuals, are not well addressed in existing literature.

Earlier activity-based travel demand models generate activities and their attributes directly from the observed activity program (i.e. list of activities to schedule, duration, timing, etc.), without specifying any underlying modelling techniques (Jones et al. 1983). Later, several methodologies are developed to model activity generation and scheduling. For instance, as discussed in the previous section, utility maximization-based econometric models utilize a series of econometric micro-behavioural models (Pinjari et al. 2006); computation process models create rules from assumed priority ranking of activity types and attributes (Arentze and Timmermans 2004); agent-based hybrid models apply ad-hoc rules, special simulation approaches and econometric modelling techniques to generate activities and schedule them (Miller and Roorda 2003). Therefore, it is evident that the majority of existing travel demand models generate activities in any of the following ways: directly from observed data, applying econometric micro-behavioural modelling techniques, or randomly drawing from a probability distribution. However, large-scale travel demand models sometimes disregard the interdependency between two consecutive activities (Allahviranloo and Recker 2013). Arguably, an individual may not be able to enumerate all possible activities to participate in a day since not all information associated with the activities is known. Instead, they might plan to participate in a subsequent activity while performing their current activity. Hence, the probability to participate in activities may depend on the precedent activities. Few studies have attempted to generate activity-travel patterns by accommodating such underlying sequential decision-making processes. For example, conditional probability models are developed by Kitamura et al. (1997) to generate sequential activity location, type and scheduling conditioned on the previous activities. Popkowski Leszczyc and Timmermans (2002) developed conditional competing risk models to estimate activity choice and duration based on the previous activity type and duration. In this regard, Markov Chain-based processes have become popular due to their ability to generate a sequence of possible events where the probability of an event occurrence depends on the state of the preceding event (Grinstead and Snell 2012). Some examples of such studies are Liao et al. (2007), Allahviranloo and Recker (2013), and Liu et al. (2015). However, one of the limitations of these studies is that they did not test the multi-year prediction capacity of Markov Chain-based processes within a microsimulation framework. Another limitation includes, disregarding the feedbacks among different activity attributes, which can accommodate changes due to interactions between activity plans (consists of sequentially generated activities) and different short-term travel decisions (e.g. shared travel choice, mode choice, vehicle allocation, etc.) within a travel demand modelling system. In particular, feedbacks derived from the underlying decision process of shared travel choices (e.g. travel alone, travel with partner/spouse, travel with children, travel with parents/other family members and travel with roommates/friends/colleagues) while deciding to participate in activities have not yet been explored explicitly in existing studies. Also, a microsimulation of the underlying behavioural processes of shared travel choices has not yet occurred within an activity-based travel demand forecasting model. Decisions to travel with a companion are critical, since they deal with a person's social interactions with household and non-household members. Such interactions contribute to rescheduling daily activities, mode choice and vehicle allocation decisions, hence, there is a need for these interactions to be addressed within an activity-based travel demand modelling framework (Auld 2011).

In an agent-based activity-travel modelling system, one of the critical components is mobility assignment that involves modelling of the inherent process mechanisms of travel related components, for instance, mode choice and vehicle allocation. With the increasing concerns regarding vehicular emissions and energy consumption, the investigation of disaggregate-level mobility choice decisions has become an important issue in travel behaviour research. Exploring mode choice and vehicle allocation decisions within an activity-based travel demand forecasting system is more suitable since these decisions not only affect a person's daily activity schedule, but also have direct impacts on the traffic network (Yagi and Mohammadian 2008). To improve the underlying behavioural process representation and prediction capacity of mobility decisions, researchers have invested substantial efforts to implement mobility choice models in a microsimulation framework. Such implementation assists to understand the evolution of mode choice and vehicle allocation decisions, as well as supports the evaluation of emerging policy interventions. In addition, short-term mode choice and vehicle allocation decisions are dependent on long-term decisions, such as vehicle ownership, driver's license ownership and transit pass ownership, among others. Therefore, an integrated urban model that consists of an activity-based travel demand modelling system could be a potential microsimulation platform to predict the mode choice and vehicle allocation decisions. A number of activity-based travel demand modelling systems include predicting mode choice decisions within their microsimulation framework by accommodating individuals' interactions with household members only (e.g. Pinjari et al. 2006; Miller and Roorda 2003; Arentze and Timmermans 2004). However, limited studies facilitate the prediction of vehicle allocation decisions within the microsimulation framework. Among them, one of the notable models is TASHA (Miller and Roorda 2003), which develops a mode choice model that includes vehicle allocation alternatives within the mode choice structure. Vehicle allocation process within mode choice in TASHA basically identifies whether auto mode can be chosen during an activity-based tour depending on vehicle availability. When tours generated in car-deficient households overlap each other, all possible vehicle allocation settings are evaluated, and vehicles are allocated to those tours that provides maximum household utility with a vehicle in it. Individuals who are not allocated a vehicle due to this evaluation process, are assumed to choose non-auto mode that provides them the maximum utility. However, explicit behavioural processes to allocate a specific type of vehicle considering individuals' interactions with household and non-household members did not occur within this modelling process. ALBATROSS also investigates car allocation decisions in car-deficient households as a part of the activity scheduling process (Anggraini et al. 2008, 2012). It follows a sequential heuristic approach to predict vehicle allocation decisions between two household heads who have driving license and live in a one-car household. SimAGENT is another activity-based travel demand model, which first simulates the primary driver of the existing vehicles in the household utilizing a multinomial logit model (Goulias et al. 2011). Following this, different types of vehicles are allocated to different types of tours, where vehicles with primary drivers are used to form the available vehicle fleet choice sets. However, an individual's interaction with their travel companion was not addressed within this model's vehicle allocation microsimulation process. Therefore, it is evident that although the simulation of mode choice decisions is common, microsimulation of mobility assignment, which simulates mode choice and vehicle allocation decisions as an integrated process within an activity-travel modelling system, is limited in existing studies. Particularly, accommodating individuals' social interactions within the mobility assignment empirical and computational settings is not well addressed in literature. The microsimulation processes in mobility assignment is dynamic in nature since the choice of mode triggers the decision to allocate a vehicle for a specific activity-based tour from the corresponding household's existing vehicle fleet, and failure to assign a vehicle results in the re-evaluation of mode choice decisions.

2.3 Research Questions

In recognition of the above discussion, it is evident that considerable attempts have been made by researchers to explore activity and travel decisions by applying a wide range of micro-behavioural modelling methods as well as microsimulation approaches. However, alternative methods to couple individuals' activity and travel decisions to represent their short-term travel behaviour require further investigation. In addition, a comprehensive microsimulation model to depict individuals' activity and travel behaviour in a more plausible way by simulating realistic process mechanisms is warranted due to the emergence of recent travel alternatives, such as shared travel options. In particular, the following research questions require attention:

1. How to represent the behavioural process mechanisms to couple the key activity and travel decisions within a micro-behavioural modelling framework?
2. How to address individuals' social interactions within a micro-behavioural modelling framework, and accommodate such interactions within the computational procedure of an activity-based travel demand microsimulation model to represent different activity and travel decisions?
3. How to contribute to current travel demand modelling research by developing an advanced activity-based travel demand forecasting model that predicts disaggregate-level critical activity and travel decisions of a region?

This thesis addresses the research questions discussed above by developing alternative econometric modelling techniques, and a prototype agent-based microsimulation model to forecast individuals' activity and travel decisions. Alternative empirical methods are developed to evaluate the interdependencies between activity attributes (e.g. activity participation, time allocation) and travel attributes (e.g. shared travel choice, mode choice). The activity-based travel demand microsimulation model is developed by accommodating individuals' social interactions with their household and non-household members to predict key activity-travel decisions, namely activity generation, activity scheduling and mobility assignment. Advanced heuristics and micro-behavioural modelling techniques are developed to predict different components of the major activity-travel decisions (e.g. activity types, duration, destination locations, shared travel choice, mode choice, vehicle allocation, etc.), and their disaggregate-level spatial-temporal evolution. The activity-travel microsimulation model is developed within an integrated urban modelling platform. To make the full integration of the urban model, the activity-based travel demand model proposed in this study uses a modal accessibility to provide feedback to long-term residential location transition. The modal accessibility is represented by the logsum measure of the utility of mode choices. Since mode choice decisions in the proposed activity-travel microsimulation model is estimated based on various socio-demographic, neighbourhood and travel characteristics, such integration can explicitly capture the influence of households' travel alternatives on their residential mobility and location choice decisions and provide behavioural consistency within the integrated urban model. However, this thesis focuses to develop a prototype activity-based travel demand microsimulation model. The integration procedure between the land use and travel demand components is out of the scope of this research. Following is a brief discussion of the modelling framework of the proposed travel demand model.

2.4 Modelling Framework of the Proposed Activity-based Travel Demand Forecasting System

The proposed activity-based shorter-term decisions simulator (SDS) in this research is an agent-based microsimulation model for travel demand forecasting systems. The SDS model is an integral part of an urban model, namely an integrated Transportation Land use and Energy (iTLE) model, which is developed by addressing process mechanisms and multi-domain interactions among a number of decisions. The integrated urban model is designed as a modular-based system, so that each module and subsequent micro-behavioural models are implemented in isolation, hence, provide opportunity to improve any sub-module and/or component without influencing the whole microsimulation process. Figure 2-1 presents the conceptual framework of iTLE.

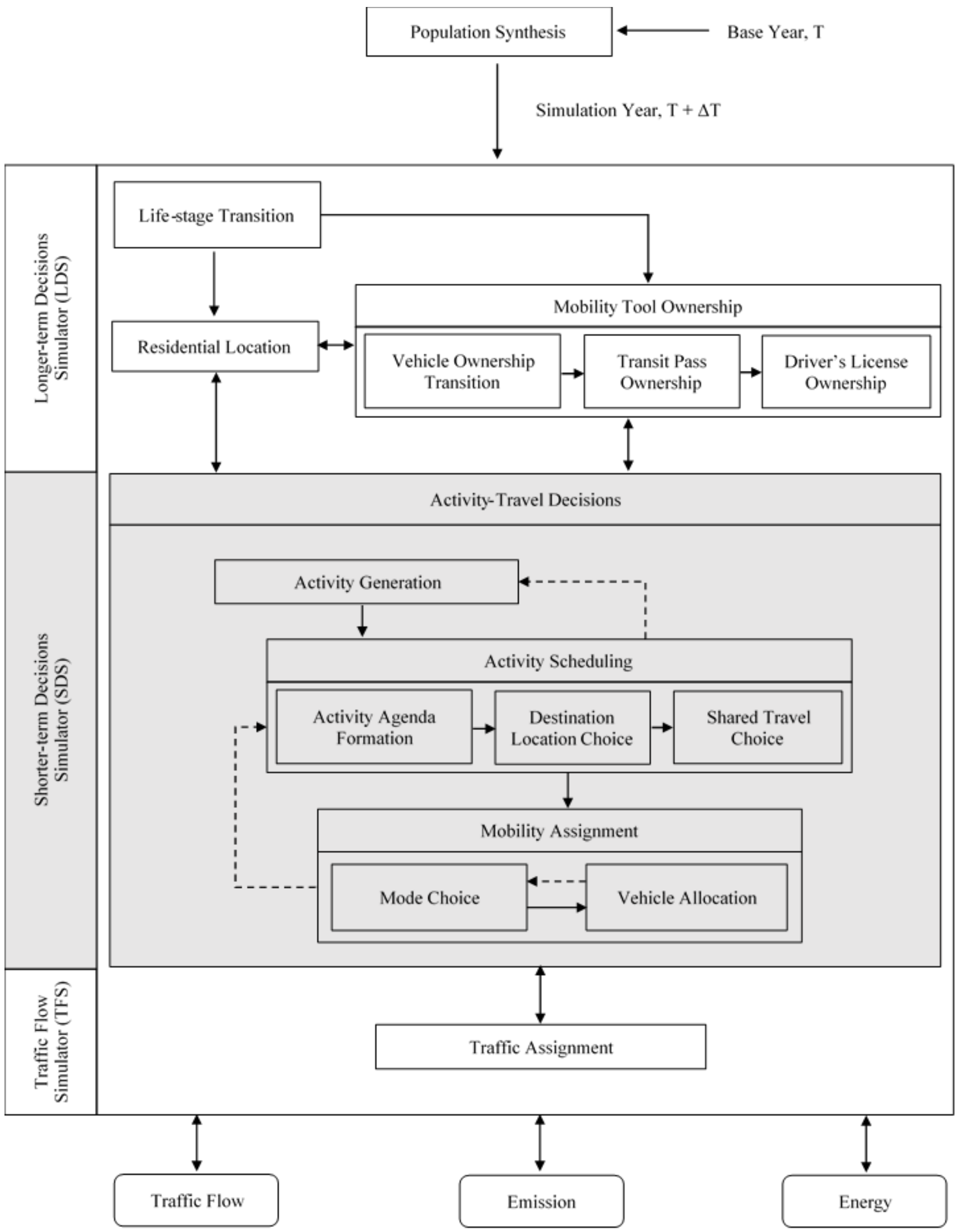

Figure 2-1 Conceptual Framework of the integrated Transportation, Land use and Energy (iTLE) Model

The iTLE modelling system consists of three core modules: longer-term simulator (LDS), shorter term simulator (SDS) and traffic flow simulator (TFS). It follows a life-oriented approach that focuses on the dependencies among different decisions and changes along the life-course of individuals and households (Fatmi and Habib 2017). The LDS module of iTLE is already implemented in Halifax, Canada and simulates different individual- and household-level life-stage transitions (Fatmi and Habib 2017), residential location transitions (Fatmi and Habib 2018a) and vehicle ownership transitions (Fatmi and Habib 2018b) occurring in their different life domains. The SDS module includes modelling and microsimulation of individuals' short-term activity and travel decisions. Finally, TFS simulates different trips of individuals within a predefined traffic network using a dynamic traffic assignment method. This module is currently under development and beyond the scope of this thesis. Note that, the shaded area in Figure 2-1 depicts the scope of this thesis.

The focus of this research is to develop the conceptual and operational framework of the SDS module within the iTLE microsimulation platform. SDS follows an agent-based hybrid modelling approach and consists of three sub-modules, namely activity generation, activity scheduling and mobility assignment. Each sub-module includes different activity and travel decision components, which are developed utilizing various advanced heuristics and econometric micro-behavioural modelling approaches. The microsimulation process of SDS takes inputs from the LDS module of iTLE, which is currently implemented in Halifax, Canada. LDS generates a list of households and individuals for a 30-year period, starting from the base year 2006 to simulation year 2036. SDS takes information on residences, households, vehicles and individuals, and generates individuals' activity-travel decisions for a typical weekday of each year from 2006 to 2036. To start the microsimulation process in SDS, at first individuals are heuristically categorized into multiple population segments to develop different activity attributes distributions. Population segmentation follows a series of empirical tests. After testing with various variables, living arrangements in the households and employment status of the household heads are found better predictors of activity-travel pattern. Such segmentation criteria assist to accommodate social interactions within modelling methodologies as well as simulation framework. The SDS model categorizes individuals into fourteen segments: 1) full-time employed – living alone, 2) full-time employed – living with partner/spouse, 3) full-time employed – living with children, 4) full-time employed – living with parents/other family members, 5) full-time employed – living with roommates/friends/colleagues, 6) part-time employed – living with household members (i.e. partner/spouse, children), 7) part-time employed – living alone and/or with non-household members (parents/other family members, roommates/friends/colleagues), 8) students – living alone and/or with non-household members (parents/other family members, roommates/friends/colleagues), 9) retired – living alone, 10) retired – living with partner/spouse, 11) retired – living with children, 12) retired – living with parents/other family members, 13) retired – living with roommates/friends/colleagues, and 14) unemployed – living alone, with household and/or non-household members. SDS simulates activity and travel decisions for the individuals belonging to these population segments. The conceptual framework of SDS is shown in Figure 2-2. A brief discussion of different elements of SDS is given below.

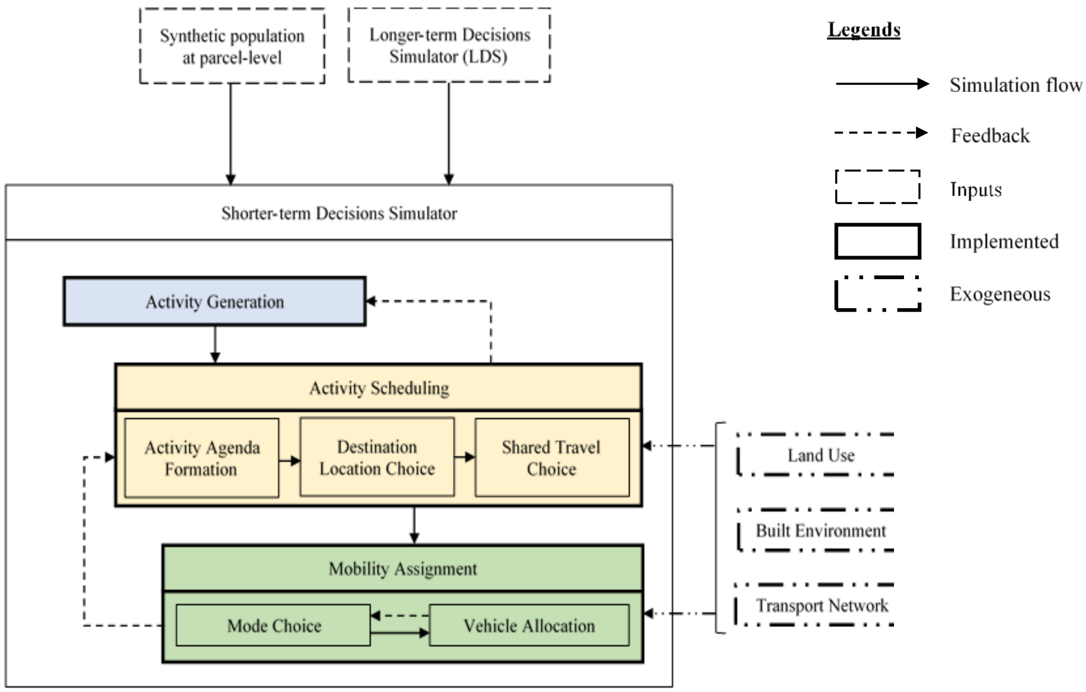

Figure 2-2 Shorter-term Decisions Simulator (SDS) Conceptual Framework

2.4.1 Activity Generation

The activity generation sub-module simulates daily activity programs that include individual-level choice of different types and number of activities in a typical weekday. The sub-module takes information from the LDS and population synthesis components of iTLE that includes various individual- and household-level characteristics. Out-of-home activities are classified into seven categories: work, school, escort, shopping, personal business, recreation and dine out. Activity generation first simulates activities in an orderly fashion for each individual in the household following a heuristics approach. After that, the total number of activities are simulated, and activity programs are generated for the individuals. Chapter six describes the detailed activity generation procedure.

2.4.2 Activity Scheduling

The activity scheduling sub-module consists of different components, namely activity agenda formation, destination choice, shared travel choice and an activity conflict resolution manager. At first, the activity agenda component simulates activity durations and start times following the generation of activities. After that, the destination location choice component assigns appropriate locations to each activity generated following an econometric micro-behavioural modelling approach. Following this, travel time and distance is also generated from origin and destination pair, which provides feedbacks to update daily activity programs. At this stage, multiple conflicts may occur within the modelling process. These are resolved by the activity conflict resolution manager. Once the conflicts get resolved, activity-based tours are formed following an activity hierarchy. The final step of the activity scheduling sub-module is to simulate individuals' shared travel choices, which addresses individuals' social interactions. This component also gives feedback to activity plans that consists of activity program, duration, start time, destination location and skim travel time. Finally, planned activity schedules are formed for each individual generated in the LDS module of iTLE. The micro-behavioural models, and microsimulation process and results of activity scheduling components are discussed in chapter six.

2.4.3 Mobility Assignment

Mobility assignment sub-module is conceptualized as a two-stage dynamic process: mode choice and vehicle allocation. The mode choice component simulates mode choice decisions for four modes at the activity-based tour-level: auto, transit, walk and bike. Probabilities to choose a mode are estimated by developing econometric models (see chapter three). To simulate behaviourally realistic mode choice decisions, this research considers variable choice sets within the micro-behavioural and microsimulation modelling frameworks based on the availability of modes. Once mode choice component assigns modes to individuals' daily activity-based tours, the vehicle allocation component starts allocating vehicles to different auto-based activity-tours. This component is coupled with the LDS module that exchanges information with the SDS module. It takes information from several long-term decision components, such as numbers and types of vehicles owned by the households and driver's license ownership. The vehicle allocation process involves assigning five types of vehicles to different activity-based tours: subcompact vehicle, compact vehicle, midsize vehicle, sport utility vehicle (SUV) and vans (includes passenger trucks, minivans, vans, etc.). This component also uses variable choice sets based on the types of vehicles the households own in their existing vehicle fleet. Similar to the mode choice component, vehicle allocation probabilities are also estimated by developing micro-behavioural models (see chapter five). During the microsimulation process of mobility assignment, multiple conflicts may arise while assigning vehicles to different activity-based tours and are resolved by implementing a vehicle conflict resolution manager. Following conflict resolutions, individuals who are not allocated any vehicle for their tours, are allowed to reassess their mode choice decisions. The mobility assignment sub-module generates travel time by each mode and provides feedback to the activity plans and updates them. One of the unique features of both the mode choice and vehicle allocation components is that they consider individuals' social interactions within both econometric and computation procedures. A description of the micro-behavioural models and microsimulation process and results of mobility assignment components are presented in chapter three, five and chapter seven.

2.5 Data Sources

This thesis utilizes multiple data sources to develop the micro-behavioural and microsimulation models of activity and travel demand. In particular, to represent the activity and travel decisions within both empirical settings as well as simulation process mechanisms, it is required to obtain data from an activity-travel survey that can offer detailed activity and travel information. The primary data source utilized in this research is the Nova Scotia Travel Activity (NovaTRAC) survey. In addition, some other data sources are utilized to develop the heuristics and econometric micro-behavioural models, including land use data, Canadian Census data, and transport network data, among others. The following is a brief discussion of the data sources used in this thesis.

2.5.1 Primary Data Source: NovaTRAC Survey

The Nova Scotia Travel Activity (NovaTRAC) survey is a cross-sectional survey that was initiated in 2015 by the Dalhousie Transportation Collaboratory (DalTRAC) in partnership with the Province of Nova Scotia. The goal of the survey was to better understand and improve the transportation systems of the region. It was the first randomly sampled travel survey in Halifax. The survey collected Halifax residents' activity and travel information in two stages. At first, a cellular phone-based sampling method was utilized to invite households to participate into the survey. After that, a survey package was mailed to the households that were randomly selected through a land phone-based sampling approach. Survey respondents were offered to complete the survey online through a novel Computer Assisted Web Interviewing (CAWI) survey tool developed by DalTRAC, or by mail with a supplied return envelope. Follow-up calls were made to each household by a telephone interviewer, providing an opportunity to respond by phone. The survey collected information via three components: household characteristics, household member characteristics, and a 24-hour travel log for each member of the household. At first, respondents were asked to provide information about their household and each member residing in the household. After that, each member was asked to record their travel activities for a 24-hour period of a typical weekday. Following is a brief discussion of these three survey components:

1. Household characteristics: The household characteristics component collected general household information and household vehicle information. During the survey, respondents were asked to provide the following:
    - General household information including household size, annual household income before tax, current address of residence, years living in the current residence, home ownership status, and type of dwelling structure.
    - Household vehicle information that includes number of vehicles in the households, number of bicycles in the households, and the detailed make-model-year information of the existing vehicles in the households.
2. Household member characteristics: This component asked the respondent about socio-demographic characteristics of all current household members. This included

members' gender, age, highest level of education, current employment status, occupation category, driver's license and monthly transit pass ownership.

3. 24-hour travel log: The travel log collected all the information regarding the activity and travel of each household member for a typical weekday. It asked respondents to record each place visited, starting with the location at 3:00 am on the travel day. The following are the specific activity and travel information that each member of the household was asked to record: a) day of travel, b) activity location, c) activity purpose, d) arrival and departure time, e) mode of travel, f) vehicle used for the activity, and g) travel companion.

In addition, the survey collected information on respondents' health, attitudes and lifestyle preferences. It contained six health related questions, such as height, weight, level of physical activity in a given week, health status, attitude towards life and stress level in a typical weekday. There were eleven attitudinal and lifestyle preference questions, where respondents were asked to specify their level of agreement or disagreement using a five-point Likert scale.

The NovaTRAC 2016-17 survey yields responses from 2333 households and 4159 individuals. The sample is spatially well distributed across Halifax Regional Municipality (HRM). 52% of the total households are from suburban areas and 30% are from regional centres. A demographic analysis of the survey suggests that about 51% of the respondents are female and about 49% are male. 63% respondents belong to 15-59 years age group, 22% are above 60 years. The majority of the respondents are full-time employed (approximately 45%), 13% are students and 10% are part-time employed. 41% of the respondents belong to households that earn above C$100,000 yearly, whereas, 39% of the respondents' annual household income is below C$50,000. In the case of household size, the average number of people in the household is 2.70. The majority of the respondents (39%) live in two-person households, whereas, 17% of respondents live alone. The NovaTRAC survey sample is compared with the 2016 Canadian Census, and found that the majority of the household and individual characteristics are within a maximum of 4% difference. Based on this, the NovaTRAC survey can be considered as a representative sample of Halifax population. Further details about the NovaTRAC data is available in Habib (2017).

While developing the micro-behavioural models, the NovaTRAC survey is utilized to extract and derive certain socio-demographic characteristics, as well as activity and travel attributes. The socio-demographic variables utilized in this research to develop micro-behavioural models include, age, household annual income, household size, household vehicle ownership, household bike ownership, employment status, dwelling type, driving license ownership, and monthly transit pass ownership, among others. Activity and travel attributes include activity duration, activity arrival and departure time, travel duration, travel distance, and travel arrangements, among others. Finally, the survey is also used to create probability distributions for different activity attributes during the development of the SDS microsimulation model.

2.5.2 Secondary Data Sources

This research utilizes secondary data sources to develop the micro-behavioural and microsimulation modelling processes. Such data sources include Canadian Census, National Household Survey (NHS), Halifax Regional Municipality (HRM) land use database, Desktop Mapping and Technologies Inc. (DMTI) database, HRM road network, transportation network-level skim datasets, Info Canada Business Establishment dataset, and households' long-term decisions datasets from iTLE. Secondary data sources are utilized to derive various land use, neighbourhood characteristics and accessibility measures. The following is a brief discussion on such variables:

- NHS dataset and 2016 Canadian Census dataset are utilized to derive the neighbourhood characteristics at DA-level to develop the micro-behavioural models. These include, population density, dwelling density, percentage of owned and rented dwellings, percentage of dwelling types, labour force participation rate, and employment rate in the neighbourhood, among others.
- Land use information is derived from HRM land use database. It includes the percentage of different land uses at DA-level, such as residential, commercial, open space, park, industrial, government and water body. The land-use index can be computed utilizing land use percentages, as proposed by Bhat and Gossen (2004). A land-use index value of 0 indicates a complete homogeneous and a value of 1 indicates a complete heterogeneous land use.
- Accessibility measures are defined as the distance between home and other activity points. The location of different activity points, such as central business district (CBD), nearest school, nearest transit stops, nearest business centre, nearest health services, nearest shopping areas, and nearest recreational parks, are collected from the DMTI (Desktop Mapping Technologies Inc.) database. Using the Network

Analyst Tool in ArcGIS and HRM road network, the distance between home and other activity points are generated.

- Info Canada Business Establishment dataset is used in this thesis to develop the destination location choice models that are required to derive destination location attributes, such as population density, land use index, percentage of property owners, average property value, sales volume, and number of employees, among others.
- The network-level skim datasets are used to extract skim matrices of travel time from home to a destination from a transport network model generated in EMME.
- During the microsimulation process, different datasets generated in the LDS module of iTLE are utilized as inputs into the SDS modelling system. LDS generates agents' (i.e. households and individuals) longitudinal information from the year 2006 to 2036 that include residence lists, household lists, individual lists and vehicle lists. These datasets are dynamic and provide agents' detailed information in each year.
- The SDS microsimulation model is calibrated to the 2011 National Household Survey dataset. Finally, 2006 and 2016 Canadian Census datasets are utilized in this study to validate the SDS model.

2.6 Concluding Remarks

This chapter discusses the existing research on developing different activity-based travel demand models. It also presents a synthesis on the existing activity-travel microsimulation models that are utilized to predict individuals' various activity and travel decisions. Based on the discussion, it determines the research gaps in existing travel demand modelling research and presents three research questions. After which, this chapter proposes the development of a prototype agent-based activity-travel microsimulation modelling system within an integrated urban model and discusses the modelling framework to develop the micro-behavioural and microsimulation models of different decision processes. The proposed prototype model accommodates individuals' social interactions within the empirical settings as well as computational procedures of different activity and travel decisions. The essential components of an activity-based travel demand forecasting model are identified in this chapter, including activity types, frequencies, duration, start time, travel time, destination location, shared travel choice, mode choice and vehicle allocation. Finally, this chapter discusses the data sources that are utilized to develop the micro-behavioural and microsimulation models in this thesis. For instance, the 2016-17 NovaTRAC survey is used in this thesis as the primary data source; Canadian Census, National Household Survey (NHS), DMTI database, Info Canada Business Establishment database, datasets generated in LDS module, etc. are used as secondary data sources. These sources are utilized to derive information to develop different econometric and heuristics models. The next three chapters (chapter three, four and five) present the alternative empirical modelling approaches to estimate different activity and travel decisions. Chapter six and chapter seven discuss the modelling procedures and simulation results of activity generation, activity scheduling and mobility assignment sub-modules of the activity-based SDS microsimulation model.

Chapter 3

Modelling Activity Participation, Time Allocation and Mode Choice

3.1 Introduction

This chapter focuses to develop an alternative econometric modelling framework to explore individuals' activity participation, time allocation and mode choice decisions. The contribution of this research is three-fold: 1) investigating the join decision of participation and time allocation into multiple activities within a single modelling framework, where 'time' is considered as a continuous entity, 2) developing econometric models to explore mode choice decisions for different types of activities that capture unobserved heterogeneity arises due to repeated choice of modes, and 3) evaluating how modal accessibility affects daily activity engagement decisions. Individuals' daily activity participation, time allocation and mode choice decisions are conceptualized in this chapter at activity-based tour-level. This study first develops mode choice micro-behavioural models for mandatory and non-mandatory activity-based tours using a mixed logit (MXL) modelling technique. After that, tour-level activity engagement (i.e. participation and time allocation) decisions are estimated by developing a multiple discrete continuous extreme

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This chapter is derived from following papers:

- Khan, N. A., Enam, A., Habib, M. A., & Konduri, K. C. (2018). Investigation of Tour Participation, Time Allocation and Mode Choice: An Application of Multiple Discrete Continuous Extreme Value-Mixed Multinomial Logit Modeling Approach. Published in the peer-reviewed proceedings of the *Transportation Research Board 97th Annual Meeting*. Washington, D. C., U.S.A., January 7-11, 2018.
- Khan, N. A., Enam, A., Habib, M. A. & Konduri, K. C. (2020). Joint Modeling of Activity-Tour Participation, Time Allocation and Mode Choice. *Journal of Urban Planning and Development*. (Conditionally accepted).

value (MDCEV) model. Finally, it implements a coupling mechanism within the modelling process, which provides feedback from the mode choice decisions to the activity engagement decisions. This assists to maintain the behavioural integration of the MDCEV and MXL modelling systems, and explores the influence of the mode choice (dis)utility on individuals' tour-level activity participation and time allocation decisions. In this research, the coupling mechanism is termed as modal accessibility and is implemented in the form of logsum values that are computed from the mode choice micro-behavioural models. Logsum values are measured based on various socio-demographic characteristics, activity and travel attributes, neighbourhood characteristics and accessibility measures that are utilized to estimate mode choice decisions.

The rest of the chapters are organized as follows: section 3.2 describes the modelling methodologies that are developed to explore activity-based tour participation, time allocation and mode choice decisions. Section 3.3 presents a brief discussion on the model estimation results. Finally, section 3.4 presents a summary of contributions and limitations of this research, and probable directions for future research.

3.2 Modelling Methods

3.2.1 Formation of Activity-based Tours

In this research, tours are formed based on the primary activities of the activity chains. Formation of activity-based tours includes several steps. Based on respondents' location and departure-arrival time, home-based tours (HBTs) performed by the respondents that start and end at home, are identified first. Then the stops within the activity-tours are identified based on the activity purpose at destinations. Respondents' activity purposes are categorized into the three groups: 1) mandatory activities: work/job and all other activities at work location as well as attending class and all other activities at school; 2) maintenance activities: escorting (i.e. drop-off or pick-up passenger), routine shopping, household and work-related errands, personal business, and healthcare; and 3) discretionary activities: dine out, civic or religious activities, recreation, entertainment and visiting friends. Consequently, a primary activity is identified for each respondent's HBTs. Primary activities are determined according to activity priority and dwelling time, i.e. the sum of the travel episode and activity episode at the activity destinations. Mandatory activities are given the highest priority. An HBT is defined as 'mandatory activity-tour' if the respondent conducts at least one mandatory activity within the corresponding tour. All other activities in a mandatory activity-tour are then assigned as the intermediate stops. If a respondent does not conduct any mandatory activity within his HBTs, the activity with highest dwelling time at destination is considered as the primary activity of the tour. For instance, between a maintenance activity and a discretionary activity performed by a respondent, if the dwelling time is higher at discretionary activity destination, the tour is designated as 'discretionary activity-tour' and the maintenance activity destination is assigned as intermediate stop. For the multiple activities with same purpose, highest priority is given to the activity with higher dwelling time and assigned as the primary activity to characterize the tour. All other activities within the tour are included as intermediate stops. In addition to the mandatory, maintenance and discretionary activity-tours, time spent at home is considered as an alternative in this research. Hence, the temporal constraint of 24 hours (1440 minutes) in a given day is incorporated in the modelling framework. In addition, considering at-home time spent provides the advantage of exploring individuals' at-home and out-of-home activity engagement trade-offs within a 24-hour time frame. Since the activity-tours are specified based on the primary activities, for the analysis of activity-based tour mode choice models, modes used to get to the primary activity destination are also assumed as the primary mode used for the tour. Two mode choice models are developed in this study based on the activity purpose, a mandatory activity-tour mode choice and a non-mandatory activity-tour mode choice model. Four types of modes are considered, a) auto, b) transit, c) walk, and d) bike. Mode choice models utilize variable choice sets to estimate individuals' behaviour to choose modes based on the availability of modes. Alternatives are eliminated from the choice sets if a particular mode is not available to the individuals. Travel time and distances for each mode are calculated by the respondents' reported departure and arrival times, and residential and activity destination locations. In addition, travel time and distances for non-chosen modes are calculated through Google API using respondents' reported home location, departure time and primary activity location.

3.2.2 Mode Choice: A Mixed Logit (MXL) Modelling Approach

This study employs a random utility-based discrete choice modelling approach, specifically the mixed logit (MXL) modelling technique to investigate individuals' mode choice behaviour for different activity-based tours. Assuming that U_{ji} is the utility of an alternative (mode) i chosen by an individual j, which can be expressed as:

$$U_{ji} = \alpha_{ji} + \beta_j X_{ji} + \varepsilon_{ji} \quad (1)$$

Where, alternative-specific constants (ASCs) for mode *i* and individual *j* is denoted by α, one of which is zero, hence considered as the reference. In this paper, 'bike' and 'walk' are considered as the reference for mandatory and non-mandatory activity-tour models respectively. β is the individual specific taste parameters. X is a column vector of the observed attributes. In the paper, α and β are assumed to be normally distributed across individuals. ε_{ij} is a random error term that is independent and identically distributed (IID).

Traditional multinomial logit models do not account for unobserved heterogeneity pertaining to individuals. In the current study, multiple mandatory and non-mandatory activity-tours are considered for the same individual resulting in repeated choices of the same observation, which violates the IID assumption. Therefore, a flexible mixed logit (MXL) model that relaxes the IID assumption is used in this study. The parameters in equation 1 are estimated using simulated maximum likelihood technique (SMLE). The Halton sequence is used in this study as it requires substantially lower number of draws than random draws. 150 Halton draws have been used for estimating the parameters of the final models presented in the study.

3.2.3 Measurement of Mode Choice Logsum

To implement coupling between mode choice and activity engagement decisions, which can capture the effects of modal accessibility (offered via mode choice alternatives) on individuals' tour-level activity participation and time allocation decisions, logsum values (L_{jm}) are calculated for each respondent *j* for each tour type using equation 2 below (Vij and Walker 2013):

$$L_{jm} = \frac{1}{K_{jm}} \sum_{k=1}^{K_{jm}} log\left[\sum exp\left(\beta_j X_{jm}\right)\right] \tag{2}$$

In the above equation, L_{jm} represents mode choice logsum and the suffix m represents mandatory and non-mandatory tour types. K_{jm} represents the number of tours made by individual j of tour type m. Note that, a higher value of logsum would indicate a higher mode choice accessibility for mandatory and non-mandatory activity-tour types and vice versa (Ben-Akiva and Lerman 1985).

3.2.4 Tour-level Activity Participation and Time Allocation: A Multiple Discrete Continuous Extreme Value (MDCEV) Modelling Approach

In the current study, the participation (whether to participate in an activity-based tour?) and time allocation (how much time to allocate?) decision into different activity-tours, namely at-home, mandatory activity-tour 1, mandatory activity-tour 2, maintenance activity-tour and discretionary activity-tour are modelled using multiple discrete continuous extreme value (MDCEV) framework following Bhat (2008). According to the MDCEV formulation, an individual allocates a certain available budget (i.e. 1440 minutes available in a day) across multiple activity-tours such that the utility derived by engaging in the combination of tours is maximized. This approach allows the simultaneous modelling of tour-level activity participation and time allocation choices using a single framework.

The optimization problem where an individual allocates $q = \{q_1, q_2, \ldots\ldots, q_k\}$ amounts of time to K activity-tour types can be formulated as shown in equation 3 below:

$$\max U(x) = \Psi_1 \ln(q_1) + \sum_{k=2}^{K} \gamma_k \Psi_k \ln\left(\frac{q_k}{\gamma_k} + 1\right) \tag{3}$$

subject to$\sum_{k=1}^{K} q_k = T$ (4)

Where, q is a ($K \times 1$) vector of time allocated to tours 1, 2, ….., K. From the analyst's point of view the decision maker tries to maximize the total utility U given by equation 3, subject to the time budget constraint T given by equation 4. $\Psi_{k,}$ (> 0) is known as the baseline marginal utility parameter and represents the gain in utility realized by allocating 1st unit of time to tour k. On the other hand, γ_k (> 0) is known as the translation/satiation parameter and controls the amount of time allocation into different activity-tour types. The Ψ and γ are further parameterized as in equation 5 and 6 below:

$$\Psi = \exp(\nu\mu + L_m\theta + \varepsilon) \quad (5)$$

$$\gamma = \exp(\eta\lambda) \quad (6)$$

Where, Ψ and γ are ($K \times 1$) vectors of baseline marginal utility and satiation parameters respectively, $\boldsymbol{\nu}$ and η are ($K \times D$) matrices of exogenous variables, μ and λ are ($D \times 1$) vectors of coefficients, and ε is a ($K \times 1$) vector of stochastic error term. In the current study, ε is assumed to be independent and identically type I extreme value distributed across activities and individuals.

Note that, the matrices, ν and η allow for the exploration of the heterogeneity in the tour-level activity participation and time allocation behaviour due to different individual and household level socio-demographic, neighbourhood characteristics and accessibility measures. Additionally, in the current formulation, the activity-tour participation propensity is also assumed to be influenced by the activity-tour mode choice logsum. In equation 5, L_m and θ respectively represent the ($K \times K$) diagonal matrix of mode choice logsum calculated using equation 2 and the K by 1 vector of corresponding coefficient. It can be noted that, in equation 5, it is desirable for the logsum coefficient, θ to attain a positive value, since an increase in the accessibility offered by the mode choice options should lead to an increase in the corresponding tour-level activity participation propensity and vice versa.

3.3 Result Discussion of the Micro-behavioural Models

A number of socio-demographic characteristics, activity and travel attributes, neighbourhood characteristics and accessibility measures are utilized in both activity-based tour mode choice, and participation and time allocation model. Table 3-1 shows the descriptive statistics of the variables retained in the final models. A brief discussion of the parameter estimation results of micro-behavioural models can be found after the descriptive statistics.

Table 3-1 Descriptive Statistics of Mode Choice, Activity Participation and Time Allocation

Activity-based Tour-level Mode Choice			
Type of Modes	Mandatory Activity-tour	Non-mandatory Activity-tour	
Auto	70.77%	74.66%	
Transit	12.83%	6.16%	
Walk	10.08%	13.70%	
Bike	6.31%	5.48%	
Distribution of Independent Variables			
Variables	Description	Mean/Proportion	Standard Deviation
Mandatory Activity-tour			
Individual age more than 60	Dummy, if individual's age is more than 60 years = 1, 0 otherwise	8.05%	-
Annual household income between $35,000 and $75,000	Dummy, if individual's annual household income is between $35,000 and $75,000 = 1, 0 otherwise	20.27%	-
Highest educational degree: High-school	Dummy, if individual's highest educational degree is High-school = 1, 0 otherwise	15.58%	-
Number of vehicles in household	Number of vehicles in the household	1.20	1.10
Number of bikes in household	Number of bikes in the household	0.99	1.40
Number of stops within tour	Number of stops within the tour	0.65	1.01
Travel with partner/spouse	Dummy, if individual travel with partner/spouse = 1, 0 otherwise	6.11%	-

Travel time	Travel time to the activity destination (minutes)	30.51	24.16
Activity duration at destination	Time spent at activity destination (minutes)	451.07	202.96
Tour duration	Total time spent within the whole tour (minutes)	522.25	192.27
Land-use index	Land-use index of the neighbourhood	0.20	0.21
Dwelling density	Dwelling density of the neighbourhood (per square kilometers)	26.09	49.45
CBD (central business district) distance from home	Individual's home to CBD (central business district) distance (kilometers)	37.96	77.46
Non-mandatory Activity-tour			
Household income more than \$75,000	Dummy, if individual's annual household income is more than \$75,000 = 1, 0 otherwise	37.67%	-
Gender: Female	Dummy, if individual's gender is female = 1, 0 otherwise	56.51%	-
Household size: 2 persons	Dummy, if individual's household size is two = 1, 0 otherwise	35.96%	-
Number of vehicles in household	Number of vehicles in the household	1.15	1.01
Number of bikes in household	Number of bikes in the household	1.01	1.32
Travel with partner/spouse	Dummy, if individual travel with partner/spouse = 1, 0 otherwise	13.70%	-
Travel time	Travel time to the activity destination (minutes)	27.27	29.12
Activity duration at destination	Time spent at activity destination (minutes)	133.84	119.89
Tour duration	Total time spent within the whole tour (minutes)	148.37	142.18
Transit pass_no	Dummy, if individual does not have a monthly transit pass = 1, 0 otherwise	69.86%	-
Driving license_no	Dummy, if individual does not have a driving license = 1, 0 otherwise	6.51%	-
Dwelling density	Dwelling density of the neighbourhood (per square kilometers)	21.83	44.08
CBD distance from home: more than 5 kilometers	Dummy, if individual's home to CBD (central business district) distance is more than 5 kilometers = 1, 0 otherwise	51.37%	-
Closest bus-stop distance from home: more than 2 kilometers	Dummy, if individual's home to closest bus-stop distance is more than 2 kilometers = 1, 0 otherwise	58.56%	-

Tour-level Activity Participation and Time Allocation

Activity-based Tours	Participation	Duration (average)
At home	100%	922 minutes
Mandatory Activity-tour 1	87.14%	539 minutes
Mandatory Activity-tour 2	4.38%	197 minutes
Maintenance Activity-tour	14.07%	149 minutes
Discretionary Activity-tour	13.14%	148 minutes

Distribution of Independent Variables

Variables	Description	Mean/Proportion	Standard Deviation
Female Indicator	Dummy, if individual's gender is female = 1, 0 otherwise	55.73%	-
Age group: 18 to 24 years	Dummy, if individual's age is between 18 and 24 years = 1, 0 otherwise	21.97%	-
Age group: 25 to 34 years	Dummy, if individual's age is between 25 and 34 years = 1, 0 otherwise	23.99%	-
Age group: 35 to 44 years	Dummy, if individual's age is between 35 and 44 years = 1, 0 otherwise	14.64%	-
Age group: 45 to 54 years	Dummy, if individual's age is between 45 and 54 years = 1, 0 otherwise	17.44%	-
Age group: 55 to 64 years	Dummy, if individual's age is between 55 and 64 years = 1, 0 otherwise	15.41%	-
Number of vehicles 1	Dummy, if number of vehicles in individual's household is one = 1, 0 otherwise	36.53%	-
Number of vehicles 2	Dummy, if number of vehicles in individual's household is two = 1, 0 otherwise	26.37%	-

Number of vehicles 3 or more	Dummy, if number of vehicles in individual's household is three or more = 1, 0 otherwise	8.95%	-
Living alone	Dummy, if individual's household size is one = 1, 0 otherwise	7.18%	-
Annual household income less than $25,000	Dummy, if individual's annual household income is less than $25,000 = 1, 0 otherwise	16.40%	-
Annual household income between $75,0000 and $99,0000	Dummy, if individual's annual household income is between $75,000 and $100,000 = 1, 0 otherwise	13.61%	-
Annual household income between $100,0000 and $149,0000	Dummy, if individual's annual household income is between $100,000 and $150,000 = 1, 0 otherwise	14.54%	-
Annual household income equal and above $150,0000	Dummy, if individual's annual household income is equal or above $150,000 = 1, 0 otherwise	8.29%	-
Full-time employment	Dummy, if individual is a full-time employee = 1, 0 otherwise	46.88%	-
Part-time employment	Dummy, if individual is a part-time employee = 1, 0 otherwise	8.67%	-
Retired	Dummy, if individual is a retired person = 1, 0 otherwise	7.08%	-
Student	Dummy, if individual is a student = 1, 0 otherwise	23.49%	-
Driving license_yes	Dummy, if individual has a driver's license = 1, 0 otherwise	88.35%	-
Transit pass_yes	Dummy, if individual has a monthly transit pass = 1, 0 otherwise	27.59%	-
Land-use index	Land-use index of the neighbourhood	0.20	0.21
Distance to the nearest religious center from home	Individual's home to the nearest religious center distance (kilometers)	24.00	13.40

3.3.1 Activity-based Tour Mode Choice

Table 3-2 presents the model fits of the mixed logit models. The goodness-of-fit values for the models are evaluated on the basis of Log-likelihood values at convergence, AIC and R-square values. The mixed logit model (MXL) is found to perform better than a traditional multinomial logit model (MNL) as indicated by the higher adjusted R-square and log-likelihood at convergence values, and lower AIC and BIC values (Table 3-2). Table 3-3 and 3-4 exhibit the mandatory and non-mandatory activity-tour mode choice estimation results, respectively. Majority of the parameters are found statistically significant at least at 5% significance level for both tour mode choice. Following is a brief discussion of the estimation results.

Table 3-2 Model Fits

Goodness-of-fit	Mandatory Activity-tour Mode Choice		Non-mandatory Activity-tour Mode Choice		Tour-level Participation and Time Allocation	
	MNL	MXL	MNL	MXL	MDCEV (constant only model)	MDCEV (final model)
Log-likelihood	-663.154	-650.821	-111.738	-104.828	-10422.349	-9945.101
AIC	1.42	1.40	0.985	0.965	19.44	18.66
R-square	0.261	0.2748	0.4426	0.4770	0.5618	0.5818

3.3.1.1 *Mandatory Activity-tour Mode Choice*

Model results suggest that older people (age is more than 60 years) are more likely to choose auto as their primary mode rather than bikes during a mandatory activity-tour, as expected. Higher number of vehicles in the households increase individuals' probability to prefer auto and transit, although higher coefficient value for auto (1.200) reveals individuals' higher preference for auto during a mandatory activity-tour. Presence of higher number of bikes in the households might indicate the individuals who are pro-active transportation users. Hence, individuals belong to those households are more likely to choose bikes rather than transit as their primary mode for mandatory activity-tour. In addition, individuals' who at least have high-school degrees, tend to prefer bikes during their mandatory activity-tour, perhaps indicating university students who most likely use bikes in their school tours. Complex activity-based tours (i.e. higher number of stops within the tour) also increase individuals' likelihood to choose auto rather than bikes, which supports the findings of Yun et al. (2014). As expected, traveling with partner/spouse show positive relationship with auto, and negative relationship with transit. Higher travel time implies higher distance to the activity stop, therefore, individuals' higher probability to choose transit rather than walk and bike mode for mandatory activity-tour is plausible. Negative coefficient value of walk mode for the interaction variable (female*number of stops) suggests that, if the individual is female and higher number of stops are present within their mandatory activity-tour, their tendency of preferring walk is lower during a mandatory activity-tour.

Furthermore, land-use index exhibits positive parametric values for transit, bike and auto during mandatory activity-tour. The coefficient for transit is higher (3.945), indicating perhaps the availability of better transit facilities in urban areas (i.e. higher mixed land-use areas). The variable also shows significant standard deviation for auto, which reflects some individuals' preference variation towards auto during a mandatory activity-tour. Similar to the land-use index, higher dwelling density also exhibits positive coefficient values for transit and bike, which might demonstrate better transit and biking facilities in urban areas.

For mandatory activity-tour mode choice model, bike mode is considered as the reference mode. Alternate specific constant for auto and transit modes are found negative, while constant for walk mode is positive. However, significant standard deviations of the constants indicate considerable preference variations of the individuals while choosing mode for mandatory tours.

Table 3-3 Parameter Estimation Results of the Mandatory Activity-Tour Mode Choice Model

Variables	Modes			
	Auto	Transit	Walk	Bike
	Coefficient (*t*-stat)	Coefficient (*t*-stat)	Coefficient (*t*-stat)	Coefficient (*t*-stat)
Constant	-0.727 (-0.59)	-3.789 (-3.04)	3.59 (3.07)	*Reference*
Individual age more than 60	0.623 (1.27)			-0.825 (-2.02)
Annual household income between C$35,000 and C$75,000			1.051 (1.91)	
Highest educational degree: High-school	-0.364 (-1.67)			1.136 (1.87)
Number of vehicles in household	1.200 (5.94)	0.447 (1.90)		
Number of bikes in household		-0.232 (-1.80)		0.511 (4.60)
Number of stops within tour	1.331 (4.42)			-1.287 (-3.80)
Travel with partner/spouse	1.388 (2.62)	-1.619 (-1.08)		
Travel time		0.020 (2.83)	-0.096 (-4.37)	-0.012 (-3.81)
Activity duration at destination	0.003 (3.01)	0.004 (3.69)		0.003 (4.14)
Interaction variable: Female*Number of stops			-0.523 (-1.73)	
Interaction variable: tour duration*Number of stops		-0.002 (-4.19)		
Land-use index	3.747 (2.40)	3.945 (2.31)		3.000 (1.73)
Dwelling density		3.295 (4.64)		5.695 (2.21)
CBD (central business district) distance from home		-0.006 (-1.10)	-1.791 (-1.98)	
Standard deviation of random parameters				
Alternate specific constants	0.688 (1.96)	1.265 (2.23)	3.656 (3.63)	
Land-use index	2.075 (1.96)			

Note: 1.64 ≤ |*t*-stat| ≤ 1.96 indicates 90% confidence level; 1.96 < |*t*-stat| ≤ 2.57 indicates 95% confidence level; |*t*-stat| > 2.57 indicates 99% confidence level.

3.3.1.2 *Non-mandatory Activity-tour Mode Choice*

Individuals belonging to the households of higher income (annual income more than C$75,000) and higher number of vehicles, are found to exhibit higher preference for auto as their primary mode during non-mandatory activity-tours, as expected. In addition, female respondents are also highly likely to choose auto rather than bike during a non-mandatory activity-tour. Households consisting of two persons exhibit positive coefficient values for transit and bike, however, negative value for walk. Higher coefficient value (7.815) for transit is observed indicating the higher preference of transit during non-mandatory activity-tour. Expectedly, with the increase in number of bikes in households, individuals' probability to choose bikes as their primary mode increase during a non-mandatory activity-tour. Higher travel time also demonstrates higher likelihood of preferring bikes rather than walk as the primary mode choice. While traveling with partner/spouse, individuals tend to choose auto in a non-mandatory activity-tour. As expected, individuals having no transit pass and driving license demonstrate positive inclination for bike.

Table 3-4 Parameter Estimation Results of the Non-mandatory Activity-Tour Mode Choice Model

Variables	Modes			
	Auto	Transit	Walk	Bike
	Coefficient (*t*-stat)	Coefficient (*t*-stat)	Coefficient (*t*-stat)	Coefficient (*t*-stat)
Constant	3.684 (1.89)	-8.576 (-2.39)	*Reference*	-4.789 (-2.41)
Household income more than C$75,000	0.241 (1.75)		-1.281 (-1.65)	
Gender: Female	2.459 (2.46)			-3.807 (-2.07)
Household size: 2 persons		7.815 (2.63)	-1.681 (-1.40)	2.963 (2.10)
Number of vehicles in households	2.544 (3.55)			
Number of bikes in households		-8.475 (-1.96)		0.689 (1.32)
Travel with partner/spouse	8.657 (2.80)			-0.025 (-0.81)
Travel time			-0.122 (-2.66)	0.091 (2.01)
Activity duration at destination				-0.616 (-0.25)
Transit pass_no	-5.273 (-2.67)	-8.863 (-2.31)		4.02 (1.84)
Driving license_no	-6.117 (-2.53)			4.928 (1.67)
Interaction variable: tour duration*Number of stops	-0.006 (-2.08)			-0.022 (-2.11)
Dwelling density	-2.199 (-2.10)			4.611 (2.23)
CBD distance from home: more than 5 kilometers	3.093 (2.89)	-5.017 (-2.22)		
Closest bus-stop distance from home: more than 2 kilometers		6.082 (1.66)	-1.363 (-1.20)	
Standard deviation of random parameters				
Alternate specific constants	3.179 (3.08)	2.494 (1.65)		3.959 (2.29)
Activity duration at destination				6.314 (1.94)

Note: 1.64 ≤ |*t*-stat| ≤ 1.96 indicates 90% confidence level; 1.96 < |*t*-stat| ≤ 2.57 indicates 95% confidence level; |*t*-stat| > 2.57 indicates 99% confidence level.

In terms of neighbourhood characteristics, higher dwelling density is found to influence individuals' auto mode choice negatively, and bike mode choice positively during non-mandatory activity-tour, perhaps indicating better biking facilities and availability of non-mandatory activity points within short distances in an urban area. Interestingly, 'nearest bus-stop distance from home more than 2 kilometers' exhibits positive coefficient value for transit, and negative value for walk mode, which might suggest individuals' pro-transit attitude.

In case of non-mandatory activity-tour mode choice model, walk mode is considered as the reference mode. Alternate specific constants for auto mode is positive in non-mandatory activity-tour mode choice, however, transit and walk mode constants are found negative. Nevertheless, standard deviations of the constants confirm existence of significant heterogeneity across individuals' mode choice.

3.3.2 Tour-level Activity Participation and Time Allocation

Table 3-5 presents the parameter estimation for the tour-level participation and time allocation model, where 'at-home' is the baseline alternative. 'At-home' alternative is considered as the outside good in this study, meaning that all individuals will participate and allocate some time at this alternative. Table 3-2 indicates the goodness-of-fit values for the MDCEV model. Below is the discussion of the baseline marginal utility, satiation parameters and modal accessibility (logsum) parameters that are estimated during model analysis.

Table 3-5 Parameter Estimation Results of the Activity Participation and Time Allocation Model at Tour-level

Variables	Mandatory Activity-tour 1	Mandatory Activity-tour 2	Maintenance Activity-tour	Discretionary Activity-tour
	Coefficient (*t*-stat)	Coefficient (*t*-stat)	Coefficient (*t*-stat)	Coefficient (*t*-stat)
Baseline Utility Specification				
Base alternative: At-home				
Constants	-7.732 (-31.84)	-11.968 (-20.82)	-8.879 (-24.37)	-8.787 (-23.12)
Female		0.553 (1.71)		
Age group: 18 to 24 years	1.516 (4.23)	0.410 (0.95)	-0.792 (-1.85)	0.021 (0.06)
Age group: 25 to 34 years	0.964 (3.22)		0.053 (0.20)	-0.141 (-0.53)
Age group: 35 to 44 years	0.744 (2.26)			-0.821 (-2.42)
Age group: 45 to 54 years	0.561 (1.89)			
Age group: 55 to 64 years	0.404 (1.41)	0.943 (2.3)		
Number of vehicles 1			0.457 (2.34)	-0.614 (-2.43)
Number of vehicles 2				-0.680 (-2.46)
Number of vehicles 3 or more		-1.449 (-1.39)		-0.847 (-2.06)
Living alone		0.626 (1.77)		
Annual household income less than C$25,000		1.006 (2.22)		
Annual household income between C$75,000 and C$100,000		1.194 (2.50)		0.454 (1.60)
Annual household income between C$100,000 and C$150,000		1.137 (2.26)		0.488 (1.59)
Annual household income more than C$150,000	-0.086 (-0.50)	1.342 (2.14)		0.236 (0.59)
Full-time employment	0.375 (3.25)		-0.443 (-1.45)	-0.429 (-1.37)
Part-time employment			0.275 (0.74)	-0.204 (-0.51)
Retired	-0.829 (-3.03)		1.068 (3.07)	-1.023 (-2.30)
Student		0.715 (1.60)	-0.655 (-1.59)	-0.171 (-0.44)
Driving license_yes			-0.143 (-0.43)	0.339 (0.96)
Transit pass_yes				-0.568 (-1.94)
Land-use index			-1.348 (-2.87)	
Distance to the nearest religious center from home				0.009 (1.54)
Logsum Parameters				
Logsum_mandatory activity-tour mode choice	0.332 (15.5)	0.092 (1.27)		
Logsum_non-mandatory activity-tour mode choice			0.212 (12.81)	0.216 (12.99)
Satiation Parameters				
Base alternative: At-home				
Constant	4.982 (18.14)	5.386 (22.03)	4.06 (19.89)	4.728 (28.29)
Female			0.473 (1.75)	
Age group: 18 to 24 years	-1.305 (-3.29)			
Age group: 25 to 34 years	-0.651 (-1.88)			
Age group: 35 to 44 years	-0.678 (-1.79)			-0.379 (-0.85)
Age group: 45 to 54 years	-0.444 (-1.26)			-0.382 (-1.11)
Age group: 55 to 64 years	-0.152 (-0.43)			

Note: $1.64 \leq |t\text{-stat}| \leq 1.96$ indicates 90% confidence level; $1.96 < |t\text{-stat}| \leq 2.57$ indicates 95% confidence level; $|t\text{-stat}| > 2.57$ indicates 99% confidence level.

3.3.2.1 *Baseline Marginal Utility*

The alternate specific constants for all four activity-tour types are found negative. This indicates a lower propensity to participate in different activity-based tours compared to the at-home activities. Female respondents exhibit higher likelihood to participate in a second mandatory activity-tour compared to their male counterparts. Individuals belonging into 18 to 24 years age group show higher propensity to participate in mandatory and discretionary activity-tour, and lower propensity to participate in maintenance activity-tours. This age group are more likely to be students and statistically significant positive coefficient value (1.516, t-stat 4.23) for the first mandatory activity-tour might indicate their participation into school tour. The negative coefficient for the maintenance activity might be indicative of the household role for this age group – as this age group might not be all that accountable for carrying out the maintenance responsibilities of their respective households. Age 55 to 64 indicator also exhibits positive values in both mandatory activity-tours where coefficient value is found higher for second mandatory activity-tour. The positive coefficient for both the first and second mandatory activity-tours might be indicative of this age groups' tendency to visit home during midday. Individuals of middle age group (age 25 to 34, age 35 to 44 and age 45 to 54) are observed to participate more in one mandatory activity, perhaps indicative of the full-time workers. Presence of at least one vehicle in the household increases individuals' probability to participate in maintenance activity-tour and decreases probability to participate in discretionary activity-tour. This suggests individuals' use of the available vehicle to regular shopping, escorting, personal business activities rather than eating out, recreation, entertainment, and so on. Interestingly, higher number of vehicles (indicated by number of vehicles = 2, and number of vehicles = 3 or more) in the households exhibits lower likelihood to participate any mandatory and discretionary activity-tour. As expected, individuals living alone and earning less than C$25,000 annually are highly likely to participate in mandatory activity-tour. Individual belonging to higher income households (income indicator 2, 3 and 4), exhibit higher propensity of mandatory and discretionary activity-tour participation. Individuals' full-time employment has positive effect on mandatory activity-tour participation, however, negative effects on maintenance and discretionary activity-tour participation. Perhaps, during weekdays the full-time work schedule leaves them less time and energy for making additional tours. Similarly, students also exhibit higher propensity to participate in mandatory activity-tour, and lower propensity to participate in maintenance and discretionary activity-tour. Interestingly, higher mixed land-use is found negatively related with maintenance activity-tour. Higher distance between home and nearest religious centre are found to increase individuals' probability of making discretionary activity-tours. This might be indicative of the fact that, longer distances between home and religious centres do not allow the religious visit to be chained with other activity purposes and hence result in generating exclusive tours for the purpose.

3.3.2.2 *Logsum Parameter Coefficients*

The coefficient to the logsum parameter in the two mandatory as well as in the maintenance and discretionary activity-tour baseline utility turned out to be positive. All the logsum coefficients except the one corresponding to the second mandatory activity-tour are significant at more than 95% level of confidence. This indicates a strong positive influence of the modal accessibility on the tour-level activity making propensity of individual.

3.3.2.3 *Satiation Parameters*

All the age indicators exhibit high satiation for mandatory activity-tours, meaning that individuals less than 65 years old are more likely to spend less time while performing their mandatory activity-tours compared to the old individuals. Middle-aged individuals (age indicator 35 to 44 and 45 to 54) also have higher tendency to spend less time in discretionary tours. However, female individuals exhibit low satiation (i.e. spend more time) for maintenance activities, perhaps indicating their higher responsibilities for regular shopping, groceries, escorting or household-related errands.

3.4 Conclusions

This research presents the alternative econometric micro-behavioural modelling approaches to investigate different activity attributes, namely activity participation, time allocation and mode choice decisions and interdependencies among them. Such activity attributes are explored in this study at tour-level. Activity-based tours are formed based on the primary activities. The activity-based tour-level mode choice models are developed for mandatory and non-mandatory activities following a mixed logit modelling technique that capture unobserved heterogeneity for repeated observations from same individual. The tour-level activity participation and time allocation decisions into mandatory, maintenance and discretionary activities (in addition to an ‘at-home’ alternative) are modelled jointly using a multiple discrete continuous extreme value (MDCEV) modelling framework. Additionally, the mode choice and activity engagement decisions are coupled within the modelling framework through the logsum-based feedback mechanism in order to ensure the integrity of the modelling system and explore the influence of the transportation network level modal accessibility on the activity engagement decisions. The logsum values, calculated from mode choice models, are incorporated into the MDCEV model that provides behavioural consistency within the modelling framework.

The model estimation results are found plausible and provide interesting insights about the travel behaviour of the Halifax region. A number of socio-demographic characteristics, activity-travel attributes, neighbourhood characteristics and accessibility measures are found to affect individuals' mode choice decisions at tour-level. For instance, older individuals exhibit higher likelihood to choose auto as their primary mode during a mandatory activity-tour. Presence of higher number of activity stops within a mandatory activity-tour also increases individuals' probability of auto mode preference. Land-use index shows positive coefficient values for transit, bike and auto, although higher coefficient value for transit indicates individuals' higher preference for transit during mandatory activity-tours. However, significant standard deviation of land-use index for auto mode reveals some individuals' behavioural variation of auto preference while living in mixed land-use areas. In case of non-mandatory activity-tour, female respondents are found to choose auto rather than bike as their primary mode. Also, individuals tend to prefer auto in a non-mandatory activity-tour while traveling with partner/spouse. Moreover, higher dwelling density is found to influence individuals' auto mode choice negatively, and bike mode choice positively during non-mandatory activity-tour. The activity-based tour participation and time allocation model also exhibit reasonable estimation results. For example, individuals belonging into 18 to 24 years age group are highly likely to participate in mandatory and discretionary activity-based tours, and less likely to participate in maintenance activity-tours. However, this age group tend to spend less time on their mandatory activity-tour compared to the old individuals. The coefficients to the mode choice logsum values are found positive and highly significant in the MDCEV model of activity-tour participation and time allocation, which suggests that higher modal accessibility in the transportation network increases individuals' probability to engage in more activity-based tours.

The mixed logit (MXL) model of mode choice revealed that heterogeneity exists in case of modal preference among the population for both the mandatory and non-mandatory activity-tour types. The standard deviations of the modal constants are found statistically significant, which indicate significant variability in the modal preference among the individuals of the region. This observation can potentially be exploited by the policy makers of the Halifax area by investing in the sustainable transportation alternatives for the region. The relevant alternatives might include improving the public transportation options as well as investing in walk and bike facilities in the region. In addition, modal accessibility measures indicate that the increase in accessibility due to mode choice options increase the corresponding activity-based tour participation propensity, therefore, it would be interesting to test the sensitivity of the tour-level activity engagement decisions in response to the variations in the network level accessibility as manifested by the changes in the mode choice logsum values.

One of the limitations of this study is that it investigated activity-based tour participation, time allocation and mode choice behaviour based on aggregate-level activity types, such as mandatory, maintenance and discretionary activities, due to small sample size. If larger datasets become available, one interesting future direction could be estimating activity engagement and mode choice behaviour for multiple types of activities, so that impacts of modal accessibility on activity engagement can be evaluated for each types of activities that an individual perform in a 24-hour timescale. Another limitation is the assumption of the same mode choice throughout the tour. A stop-level activity engagement and mode choice decisions need to be modelled in order to present activity-travel behaviour in a more plausible way. Methodologically, one of the future directions is to jointly estimate the MDCEV model of activity-tour engagement (activity participation and time allocation) and MXL model of mode choice decisions, which may improve the model estimated results. Future studies can also focus on developing latent segmentation-based mode choice models to understand individuals' mode choice behaviour across different latent population segments, and evaluate how modal accessibility from such mode choice behaviour would influence activity engagement decisions at tour-level. In summary, this study contributes significantly towards the activity-travel research by developing a modelling framework to investigate the activity-based tour participation, time allocation and mode choice decisions. It not only alleviates the need for estimating a number of independent models of different activity attributes, but also provides a behaviourally more intuitive way of presenting tour-level activity participation, time allocation and mode choice decisions of individual. It will be interesting to implement the conceptual modelling approach presented in this chapter within the microsimulation framework of the proposed prototype SDS model.

Chapter 4

Modelling Shared Travel Choices, Activity Participation and Time Allocation

4.1 Introduction

This chapter identifies two broad research gaps in the existing literature: 1) the process of activity-based tour shared travel choices, and 2) the process of activity-based tour participation and time allocation accommodating individuals' social interactions derived from their shared travel choices. The behavioural basis of choosing a travel companion by considering a person's social interactions with partner/spouse, children, parents/other family members, roommates, friends, colleagues, etc. during travel is limited in the existing studies. An explicit behavioural analysis of social interactions is critical within a travel demand modelling framework since estimation of such interactions directly contribute to reassess individuals' daily activities and travel decisions (Auld 2011). The contemporary activity-based travel demand models accommodate different constraints and interdependencies across different activity attributes, such as activity purpose, time-of-day, travel mode, etc. Such mutual relationships among different activity-travel decisions are captured through feedback mechanisms that can be represented by derived utilities as well

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- Khan, N. A., & Habib, M. A. (2019). Modeling and Simulation of Activity Participation, Time Allocation and Shared Travel Choices. Published in peer-reviewed proceedings of the *Transportation Research Board 98th Annual Meeting*. Washington, D. C., U.S.A., January 13-17, 2019.
- Khan, N. A., & Habib, M. A. (2020). Modeling Activity-based Tour Shared Travel Choices, Tour-level Activity Participation and Time Allocation. *Transportmetrica A: Transportation Science.* (Under review).

as rule-based algorithms associated with learning and adaptation of individuals in a modelling environment (Petersen and Vovsha 2005). To evaluate the effects of social interactions on individuals' activity engagement behaviour, social utilities are required to estimate from individuals' shared travel choices and implement within the micro-behavioural modelling framework. Social utilities represent people's desires to make travel choices by interacting with household members (partner/spouse and children) and non-household members (parents/other family members and roommates/friends/colleagues). In general, this type of utilities is expressed as activity-based accessibility, primarily represented by the logsum values measured from individual-level activity engagement, mode choice or destination choices (Khan et al. 2018; Eluru et al. 2010). This study implements the social utilities within the modelling framework by estimating logsum values from shared travel choice models. These utilities represent the coupling between shared travel choice and activity engagement, and accommodate both self-needs and the needs-of-others within individuals' social network.

This research contributes to existing literature in following two ways: a) investigating shared travel choice decisions by anticipating individuals' social interactions with household and non-household members while traveling, and b) exploring joint decision of activity-based tour participation and time allocation considering social interactions within the econometric modelling framework. This chapter presents the model estimation results of activity-based tour shared travel choice, activity-tour participation and time allocation decisions. It describes the process of micro-behavioural model development that follows alternative econometric micro-behavioural modelling structures. It first estimates shared travel choices for mandatory, maintenance and discretionary activities at the tour-level by developing mixed logit (MXL) models. The joint decision of activity-based tour participation and time allocation is estimated afterwards by developing a multiple discrete-continuous extreme value (MDCEV) model. Notably, the time budget is a critical element in individuals' daily activity agenda formation. While modelling, this research considers 'time' as a continuous component. To capture the effects of social interactions on daily activity engagement decisions, this research implements a coupling mechanism by providing feedback from shared travel choice to activity engagement decisions. Such mechanism is implemented via logsum values that are calculated from the MXL models of shared travel choices.

The next section of this chapter (section 4.2) describes the modelling approaches utilized to develop the econometric micro-behavioural models that investigate the shared travel choice and activity-based tour participation and time allocation decision behaviour. Section 4.3 discusses the model estimation results. Section 4.4 presents the concluding remarks of this chapter that briefly discusses the contribution, limitation and future works of this research.

4.2 Micro-behavioural Modelling Methods

4.2.1 Shared Travel Choice: Mixed Logit (MXL) Modelling Approach

This study employs a random utility-based discrete modelling approach, specifically the mixed logit (MXL) modelling technique to investigate individuals' shared travel choice behaviour for mandatory, maintenance and discretionary activity-tours. This modelling technique is similar to the model developed in the previous chapter (chapter three). The shared travel choice models consider five travel arrangement alternatives: 1) travel alone, 2) shared travel with partner/spouse, 3) shared travel with children, 4) shared travel with parents/other family members, and 5) shared travel choice with roommates/friends/colleagues. The models utilize variable choice sets, which are developed based on household size, household members' age and employment status. Let, U_{mj} represents the utility derived from a shared travel alternative j chosen by an individual m. The utility can be described as:

$$U_{mj} = \alpha_j + \beta_m X_{mj} + \varepsilon \tag{1}$$

Where α is the alternate-specific constant, one of which is zero, hence its consideration as reference alternative. 'Shared travel with other family members' is considered as the reference alternative in all three models. β is the estimable parameter that represents individuals' tastes and unobserved factors, which may vary across the sample population according to the mixed logit modelling technique. X is the vector parameter of the observed attributes of alternative j for a person m, and ε is the random error term. Mixed logit formulation states that the probability of an individual m to choose his/her travel arrangement j from a pool of alternatives K_m (variable alternative sets for each individual) can be described with as the following equation:

$$R_m = \int \frac{exp[\alpha_j + \beta_m X_{mj}]}{\sum_{j=1}^{K_m} exp[\alpha_j + \beta_m X_{mj}]} f(\beta_m | q, \pi) d\beta_m \tag{2}$$

The shared travel choice models anticipate individuals' behavioural variations by estimating the standard deviation (π) of random parameters along with their mean values (q) from a normally distributed density function f. This study estimates the parameters by using a simulated maximum likelihood estimation (SMLE) technique. All three shared travel choice models utilize Halton sequence for maximum likelihood estimation since it requires substantially lower number of draws than random draws. 200 Halton are used to estimate the parameters of the final shared travel choice models.

4.2.2 Measurement of Social Utility

In this study, social utility is represented by the logsum values (L_{mi}) calculated from the shared travel choice models. This social utility assists to couple the activity engagement (participation and time allocation) and shared travel choice decisions, and captures the effects of social interactions on tour-level activity participation and time allocation. The logsum values are calculated for each individual *m* and each activity-tour type *i* using the following equation:

$$L_{mi} = \frac{1}{N_{mi}} \sum_{n=1}^{N_{mi}} log[\sum exp(\beta_m X_{mi})] \qquad (3)$$

Where, *i* represents different types of activity-based tours (i.e. mandatory, maintenance and discretionary activity-tours), and *N* is the number of tours. These logsum values provide feedback from shared travel choice to the activity engagement decisions.

4.2.3 Tour-level Activity Participation and Time Allocation: Multiple Discrete Continuous Extreme Value (MDCEV) Model

The research evaluates tour-level activity participation and time allocation decisions into different activity-tours, namely at-home, mandatory activity-tour 1, mandatory activity-tour 2, maintenance activity-tour and discretionary activity-tour, by utilizing the same methodology developed in chapter three. It utilizes a MDCEV modelling approach to estimate individuals' activity participation and time allocation behaviour. According to the model formulation, a person always allocates a certain amount of time across multiple activity-tours from his/her daily available time budget (temporal constraint of 1440 minutes available in a day) in such a way that the utility derived from the engagement of different activity-tour combination is maximized. The modelling approach jointly estimates the participation and time allocation choices across different activity-tours within a single framework. Assuming an individual *m* allocates *t* amount of time at different activity-tours *i* in a day, it can be formulated as:

$$\max U_m(t) = \theta_{m1} ln(t_{m1}) + \sum_{i=2}^{I_m} \lambda_{mi}\theta_{mi} ln\left(\frac{t_{mi}}{\lambda_{mi}} + 1\right) \tag{4}$$

$$\text{subject to } \sum_{i=1}^{I_m} t_{mi} = T_m \tag{5}$$

Where, t_{mi} is a vector of time allocated to different activity-tours performed by individuals ($t_{mi} = t_{m1}, t_{m2}, t_{m3}, \ldots, t_{mi}$). All individuals are assumed to participate and allocate time in an 'at-home' alternative and attempt to maximize their total utility U_m subject to the time budget constraint T_m. θ_{mi} (> 0) is known as baseline marginal utility parameter for each individual's different activity-tours and demonstrates the gain in utility by allocating the first unit of time to tour n. λ_{mi} (> 0) is the translation/satiation parameter and controls the amount of time allocation into different activity-tour types. θ_{mi} and λ_{mi} can be parameterized further as:

$$\theta_{mi} = exp(\delta z_{mi} + \sigma L_{mi} + \omega_{mi}) \tag{6}$$

$$\lambda_{mi} = exp(\rho y_{mi}) \tag{7}$$

Where, z_{mi} and y_{mi} are the vectors of exogenous variables, and δ and ρ are the vectors of corresponding estimable coefficients. ω_{mi} is the error component, which is assumed to be independent and identically distributed extreme value. In equation 6, L_{mi} represents the logsum values of each individual's different tours' shared travel choice that is calculated by equation 3, and σ is the corresponding coefficient. Note that positive values of the logsum coefficients are desirable, since an increase in social utility via shared travel choice alternatives would increase the corresponding activity-tour participation probability, and vice versa.

4.3 Model Estimation Results

This section discusses the parameter estimation results of the micro-behavioural models, which are developed in this research. At first, it discusses the activity-based tour-level shared travel choice models. Then it presents a description of the parameter estimation result of the joint model of activity participation and time allocation decisions at tour-level. Table 4-1 shows the model fits based on the log-likelihood and AIC values. Table 4-2, 4-3 and 4-4 exhibit the mandatory, maintenance and discretionary activity-based shared travel choice at tour-level. Finally, Table 4-5 presents the activity participation and time allocation results at tour-level. Following is a brief discussion of the model results.

Table 4-1 Model Fits

Goodness-of-fit	Mandatory Activity-tour Shared Travel Choice		Maintenance Activity-tour Shared Travel Choice		Discretionary Activity-tour Shared travel Choice		Tour-level Activity Participation and Time Allocation	
	MNL	MXL	MNL	MXL	MNL	MXL	MDCEV (constant only model)	MDCEV (final model)
Log-likelihood	-598.14	-550.821	-291.74	-280.83	-432.54	-414.79	-11549.78	-10978.125
AIC	2.49	2.35	1.25	1.20	2.15	2.06	17.68	16.17

4.3.1 Activity-based Shared Travel Choice at Tour-level

4.3.1.1 *Mandatory Activity-tour Shared Travel Choice*

Model results in Table 4-2 suggest that individuals between the ages of 25 to 40 have a higher propensity to share their travel with children and roommates/friends/colleagues while traveling to perform mandatory activities. Individuals belonging to the age group of 41 to 60 years also tend to share their travel with children and partner/spouse rather than parents/other family members and roommates/friends/colleagues. Individuals of lower income households (annual income under C$25,000) are observed to travel alone to their mandatory activities. Interestingly, these individuals demonstrate a higher standard deviation than mean for non-shared travel (SD, 1.010; mean, 0.547), indicating some lower income individuals' higher tendency of shared travel choice during their mandatory activities. As expected, individuals of zero-vehicle households have a lower probability of traveling with children and other family members, and a higher probability of traveling with roommates/friends/colleagues during mandatory activity-tours, perhaps indicating such individuals' tendency to use transit or auto-passenger modes. Expected results are found in case of the choice of tour mode. Auto users tend to travel with their partner/spouse rather than traveling with non-household members during their mandatory activity-tour.

Table 4-2 Mandatory Activity-tour Shared Travel Choice Model

Variables	Non-shared travel	Shared travel with household members		Shared travel with non-household members	
		Partner/ spouse	Children	Parents/ other family members	Roommates/ friends/colleagues
	Coefficient (*t*-stat)	Coefficient (*t*-stat)	Coefficient (*t*-stat)	Coefficient (*t*-stat)	Coefficient (*t*-stat)
Constant	0.699 (1.70)	0.898 (1.99)	2.004 (3.79)	*Reference*	0.104 (1.29)
Socio-demographic variables					
Age group: 25-40 years	-0.772 (-1.97)	-0.849 (-1.55)	0.969 (2.42)		1.171 (3.12)
Age group: 41-60 years		0.642 (2.09)	0.801 (2.35)	-0.786 (-1.71)	-0.187 (-1.62)
Annual household income: under C$25,000	0.547 (1.96)	-0.763 (-1.78)	-0.717 (-1.70)		
Full-time employment	-1.096 (-5.43)	0.415 (1.59)	-0.883 (-1.71)		
Zero-vehicle household			-0.925 (-2.14)	-0.972 (-1.77)	0.071 (2.43)
Two-vehicle household	0.180 (1.73)	-0.371 (-3.48)	-0.614 (-1.88)	-0.166 (-2.77)	
Activity and travel attributes					
Tour mode: Auto		0.442 (1.50)		-0.904 (-1.19)	-0.662 (-3.15)
Tour mode: Transit		-0.218 (-0.69)			-1.215 (-2.16)
Travel time	-0.0003 (-0.53)	0.010 (1.75)	0.030 (1.91)		0.0007 (1.35)
Tour start time: Morning (7am-9am)	-0.386 (-1.63)	0.509 (1.77)	0.452 (1.23)		-1.355 (-3.41)
Tour start time: Evening (4pm-7pm)	0.310 (1.16)	-0.005 (-1.58)			
Neighbourhood characteristics and accessibility measures					
Dwelling density	0.0004 (1.96)	-0.0002 (-3.68)	-0.0002 (-3.22)	-0.033 (-1.45)	
Land-use index	2.104 (2.43)	7.263 (3.53)	4.086 (1.18)		
Distance from home to CBD	-0.015 (-2.11)			-0.012 (-1.73)	-0.009 (-2.42)
Standard deviation of random parameters					
Annual household income: under C$25,000	1.010 (3.37)				
Full-time employed		0.333 (1.63)			
Two-vehicle household			1.158 (2.99)		
Tour mode: Auto					0.877 (2.01)
Tour mode: Transit		1.911 (3.10)			
Travel time			0.010 (1.88)		

Note: 1.64 ≤ |*t*-stat| ≤ 1.96 indicates 90% confidence level; 1.96 < |*t*-stat| ≤ 2.57 indicates 95% confidence level; |*t*-stat| > 2.57 indicates 99% confidence level.

Moreover, with travel time, individuals are highly likely to choose shared travel arrangements, as demonstrated by the positive coefficient values of shared travel with a partner/spouse, children and roommates/friends/colleagues. In cases of performing mandatory activity-tours in the morning, individuals tend to travel with their partner/spouse and children rather than travel alone or with roommates/friends/colleagues. This shared travel behaviour may indicate such individuals' tendency to chain their morning work tour with their household members' work and school tour. Furthermore, individuals who live farther away from the central business district (CBD), exhibit negative coefficient values for non-shared and shared travel during a mandatory activity-tour, which might be indicative of their tendency for telecommuting.

4.3.1.2 *Maintenance Activity-tour Shared Travel Choice*

Individuals between 41 to 60 years old are observed to have positive parametric relationships with shared travel choices (Table 4-3). However, significant heterogeneity is observed in case of shared travel with other family members as suggested by the higher standard deviation of the parameter than its mean. Similarly, individuals from higher income households (annual income above C$75,000) exhibit a negative relationship with non-shared travel and are more likely to choose shared travel with partner/spouse and parents/other family members. As expected, individuals of zero-vehicle households decrease their likelihood of traveling to maintenance activities alone. Rather, they tend to share their travel with partner/spouse. This finding might be indicative of the shared responsibilities of households' maintenance activities carried out by members. Also, higher travel time increases individuals' tendency to travel with a partner/spouse rather than with roommates/friends/colleagues or alone. Furthermore, the probability to travel alone and with partner/spouse increases with the land-use index of the neighbourhood. Although individuals living in higher mixed land-use areas are less likely to travel with roommates/friends/colleagues, statistically significant standard deviation demonstrates behavioural variation across individuals.

Table 4-3 Maintenance Activity-tour Shared Travel Choice Model

Variables	Non-shared travel	Shared travel with household members		Shared travel with non-household members	
		Partner/ spouse	Children	Parents/ other family members	Roommates/ friends/colleagues
	Coefficient (*t*-stat)	Coefficient (*t*-stat)	Coefficient (*t*-stat)	Coefficient (*t*-stat)	Coefficient (*t*-stat)
Constant	2.629 (3.74)	2.162 (2.68)	4.587 (1.88)	*Reference*	0.963 (1.01)
Socio-demographic variables					
Age group: 41-60 years	-0.982 (-1.45)	0.619 (2.77)		1.641 (1.48)	1.637 (2.55)
Annual household income: under C$25,000			0.433 (2.53)	-1.010 (-1.76)	0.264 (3.65)
Annual household income: above C$75,000	-0.045 (-2.17)	0.034 (1.57)		0.5393 (1.61)	
Zero-vehicle household	-0.426 (-1.97)	1.667 (1.88)	-0.599 (-3.16)	-1.718 (-1.74)	
Two-vehicle household	1.066 (2.46)		0.016 (1.57)		2.170 (3.58)
Activity and travel attributes					
Tour mode: Auto	-0.460 (-2.60)				0.089 (1.32)
Travel time	-0.017 (-1.40)	7.004 (1.67)			-0.097 (-1.67)
Tour start time: Late morning (9am-12pm)	1.215 (1.46)	2.940 (1.94)	2.077 (1.15)		0.677 (1.86)
Tour start time: Afternoon (12pm-4pm)	0.100 (1.66)	0.661 (2.17)	0.303 (1.44)	-1.105 (-1.31)	
Neighbourhood characteristics and accessibility measures					
Population density	0.0002 (1.99)	0.800 (1.37)	0.300 (0.99)	-0.052 (-0.47)	
Land-use index	0.001 (2.87)	0.020 (2.00)		-0.007 (-2.47)	-0.090 (-1.13)
Distance from home to CBD	0.001 (3.55)	0.002 (0.71)	-0.0003 (-1.89)		
Distance from home to closest shopping mall	0.008 (2.11)	0.001 (1.6)	0.014 (1.58)		-0.054 (-1.46)
Standard deviation of random parameters					
Age group: 41-60 years				2.432 (1.81)	
Annual household income: under C$25,000					1.248 (2.26)
Two-vehicle household	0.865 (1.84)				
Distance from CBD	0.003 (1.82)				
Land-use index					0.0002 (2.47)

Note: 1.64 ≤ |*t*-stat| ≤ 1.96 indicates 90% confidence level; 1.96 < |*t*-stat| ≤ 2.57 indicates 95% confidence level; |*t*-stat| > 2.57 indicates 99% confidence level.

4.3.1.3 *Discretionary Activity-tour Shared Travel Choice*

Table 4-4 presents the model estimation results of the discretionary activity-tour shared travel choice. It suggests that individuals between 41 to 60 years old have a higher likelihood to travel alone and travel with spouse/partner, rather than traveling with non-household members. However, such individuals exhibit a statistically significant standard deviation at 90% confidence level for non-shared travel choice that indicates their heterogeneous behaviour across population. In terms of vehicle ownership, having no vehicle in a household increases an individuals' probability to travel with a partner/spouse and roommates/friends/colleagues, and decreases the probability to travel with other family members.

Table 4-4 Discretionary Activity-tour Shared Travel Choice Model

Variables	Non-shared travel	Shared travel with household members		Shared travel with non-household members	
		Partner/ spouse	Children	Parents/ other family members	Roommates/ friends/colleagues
	Coefficient (*t*-stat)	Coefficient (*t*-stat)	Coefficient (*t*-stat)	Coefficient (*t*-stat)	Coefficient (*t*-stat)
Constant	2.272 (1.62)	2.372 (1.34)	1.768 (1.99)	*Reference*	-1.085 (-1.89)
Socio-demographic variables					
Age group: 41-60 years	1.387 (2.23)	0.117 (1.89)		-1.669 (-2.01)	-2.007 (-3.19)
Age group: 60 years and above	0.385 (1.59)	1.513 (1.65)	-2.250 (-2.36)		
Annual household income: under C$25,000	2.676 (3.56)		1.681 (2.15)		1.734 (2.15)
Zero-vehicle household		0.740 (2.76)		-0.805 (-1.91)	0.379 (2.25)
One-vehicle household	0.201 (0.44)	0.392 (2.55)	1.156 (2.32)		
Activity and travel attributes					
Tour mode: Auto	0.609 (2.50)	0.055 (3.65)	-0.240 (-1.43)		1.567 (2.37)
Tour mode: Transit	-2.052 (-1.34)	-0.423 (-1.64)			1.461 (1.22)
Tour start time: Late morning (9am-12pm)		0.495 (1.63)	-0.442 (-1.77)	-2.006 (-2.49)	
Tour start time: Afternoon (12pm-4pm)	-0.211 (-3.89)	1.599 (2.49)			-0.842 (-1.18)
Tour start time: Evening (4pm-7pm)	-0.733 (-1.61)	-0.108 (-1.17)	-0.225 (-1.76)		
Neighbourhood characteristics and accessibility measures					
Land-use index	0.001 (1.35)	0.0002 (2.50)	0.001 (1.51)	0.0001 (1.59)	
Distance from home to CBD		0.100 (1.27)			-0.130 (-3.25)
Distance from home to closest shopping mall	0.042 (1.61)	0.013 (2.38)	0.038 (1.37)	0.018 (1.88)	
Distance from home to closest food-store	-0.038 (-2.01)		-0.039 (-2.63)		0.042 (1.63)
Standard deviation of random parameters					
Age group: 41-60 years	1.281 (1.92)				
Tour start time: Afternoon (12pm-4pm)	1.636 (2.28)				1.434 (1.98)
Tour start time: Evening (4pm-7pm)			0.689 (1.67)		

Note: 1.64 ≤ |*t*-stat| ≤ 1.96 indicates 90% confidence level; 1.96 < |*t*-stat| ≤ 2.57 indicates 95% confidence level; |*t*-stat| > 2.57 indicates 99% confidence level.

Expected results are found in case of the choice of tour modes. Auto users demonstrate a higher likelihood for non-shared travel choice and shared travel choice with a partner/spouse and roommates/friends/colleagues. Furthermore, individuals who perform discretionary activity-tours in the late morning and afternoon, tend to travel with a partner/spouse. Interestingly, evening start time exhibits negative parametric relationships with both shared and non-shared travel choices with household members. However, evening start time exhibits a statistically significant variance at 95% confidence level with standard deviations higher than the mean for traveling with children (SD, 0.689; mean, -0.225), indicating that some individuals' shared travel choice is with children in the evening. As expected, individuals' likelihood to make non-shared and shared travel during discretionary activity-tours increases with the land-use index of the neighbourhood.

4.3.2 Tour-level Activity Participation and Time Allocation

Table 4-5 demonstrates the parameter estimation results of the tour-level activity participation and time allocation model. During the model estimation, 'at-home' is considered as the base alternative, which works as the 'outside good consumption' of the model. This means that all individuals participate and allocate some time at in-home activities. Below is a brief description of the baseline marginal utility, logsum parameters and satiation parameters.

4.3.2.1 *Baseline Marginal Utility*

While estimating the joint model of participation and time allocation, alternate specific constants for all activity-tour types are found negative. This indicates individuals' higher probability to participate at in-home activities compared to out-of-home activities. All the age groups considered during the model estimation exhibit positive parametric relationships with at least one mandatory activity-tour participation. Individuals belonging to a younger age group (18 to 24 years) tend to participate in another mandatory and a discretionary activity-tour. This age group is more likely to contain students and the positive values for both mandatory activity-tours might indicate their tendency to participate at a school tour and a part-time work tour during a given day. Older individuals (55 to 64 years) are also found to participate at both mandatory activity-tours, perhaps indicating their tendency to visit home during midday. The positive coefficient value for the maintenance activity-tour might be indicative of the household role for this age group – as they might be accountable for carrying out the maintenance responsibilities of their respective households. Presence of at least one vehicle in the household increases individuals' likelihood of participating in mandatory activity-based tours and decreases the likelihood of participating in maintenance activity-tours. This suggests such individuals' tendency of using the sole household vehicle for commuting rather than regular shopping, escorting, personal business activities, and so on. However, as the number of vehicles in the household increases, so does an individuals' probability of participating in different activities, as indicated by the positive coefficient values of two- and three- or more-vehicle household indicators. Full-time employment status has a positive effect on mandatory activity-tour participation, but a negative effect on discretionary activity-tour participation. Perhaps, during weekdays, full-time work schedules leave individuals less time and energy for making additional tours. Furthermore, individuals' living in higher mixed land-use areas are found to have a lower probability of participating in mandatory activity-tours, but a higher likelihood of participating in maintenance and discretionary activity-tours. Individuals' participation in mandatory activity-tours is observed to be lower when their home is farther from CBD. This may be attributed to individuals who choose to telecommute.

Table 4-5 Parameter Estimation Results of Activity Participation and Time Allocation at Tour-level

Variables	Mandatory Activity-tour 1 Coefficient (*t*-stat)	Mandatory Activity-tour 2 Coefficient (*t*-stat)	Maintenance Activity-tour Coefficient (*t*-stat)	Discretionary Activity-tour Coefficient (*t*-stat)
Baseline Utility Specification (base alternative: At-home)				
Constants	-8.627 (-3.76)	-5.866 (-5.87)	-1.042 (-1.55)	-4.595 (-7.53)
Age group: 18-24 years	2.875 (4.89)	1.392 (1.11)		1.749 (2.84)
Age group: 25-34 years	1.664 (2.87)		-2.731 (-1.69)	
Age group: 35-44 years	0.391 (2.11)	-1.543 (-3.45)	-2.774 (-1.97)	
Age group: 45-54 years	2.165 (1.65)			
Age group: 55-64 years	0.760 (1.54)	0.886 (2.65)	0.359 (2.83)	
One-vehicle household		2.388 (1.64)	-0.543 (-1.33)	
Two-vehicle household		1.639 (1.11)		1.327 (0.68)
Three- or more-vehicle household	1.662 (2.29)	0.419 (3.43)	1.520 (2.54)	0.042 (1.59)
Annual household income: under C$25,000	1.558 (1.69)	0.487 (1.99)		
Annual household income: C$75,000 to C$100,000		2.634 (3.61)	1.639 (0.87)	-1.663 (-0.59)
Annual household income: above C$100,000			0.629 (1.79)	-1.553 (-2.93)
Full-time employment	1.829 (2.35)			-0.471 (-1.89)
Part-time employment	0.652 (1.21)	0.138 (1.49)		1.381 (0.64)
Student	2.612 (3.66)			0.618 (1.65)
Driving license_yes	0.273 (1.84)		0.651 (2.99)	
Transit pass_yes		1.528 (2.01)	-0.681 (-3.51)	0.815 (1.09)
Land-use index	-0.582 (-1.81)		1.452 (0.66)	1.126 (2.03)
Distance from home to CBD	-0.004 (-1.64)			0.005 (2.47)
Distance from home to closest bus-stop		0.695 (1.25)	-0.813 (-2.94)	
Distance from home to closest shopping mall			1.762 (2.63)	0.284 (1.70)
Social Utility (logsum) Parameters				
Logsum_mandatory activity-tour shared travel	2.761 (4.81)	1.539 (2.90)		
Logsum_maintenance activity-tour shared travel			0.514 (4.61)	
Logsum_discretinary activity-tour shared travel				0.511 (3.87)
Satiation Parameters (base alternative: At-home)				
Constant	3.714 (7.83)	5.281 (8.15)	4.719 (1.84)	2.159 (8.44)
Age group: 18-24 years	3.819 (4.89)			-0.181 (-1.41)
Age group: 25-34 years	-2.881 (-1.51)			0.748 (2.53)
Age group: 55-64 years	0.414 (2.57)	-0.391 (-1.88)	-1.871 (-2.62)	
Fulltime employment			-0.519 (-1.75)	
One vehicle household			0.017 (1.64)	-0.415 (-1.66)
Annual household income: C$100,000-C$150,000	0.514 (3.17)			
Annual household income: above C$150,000	0.772 (0.69)			-0.272 (-2.48)
Population density		-1.487 (-2.78)	1.694 (1.61)	

Note: 1.64 ≤ |*t*-stat| ≤ 1.96 indicates 90% confidence level; 1.96 < |*t*-stat| ≤ 2.57 indicates 95% confidence level; |*t*-stat| > 2.57 indicates 99% confidence level.

4.3.2.2 *Social Utility (Logsum) Parameter Coefficients*

During model estimation, all the coefficient values of social utility parameters (measured by shared travel choice model logsum values) are found positive and statistically significant at more than 95% confidence level. This suggests a strong influence of social utility on individuals' activity-tour making propensity.

4.3.2.3 *Satiation Parameters*

Model estimation results suggest that, individuals between the age of 18 and 24 have low satiation for mandatory activity-tours and high satiation for discretionary activity-tours, meaning that younger individuals tend to spend more time at mandatory activity-tours and less time at discretionary activity-tours. Middle-aged individuals (25 to 34 years) exhibit an opposite relationship. Individuals between 25 and 34 years of age tend to spend less time (high satiation) at mandatory activity-tour and more time at discretionary activity-tours. Interestingly, people living in high population density areas (i.e. urban areas) tend to spend less time at mandatory activity-tour and more time at maintenance activity-tour.

4.4 Concluding Remarks

This study presents the findings of tour-level activity participation, time allocation and shared travel choice models. The shared travel choice decisions are estimated by developing mixed logit models. Participation and time allocation in different activity-tours are estimated jointly by developing a multiple discrete continuous extreme value model, where the temporal constraint of a 24-hour time limit is accommodated within the modelling framework. One of the unique contributions of this study is to explore how social utility, which accounts for individuals' social interactions while traveling, influences the daily activity-based tour participation decisions by implementing a coupling mechanism between shared travel choice and activity engagement decisions. The parameter estimation results indicate that the social utility parameters, derived from mandatory, maintenance and discretionary activity-tour shared travel choice decisions via logsum values, are positive and statistically significant for each tour-level activity participation. This indicates individuals' higher propensity to participate in more activity-tours due to the social utility that arises from individuals' desire to fulfil self-needs and needs-of-others during their travel.

Model results offer interesting insights. For example, in a one-vehicle household, individuals exhibit higher probability to participate in mandatory activity-based tours instead of participating in other activity-tours. However, it was found during estimation that with the number of vehicles in the households, an individuals' tendency to participate in different activity-tours increases. In case of the time allocation, young individuals who are less than 25 years old tend to spend more time at mandatory activity-based tours and less time at discretionary activity-tours. An opposite relationship is found for the individuals who are 25 to 34 years old. The shared travel choice model results suggest that individuals belong to 25 to 34 years age group have higher tendency to travel with their children and roommates/friends/colleagues during their mandatory activity-tours. Also, a higher travel time increases individuals' probability to travel with a companion rather than traveling alone. They are more likely to travel with a partner/spouse, children and roommates/friends/colleagues during their mandatory activity-tours. However, a higher standard deviation of travel time in the case of traveling with children indicates some individuals' tendency to travel less with children if travel time is higher. Individuals belonging to two-vehicle households tend to travel with roommates/friends/colleagues during their maintenance activity-tours. Higher travel time to maintenance activity-based tours is found to increase individuals' propensity to travel with a partner/spouse. Individuals from zero-vehicle households are more inclined to travel with a partner/spouse and roommates/friends/colleagues during their discretionary activity-tours. Participating in discretionary activity-based tours at late morning and afternoon is found to increase individuals' probability to travel with a partner/spouse.

One of the limitations of this research is, it assumes that individuals travel with only one companion while performing an activity-based tour due to data unavailability. The fact that a shared travel arrangement could include more than one companion, for example both household members (e.g. partner/spouse and children), or one household and one non-household member (e.g. partner/spouse and a parent), is not considered in this research. Future research should focus on developing a framework accommodating such type of travel arrangements, which might provide better behavioural insights. In addition, stop-level shared travel choices should be evaluated to ensure behavioural consistency within the modelling framework. Nevertheless, this study contributes to the current travel demand modelling literature by investigating individuals' activity-based tour-level shared travel choices. Also, consideration of social interactions through coupling of shared travel choice and activity engagement decisions offer important behavioural insights to understand the interdependency between individuals' desire to travel with a companion and activity engagement decisions. The conceptualization of activity participation, time allocation and shared travel choices presented in this chapter will assist to develop the prototype SDS microsimulation model. In particular, microsimulation of shared travel choice decisions within the activity-based SDS model will be interesting since this may contribute to reassess individuals' daily activity schedules.

Chapter 5

Modelling Activity-based Tour-level Vehicle Allocation

5.1 Introduction

This chapter examines the activity-based short-term vehicle allocation decisions at tour-level during mandatory and non-mandatory activity-tours based on individuals' travel accompanying arrangements, specifically, while traveling alone (i.e. solo travel) and traveling with household/non-household members (i.e. joint travel). The vehicle allocation decisions are conceptualized in this thesis as individuals' choice of vehicles from households' existing vehicle fleet available during different activity-based tours. Contributions of this chapter in the current activity-based travel demand modelling literature include: 1) developing vehicle allocation models for different activity-based tours, 2) incorporating individuals' social interactions by considering shared travel arrangements within the modelling framework, and 3) investigating latent behavioural differences across population in case of vehicle allocation decisions. In terms of modelling approaches undertaken to explore vehicle allocation decisions in the households, existing studies applied either heuristics methods such as decision-tree models (Anggraini et al. 2012), or unordered methods such as conventional multinomial logit model (Goulias et al.

This chapter is derived from following paper:

- Khan, N. A., & Habib, M. A. (2020). Understanding Variations in Activity-Based Vehicle Allocation Decisions for Solo and Joint Tours: A Latent Segmentation-Based Random Parameter Logit Modeling Approach. *Transportation Research Procedia.* (In press).

2011) and unlabelled binary logit model (Lim 2016), among others. However, to understand the latent behavioural heterogeneity across population, this study develops latent segmentation-based random parameter logit (LSRPL) models. The models consider repeated vehicle type choice decisions by addressing correlated sequence of repeated choices. LSRPL models incorporate two layers of heterogeneity within the modelling framework. 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 modelling framework to capture 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 behaviour of individuals with similar characteristics. This research develops the vehicle allocation models by accommodating social interactions within the modelling framework to examine how vehicle allocation decisions are influenced by different shared travel choices such as travel alone, travel with partner/spouse, travel with children, travel with parents/other family members and travel with roommates/friends/colleagues.

The rest of this chapter is organized as follows: section 5.2 describes the modelling method developed to explore activity-based vehicle allocation at tour-level. Section 5.3 provides a brief discussion on the model estimation results. Finally, section 5.4 concludes with a summary of this chapter, limitations of this research and some future directions.

5.2 Modelling Method

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 activity-based 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 available vehicles from the existing household fleet might vary depending on their characteristics, attitudes, travel attributes, etc. while performing different activity-tours in a day. Therefore, this study estimates the vehicle allocation models for specific activity purposes in multi-car households in terms of shared travel choices, namely traveling alone and traveling with household/non-household members. Four separate datasets for vehicle allocation models at activity-based tour-level are prepared based on the type of activity-tours and shared travel choices:

a) *Solo mandatory activity-based tour*: traveling alone to the mandatory activity destination.

b) *Joint mandatory activity-based tour*: traveling with household/non-household members to the mandatory activity destination.

c) *Solo non-mandatory activity-based tour*: traveling alone to the maintenance and discretionary activity destination.

d) *Joint non-mandatory activity-based tour*: traveling with household/non-household members to the maintenance and discretionary activity destination.

In this study, vehicles are categorized depending on their body types. 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 activity-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.

This research also evaluates the effects of individuals' attitudes on vehicle allocation procedure. At first, it 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 5-1 shows the component loadings on each attitudinal statement variables for all four models.

Table 5-1 Principal Component Analysis of Vehicle Allocation Models

Statement variables	Solo mandatory activity-based tour		Joint mandatory activity-based tour		Solo non-mandatory activity-based tour		Joint non-mandatory activity-based 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%*

This study evaluates the preference heterogeneity among different types of individuals for households' vehicle allocation decisions in case of repeated mandatory and non-mandatory activity-based tours. As discussed in the previous section, latent segmentation-based random parameter logit (LSRPL) models are developed in this research to capture the unobserved behavioural heterogeneity. The model accommodates two layers of heterogeneity within its modelling process. In the first layer, individuals are allocated probabilistically into latent segments by developing a latent segment allocation model to evaluate heterogeneity across population. Latent segment allocation model is defined by a set of individuals' characteristics in such a way that the segments can be characterized distinctly to best describe the behavioural variations between different types of individuals. Individuals' allocation to different segments remains unknown, hence, the segments are labelled as 'latent segments'. This heterogeneity is specified as 'across-the-segments' heterogeneity in further discussion. This study develops latent 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, the probability of an individual to be allocated to segment s is:

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

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.

However, within the same latent segments, individuals with similar characteristics may not behave the same. Hence, the second layer of heterogeneity is introduced in the LSRPL modelling framework that anticipates the taste preference variations among individuals within same latent segment. The second layer heterogeneity is specified as 'within-the-segments' heterogeneity in this study. To capture within-the-segments heterogeneity, random parameters are introduced in the modelling framework that vary across individuals within the same segment following a continuous distribution. Let, β_{js} is the segment-specific parameter vector for individuals j in the segment s. 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 2:

$$g_{jt,i|s}(\beta_{js}) = \frac{exp\left[\sum_{i=1}^{I_j} C_{jt,i}\beta_s{}'X_{jt,i}\right]}{\sum_{i=1}^{I_j} exp\left[\sum_{i=1}^{I_j} C_{jt,i}\beta_s{}'X_{jt,i}\right]} \quad ; \ i = 1, 2, 3, \ldots\ldots, I_j \tag{2}$$

Here, $X_{jt,i}$ is the observed vector attributes of an individual j during an activity-tour t while getting vehicle i from the household's existing fleet. $C_{jt,i} = 1$, when a vehicle i is assigned to an individual j from the household's own existing vehicle fleet I_j during an activity-tour t, and 0 for all others. As the parameters are unknown, unconditional choice probability is required for model estimations. The unconditional probability is expressed as:

$$P_{ij} = \sum_{s=1}^{S} \theta_{js} \int g_{jt,i|s}(\beta_{js}) f(\beta_{js}|\sigma, \delta)\, d\beta_{js} \tag{3}$$

For within-the-segments heterogeneity, this study considers a normally distributed density function, f, with mean σ and covariance δ. Log-likelihood function to estimate the models is given by following equation 4:

$$LL_u = \sum_{j=1}^{J} \log\left[\sum_{s=1}^{S} \theta_{js} \int g_{jt,i|s}(\beta_{js}) f(\beta_{js}|\sigma, \delta)\, d\beta_{js}\right] \tag{4}$$

The above equation cannot be evaluated since it involves a multidimensional integral that does not have any closed form. Estimation of such integral requires applying simulation methods (Revelt and Train 1998). This study uses maximum simulated likelihood to estimate the models. Individual j's contribution to the simulated likelihood can be expressed as equation 5:

$$L = \sum_{s=1}^{S} \theta_{js} \frac{1}{R} \sum_{r=1}^{R} g_{jt,i|s}({\beta_{js}}^{r}) \tag{5}$$

Here, ${\beta_{js}}^{r}$ is the r-th random draws from the density function f, which is repeated total R times. Equation 6 displays the simulated log-likelihood that is obtained by taking the log of equation 5:

$$LL = \sum_{j=1}^{J} log\left[\sum_{s=1}^{S} \theta_{js} \frac{1}{R} \sum_{r=1}^{R} g_{jt,i|s}({\beta_{js}}^{r})\right] \tag{6}$$

The Halton sequence is used in this study instead of random draws 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.

5.3 Discussion of Results

5.3.1 Independent Variables Considered

This study examines the effects of individuals' various socio-demographic characteristics, activity-travel attributes, attitudinal factors, neighbourhood characteristics and accessibility measures on vehicle allocation decisions for different types of tours and travel arrangements. Individuals' socio-demographic characteristics retained in the final models include their age, gender, household size, annual income, employment status, and current home, among others. Flexible LSRPL 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 activity and 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 features 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

5-1), 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-based tours. In addition, various neighbourhood characteristics and accessibility measures are used during final model specifications to understand how individuals' residential location influences vehicle allocation decisions during different types of activity-tours. A detailed description of the variables retained in the final models along with their summary statistics are presented in Table 5-2.

Table 5-2 Descriptive Statistics of the Variables retained in Vehicle Allocation Models

Mandatory Activity-Tour		
Distribution of dependent variables		
Available vehicle type in multi-car households	Solo mandatory activity-based tour	Joint mandatory activity-based tour
Subcompact vehicle	7.40%	11.00%
Compact vehicle	22.07%	28.19%
Midsize vehicle	18.00%	7.26%
SUV (sport utility vehicle)	40.29%	52.18%
Van	12.24%	1.37%

Distribution of independent variables					
Variables	Description	Solo mandatory activity-based tour		Joint mandatory activity-based 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 above C$75,000	Dummy, if individual's annual income is more than C$75,000 = 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
Activity and 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
Neighbourhood characteristics and accessibility measures					
Land-use index	Land-use index of the neighbourhood	0.510	0.150	0.487	0.143
Dwelling density	Dwelling per square kilometers area in the neighbourhood	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
Non-mandatory Activity-Tour					
Distribution of dependent variables					
Available vehicle type in multi-car households	Solo non-mandatory activity-based tour		Joint non-mandatory activity-based tour		
Subcompact vehicle	17.64%		19.49%		
Compact vehicle	29.84%		29.00%		
Midsize vehicle	12.05%		10.64%		
SUV (sport utility vehicle)	36.28%		37.62%		
Van	4.19%		3.25%		
Distribution of independent variables					
Variables	Description	Solo non-mandatory activity-based tour		Joint non-mandatory activity-based 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%	-
Activity and 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 variable					
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
Neighbourhood characteristics and accessibility measures					
Land-use index	Land-use index of the neighbourhood	0.518	0.157	0.486	0.162
Dwelling density	Dwelling per square kilometers area in the neighbourhood	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	Individual's home to nearest entertainment facility (cinema) distance (kilometers)	10.223	17.136	7.735	16.296

5.3.2 Model Results

5.3.2.1 *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 5-3). Therefore, all the final models are assumed to have two segments.

Table 5-3 Model Fits for Number of Segment Determination

Goodness-of-fit	Solo mandatory activity-based tour		Joint mandatory activity-based tour		Solo non-mandatory activity-based tours		Joint non-mandatory activity-based tours	
	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

5.3.2.2 *Vehicle Allocation Models for Mandatory Activity-based Tours*

<u>Latent segment allocation component characterization</u>

For both solo and joint mandatory activity-based 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 5-4), older full-time employed individuals who earn more than C$75,000 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 5-5) suggests positive signs for variables representing age, annual income above C$75,000 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'.

Solo mandatory activity-based tour vehicle allocation model

The majority of the variables retained in the final model (Table 5-4) 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.

Table 5-4 Vehicle Allocation Model for Solo Mandatory Activity-tour

Results of the latent segment allocation component				
	Segment 1		Segment 2	
	Coefficient	*t*-stat	Coefficient	*t*-stat
Segment Membership Probabilities	0.578		0.422	
Constant	1.217	1.66	-	-
Annual income > C$75,000	2.284	2.22	-	-
Age	0.019	3.65	-	-
Full-time employment	2.708	1.99	-	-
Current home_Single detached house	0.170	2.34	-	-
Parameter estimation results				
Variables	Coefficient	*t*-stat	Coefficient	*t*-stat
Subcompact				
Constant	-0.663	-1.73	0.891	5.14
Female partner/spouse	11.162	1.94	6.480	1.45
Number of activity stops	3.717	0.63	4.820	2.09
Positive attitude towards AT	-7.238	-2.38	-3.251	-2.42
Land-use index	3.353	1.72	0.666	2.11
Dwelling density	0.003	4.91	0.008	1.98
Distance from home to CBD	-0.104	-1.85	0.052	2.37
Compact				
Constant	1.135	2.29	-12.992	-1.68
Female partner/spouse	9.522	2.38	-12.404	-1.94
Household size	-1.647	-1.91	4.586	1.66
Tour duration	0.023	1.35	0.003	1.03
Number of tours	-0.232	-2.45	4.777	2.22
Positive attitude towards driving	3.445	1.73	2.798	2.43
Positive attitude towards AT	-1.797	-1.79	-5.834	-1.99
Dwelling density	-0.003	-2.41	-0.008	-1.82
Distance from home to nearest school	-0.015	-1.24	0.012	2.30
Midsize				
Constant	Reference		Reference	
Tour duration	-0.001	-2.42	-0.009	-2.33
Positive attitude towards AT	-8.460	-2.16	-1.222	-1.86
Land-use index	-8.615	-2.11	-8.082	-2.41
Distance from home to CBD	0.035	1.98	-0.185	-2.04
Distance from home to nearest school	0.006	2.37	-0.009	-1.98
SUV				
Constant	-4.235	-2.31	-17.244	-1.77
Female partner/spouse	-0.836	-1.98	-7.560	-1.99
Household size	5.754	1.73	-3.864	-1.85
Number of activity stops	-0.648	-2.01	-0.219	-2.36
Positive attitude towards driving	4.218	2.03	-4.184	-1.84
Land-use index	-5.342	-2.11	-9.605	-4.51
Dwelling density	-0.018	-2.46	-0.008	-1.27
Distance from home to CBD	0.576	1.54	-0.595	-1.08
Vans				
Constant	-12.312	-1.66	-16.383	-2.16
Female partner/spouse	-1.060	-2.44	-0.106	-1.74
Tour duration	-0.007	-2.41	-0.034	-1.86
Number of tours	0.274	5.19	-2.677	-2.04
Positive attitude towards driving	2.650	1.98	-3.165	-1.53

Positive attitude towards AT	-0.125	-1.53	-7.086	-1.65
Distance from home to nearest school	-0.008	-1.79	-0.008	-2.39
Standard deviation of random parameters				
Subcompact_Female partner/spouse	0.041	1.68	0.075	1.94
Compact_Household size	0.056	3.43	0.020	1.83
SUV_Number of activity stops	0. 041	2.04	0.076	2.46
Van_Positive attitude towards AT	0.122	1.94	0.029	2.41
Midsize_Distance from home to nearest school	0.165	2.00	0.762	3.90

Note: $1.64 \leq |t\text{-stat}| \leq 1.96$ indicates 90% confidence level; $1.96 < |t\text{-stat}| \leq 2.57$ indicates 95% confidence level; $|t\text{-stat}| > 2.57$ indicates 99% confidence level.

In case of activity and 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.

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 behavioural variations in each segment while choosing midsize vehicles from the household's existing vehicle fleet.

Joint mandatory activity-based tour vehicle allocation model

Table 5-5 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.

Table 5-5 Vehicle Allocation Model for Joint Mandatory Activity-tour

Results of the latent segment allocation component				
	Segment 1		Segment 2	
	Coefficient	*t*-stat	Coefficient	*t*-stat
Segment allocation probabilities	0.487		0.513	
Constant	-0.046	-1.77	-	-
Annual income > $75,000 CAD	0.153	2.39	-	-
Age	0.008	2.10	-	-
Part-time employment	-0.189	-2.41	-	-
Current home_Single detached home	0.055	1.99	-	-
Parameter estimation results				
Variables	Coefficient	*t*-stat	Coefficient	*t*-stat
Subcompact				
Constant	2.366	1.73	2.552	1.88
Female partner/spouse	-1.756	-2.28	-1.727	-1.69
Traveling with partner/spouse	-2.246	-2.39	-2.219	-1.73
Traveling with children	-2.936	-5.12	-2.865	-1.71
Number of activity stops	-0.297	-2.07	-0.592	-2.45
Compact				
Constant	-0.182	-1.61	-0.261	-2.22
Female partner/spouse	-1.595	-2.33	-1.686	-1.81
Household size	-0.942	-1.66	-0.336	-2.00
Tour duration	-0.001	-2.02	-0.003	-2.06
Number of activity stops	-0.383	-2.29	0.439	2.19
Positive attitude towards AT	-0.545	-2.44	-1.127	-2.11
Land-use index	-0.268	-1.41	-0.377	-1.70
Distance from home to CBD	-0.006	-2.83	0.077	1.66
Midsize				
Constant	Reference		Reference	
Tour duration	0.003	1.08	0.003	1.48
Positive attitude towards driving	-0.092	-1.51	0.538	1.94
Positive attitude towards AT	-0.213	-2.28	-0.352	-1.99
Land-use index	2.100	2.45	1.707	2.43
Dwelling density	-0.773	-2.39	-0.042	-2.41
SUV				
Constant	0.832	3.87	0.584	1.61
Female partner/spouse	0.438	4.24	0.695	1.83
Household size	1.861	1.72	0.863	1.84
Traveling with children	0.232	1.62	0.434	1.98
Number of activity stops	1.242	2.28	-0.345	-1.69
Positive attitude towards driving	0.463	1.94	-0.065	-1.51
Dwelling density	0.002	2.41	0.001	2.45
Distance from home to CBD	0.036	1.69	-0.028	-2.09
Vans				
Constant	5.159	1.64	4.993	2.41
Female partner/spouse	-2.666	-2.19	-2.560	-2.22
Traveling with partner/spouse	-2.914	-1.72	-2.837	-4.98
Traveling with children	-1.215	-3.16	-0.861	-2.46
Tour duration	-0.004	-2.43	-0.014	-1.98
Dwelling density	0.005	1.71	0.002	1.34
Standard deviation of random parameters				
Compact_Female partner/spouse	0.005	1.86	0.006	2.08
Compact_Number of activity stops	0.109	2.29	0.062	1.66
Midsize_Positive attitude towards driving	0.028	2.00	0.013	2.43
SUV_Household size	0.027	1.98	0.011	1.76

Note: 1.64 ≤ |*t*-stat| ≤ 1.96 indicates 90% confidence level; 1.96 < |*t*-stat| ≤ 2.57 indicates 95% confidence level; |*t*-stat| > 2.57 indicates 99% confidence level.

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 travellers' 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 neighbourhoods. Midsize vehicles tend to be assigned to the individuals tours who live in higher mixed land-use areas. Perhaps, people travel longer 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.

5.3.2.3 *Vehicle Allocation Models for Non-mandatory Activity-based Tours*

<u>Latent segment allocation component characterization</u>

Table 5-6 and 5-7 exhibit the results of vehicle allocation models for non-mandatory activity-tours. Similar to mandatory activity-tour models, segment two is assumed as the reference segment for discretionary activity-tour vehicle allocation models. For solo tours (Table 5-6), results suggest positive coefficient values for the variables representing age, full-time employment and annual income more than C$75,000 in segment one. This indicates that older full-time employed individuals earning more than C$75,000 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 C$75,000 annually. The segment allocation model for joint non-mandatory activity-tour exhibits the same probabilities as solo tour (Table 5-7). Therefore, similar to mandatory activity-tour 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 non-mandatory activity-tours.

<u>Solo non-mandatory activity-based tour vehicle allocation model</u>

Model results in Table 5-6 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 non-mandatory 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 non-mandatory activity-tours irrespective of the segment individuals belong to.

Table 5-6 Vehicle Allocation Model for Solo Non-mandatory Activity-tour

Results of the latent segment allocation component				
	Segment 1		Segment 2	
	Coefficient	*t*-stat	Coefficient	*t*-stat
Segment allocation probabilities	0.515		0.485	
Constant	0.736	2.44	-	
Age	0.065	2.31	-	
Full-time employment	1.440	1.69	-	
Annual income > $75,000 CAD	0.655	2.01	-	
Parameter estimation result				
Variables	Coefficient	*t*-stat	Coefficient	*t*-stat
Subcompact				
Constant	2.903	2.13	2.845	2.17
Number of activity stops	-0.074	-2.45	-0.072	-3.81
Positive attitude towards driving	0.750	2.17	0.736	1.66
Positive attitude towards AT	0.245	1.79	0.240	2.31
Dwelling density	-0.321	-2.38	3.101	1.50
Distance from home to nearest entertainment facility (cinema)	-0.210	-1.53	0.238	2.29
Compact				
Constant	1.016	2.27	0.995	1.77
Tour duration	-0.0004	-4.65	0.005	4.53
Positive attitude towards driving	0.595	2.29	0.583	1.98
Land-use index	-5.192	-3.41	0.902	1.93
Dwelling density	5.313	2.14	-1.200	-1.69
Distance from home to nearest foodstore	-0.208	-2.37	2.700	1.73
Distance from home to nearest shopping mall	0.116	1.64	0.015	1.66
Midsize				
Constant	-4.121	-1.61	4.038	1.09
Male partner/spouse	-0.840	-1.43	0.953	1.64
Tour duration	0.003	2.40	-0.001	-1.23
Dwelling density	-2.099	-1.69	-3.682	-2.42
Distance from home to nearest foodstore	0.959	2.21	-0.113	-2.02
Distance from home to nearest shopping mall	0.367	2.39	-0.204	-1.83
Distance from home to nearest entertainment facility (cinema)	0.459	3.73	-0.057	-1.99
SUV				
Constant	-3.797	-2.29	-3.721	-2.22
Male partner/spouse	1.026	1.70	-1.005	-2.45
Number of activity stops	0.184	2.41	0.180	1.38
Positive attitude towards AT	-0.016	-2.13	-0.193	-2.29
Land-use index	2.490	2.11	-1.838	-1.98
Distance from home to nearest shopping mall	0.103	1.27	-0.088	-2.00
Vans				
Constant	Reference		Reference	
Male partner/spouse	1.404	1.80	-1.376	-2.39
Tour duration	-0.003	-1.94	-0.007	-1.66
Positive attitude towards driving	-1.150	-1.76	-1.127	-1.90
Positive attitude towards AT	-0.491	-2.44	-0.481	-1.53
Distance from home to nearest entertainment facility (cinema)	-1.337	-1.89	-3.149	-2.08
Standard deviation of random parameters				
Subcompact_Number of activity stops	0.109	2.38	0.366	1.64
Compact_Tour duration	0.255	1.64	0.070	1.98
Compact_Distance from home to nearest shopping mall	0.012	4.19	0.001	2.45
Midsize_Tour duration	0.361	1.78	0.280	1.83
SUV_Positive attitude towards AT	0.011	2.26	0.005	4.55
Van_Positive attitude towards driving	0.068	2.22	0.154	2.09

Note: 1.64 ≤ |*t*-stat| ≤ 1.96 indicates 90% confidence level; 1.96 < |*t*-stat| ≤ 2.57 indicates 95% confidence level; |*t*-stat| > 2.57 indicates 99% confidence level.

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 non-mandatory 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 non-mandatory 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 neighbourhood characteristics, 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 non-mandatory 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.

<u>Joint non-mandatory activity-based tour vehicle allocation model</u>

Table 5-7 shows the final vehicle allocation model results for joint non-mandatory activity-tours. Results demonstrate that while traveling with household/non-household members in a non-mandatory 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 non-mandatory activity-tours as indicated by the statistically significant standard deviations. If the accompanying person is the partner/spouse during the joint non-mandatory 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 in the tour increases probability of SUV allocation across segments.

Table 5-7 Vehicle Allocation Model for Joint Non-mandatory Activity-tour

Results of the latent segment allocation component				
	Segment 1		Segment 2	
	Coefficient	*t*-stat	Coefficient	*t*-stat
Segment allocation probabilities	0.591		0.409	
Constant	1.601	2.39	-	-
Age	0.035	1.98	-	-
Full-time employment	0.695	2.14	-	-
Annual income > $75,000 CAD	1.812	2.06	-	-
Parameter estimation results				
Variables	Coefficient	*t*-stat	Coefficient	*t*-stat
Subcompact				
Constant	-1.666	-1.43	-0.303	-1.69
Traveling with children	-1.443	-2.28	-0.887	-2.22
Number of activity stops	-5.783	-1.54	-2.948	-1.37
Positive attitude towards AT	1.529	2.13	1.566	1.66
Distance from home to nearest shopping mall	-0.299	-5.07	-0.761	-1.84
Compact				
Constant	-1.713	-1.81	-0.482	-1.88
Male partner/spouse	-0.034	-1.78	-0.623	-2.39
Traveling with children	-2.949	-1.94	-2.225	-3.84
Positive attitude towards driving	-0.058	-2.37	-1.225	-2.06
Land-use index	-0.054	-1.66	0.019	4.18
Distance from home to nearest shopping mall	-0.295	-2.16	0.388	1.66
Midsize				
Constant	-4.764	-2.22	-5.127	-2.43
Traveling with partner/spouse	-0.048	-1.59	0.064	1.98
Positive attitude towards AT	-0.590	-2.38	-0.002	-1.14
Land-use index	2.863	4.80	-3.164	-2.31
Distance from home to nearest entertainment facility (cinema)	0.160	1.76	0.687	1.64
SUV				
Constant	2.507	2.05	0.023	2.00
Male partner/spouse	4.876	2.29	5.005	5.02
Traveling with children	1.415	2.18	0.001	1.70
Number of activity stops	0.545	2.77	0.292	2.42
Land-use index	1.652	2.00	-0.052	-1.69
Distance from home to nearest shopping mall	0.210	2.94	-0.503	-1.66
Distance from home to nearest entertainment facility (cinema)	-0.249	-2.13	0.328	1.01
Vans				
Constant	Reference		Reference	
Male partner/spouse	-1.739	-2.25	-2.885	-1.73
Traveling with partner/spouse	0.060	1.98	-0.009	-2.45
Positive attitude towards driving	0.645	2.16	0.299	1.29
Distance from home to nearest entertainment facility (cinema)	0.656	1.80	-0.288	-3.33
Standard deviation of random parameters				
Subcompact_Number of activity stops	0.185	2.40	0.026	1.67
Compact_Male partner/spouse	0.159	1.74	0.061	2.83
SUV_Land-use index	0.782	2.36	0.883	1.89
Van_Positive attitude towards driving	0.079	1.98	0.049	2.22

Note: $1.64 \leq |t\text{-stat}| \leq 1.96$ indicates 90% confidence level; $1.96 < |t\text{-stat}| \leq 2.57$ indicates 95% confidence level; $|t\text{-stat}| > 2.57$ indicates 99% confidence level.

Complex joint non-mandatory 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 non-mandatory activity-tours, standard deviations confirms the existence of heterogeneity within segments for subcompact vehicle allocation.

Irrespective of segments, 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 non-mandatory 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 non-mandatory activity-tour.

5.4 Conclusions

This study presents the findings of a comprehensive investigation on activity-based vehicle allocation decisions at tour-level in multi-car households utilizing individuals' socio-demographic characteristics, attitudinal factors, activity-travel attributes, neighbourhood characteristics and accessibility measures. This study contributes to the current literature by offering insights on the behavioural variations of activity-based vehicle allocation decisions, while incorporating individuals' social interactions within the modelling frameworks through their shared travel choices, namely traveling alone (i.e. solo travel) or traveling with partner/spouse, children, parents/other family members, and roommates/friends/colleagues (i.e. joint travel). Following a latent segmentation-based random parameter logit (LSRPL) modelling approach, four vehicle allocation models are developed in this research for solo mandatory activity-based tours, joint mandatory activity-based tours, solo non-mandatory activity-based tours and joint non-mandatory activity-based tours. The models capture taste preference heterogeneity across individuals by implicitly sorting them into two discrete latent segments. Results of the latent segment allocation components of all four vehicle allocation models suggest that segment one can be probabilistically identified as the segment of older-higher income individuals, whereas, segment two as the segment of younger-lower income individuals based on their socio-demographic characteristics. In addition, individuals' unobserved preference heterogeneity within each latent segment are also captured during model estimation by introducing random parameters within the modelling process.

The model results suggest that individuals' activity-travel characteristics, attitudinal variables, neighbourhood characteristics and accessibility measures have considerable impacts on vehicle allocation decisions in multi-car households. For instance, during joint mandatory and non-mandatory activity-tours, individuals' probability of getting SUVs is found higher while traveling with children. 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.

This study demonstrates the existence of substantial heterogeneity 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. Interestingly, no heterogeneous effects are observed for 'positive attitude towards driving' across segments during non-mandatory activity-tours. Individuals with positive attitude towards driving are more likely to choose subcompact vehicles for solo non-mandatory activity-tour, and vans for joint non-mandatory 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 non-mandatory activity-tours. Although mixed land-use area dwellers show homogeneous behaviour during mandatory activity-tours, their preference vary while performing non-mandatory activity-tours.

Results presented in this study have important policy implications. For example, people living in mixed land-use areas more likely to get smaller subcompact vehicles than midsize vehicles and SUVs in suburban areas for solo mandatory activity-tours. Therefore, creating better designed neighbourhoods with diverse land uses and sustainable transportation alternatives might decrease the usage of larger vehicles, thus reducing daily fuel consumption. Also, results suggest that positive attitude towards active transportation decreases the likelihood of vehicle usage for mandatory activity-tours. This information could be used for target marketing that encourages active transportation by offering improved walking and biking facilities. Moreover, vehicle allocation models developed in this study confirm that considerable unobserved heterogeneity exists across individuals for different activity-based tours and travel accompanying arrangements. Therefore, flexibility should exist in policy interventions to achieve better outcomes for all types of travellers. One of the limitations of this study is to categorize activity-based tours in terms of primary activities only. However, it could be interesting to explore vehicle usage decisions for multiple intermediate activity purposes along the tour within the modelling process. Therefore, future research should focus on developing 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 contributes significantly in the activity-based travel demand modelling literature by developing vehicle allocation models for different types of activity-based tours that incorporate individuals' social interactions within modelling process. Results of this study offer critical behavioural insights that could be useful to test policies related with vehicular emission and energy consumption. Finally, the vehicle allocation modelling approach developed in this chapter is expected to be a crucial component within the activity-based SDS modelling system framework due to its potential to reassess daily activity and travel decisions. Implementation of such decision component will also provide behavioural consistency of an integrated urban modelling system since vehicle allocation is a coupled decision with the medium-term vehicle ownership decisions in the households.

Chapter 6

Microsimulation of Activity Generation and Activity Scheduling

6.1 Introduction

This chapter presents the implementation of activity generation and activity scheduling sub-modules of the agent-based activity-travel microsimulation model – shorter-term decisions simulator (SDS). Activity generation simulates number and types of daily activities for each individual in an orderly fashion utilizing a Markov Chain Monte Carlo modelling approach, where occurrence of the next activity depends on the current activity. Activity scheduling is simulated as a process of activity agenda formation, destination location choice and shared travel choices utilizing heuristics and econometric modelling approach. Shared travel choice component is implemented by utilizing the micro-behavioural models developed in chapter four. This research contributes to the microsimulation of activity generation and scheduling paradigm in four ways: 1) generating sequential activities by implementing Markov Chain Monte Carlo process within a microsimulation framework, 2) addressing individuals' social interactions with household and non-household members within their social realm by simulating shared travel choice decisions, 3) implementing feedback mechanisms from shared travel choices

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This chapter is derived from the following paper:

- Khan, N. A., & Habib, M. A. (2020). Development of a Shorter-term Decisions Simulator (SDS) within an Integrated Urban Model: Microsimulation of Activity Generation, Activity Scheduling and Shared Travel Choices. *Transportation.* (Under review).

to the sequentially generated activities to provide a set of reasonable activity plans (including activity types, frequencies, duration, start time, travel time and destination locations), and 4) predicting the spatial-temporal evolution of various activity and travel decisions. This chapter also discusses the validation procedure of the SDS model.

This chapter is organized as follows: section 6.2 presents the implementation of the prototype activity-based shorter-term decisions simulator (SDS). Section 6.3 describes the microsimulation process of the activity generation and scheduling sub-modules of the proposed SDS model. After that, microsimulation results are discussed briefly in section 6.4. Finally, a summary of this chapter is presented in section 6.5.

6.2 Implementation of the Prototype SDS Microsimulation Model

A prototype version of the shorter-term decisions simulator (SDS) is currently operationalized in Halifax, Canada. The SDS model implements activity generation, activity scheduling, and mobility assignment sub-modules within an agent-based microsimulation platform called 'iTLE Sim'. iTLE Sim is programmed using C# language under the .NET framework. iTLE generates a 100% synthetic population of Halifax is generated in iTLE for the base year 2006. However, 10% synthesized population sample (approximately 37,000) is considered for the 30-year simulation run. The SDS modelling system takes inputs from LDS and simulates individuals' activity-travel decisions for a typical weekday. This chapter focuses on implementing activity generation and activity scheduling sub-modules of the SDS prototype. It specifically presents the simulation procedure and results of generating activity types, activity frequency, activity durations, start times, destination location and shared travel choices.

The SDS modelling codebase is established as a model-view-viewmodel (MVVM) framework, which separates user interface from the back-end program logic. Such framework allows for more efficient implementation. Figure 6-1 exhibits a partial class diagram of SDS algorithm types. These are some examples of algorithm types; however, the program contains more algorithm types that implements the SDS microsimulation model. Microsimulation of SDS for each time-step takes about 15 minutes on a computer with Core i7-4770 processor and 16 GB of RAM, running on a 64-bit Windows 7 operating system.

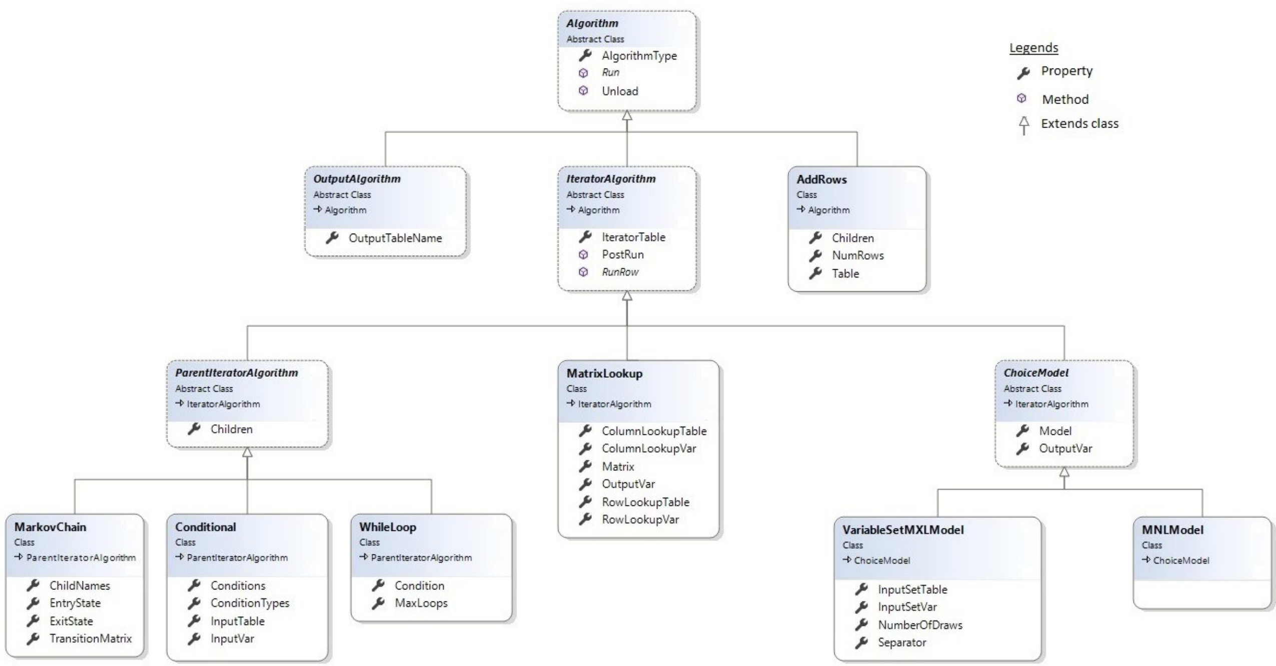


Figure 6-1 Partial Class Diagram of the SDS Model Algorithm Types

6.3 Description of the Microsimulation Process

6.3.1 Activity Generation

The activity generation sub-module simulates a daily activity program that includes types and number of activities. To reduce complexities while implementing the SDS model, activities are categorized into seven groups: work, school, escort (drop-off and pick-up passengers), personal business (including work and household related errands, healthcare, civic/religious activities), shopping (routine shopping and shopping for major purchases), dine out and recreation (including visiting friends/relatives and entertainment activities). The microsimulation process starts with generating the activity information for the year 2006. It takes inputs from the LDS module of iTLE that provides all the information of the synthesized population at dissemination area (DA)-level, such as residence, household and individual information. Activities are generated for each individual in the household for the base year 2006. By applying a Markov Chain Monte Carlo (MCMC) method, the model simulates the types of out-of-home activities that a person participates in a typical weekday. This is a stochastic procedure that generates sequential possible activities, where the likelihood of occurring each activity depends on the prior activity (Brooks et al. 2011). This method allows random sampling of activities from the transition probability distribution that maintains the probabilistic dependence between two consecutive activities by creating a Markov Chain. The MCMC technique is applied to generate each individual's activity chain (combination of all types of activities) in a day. Let, P_{ij} be the fixed conditional probability to perform an activity i at time $t+\Delta t$ given that the individual already performed an activity j at time t. The conditional probability can be expressed as:

$$P_{ij} = Prob\ [activity\ i\ at\ time\ (t\ +\ \Delta t)|at\ time\ t\ activity\ is\ j] \tag{1}$$

Let, p_j is the transition probability that contains all the conditional probability of performing activity i based on previous activity j, which can be written as following:

$$p_j = [P_{1j} \quad P_{2j} \quad P_{3j} \quad \dots \quad P_{ij}] \tag{2}$$

The transition probabilities are estimated from NovaTRAC survey data by measuring the occurrences of transitions between each pair of activity types. In total, fourteen sets of transition probabilities are estimated for individuals belonging to fourteen different population segments. The transition probability matrices are shown in Appendix B. It represents the probabilities of transitioning from one activity type to the next activity type. Figure 6-2 presents the MCMC process diagram for activity generation. The SDS model assumes that individuals' daily activities start at 3.00 am. The first activity of a day is randomly drawn from the probability distribution of NovaTRAC datasets conditioned on the assumed start time. A person starts his day with the first activity and has fixed conditional probabilities of transitioning to other activity types (e.g. work, school, shopping, intermediate home return, end-of-day return home, etc.). At each activity, there is a probability distribution for all other activities based on the current activity type. The subsequent activity is generated from the corresponding transition probability distribution of the current activity. Thus, activities are generated in an orderly fashion for each person. The modelling process continues until it generates an 'end-of-day return home activity', which represents being home for rest of the day. Note that, when the model generates an 'intermediate home return' activity, it allows to start another activity from the transitional probability of intermediate home return activity; whereas, generation of an 'end-of-day return home' activity indicates the end of the process. Finally, activity frequency is estimated based on the number of activities generated for an individual in a day. Consequently, an activity program is formed that includes types of activities in-order and total number of activities simulated for an individual.

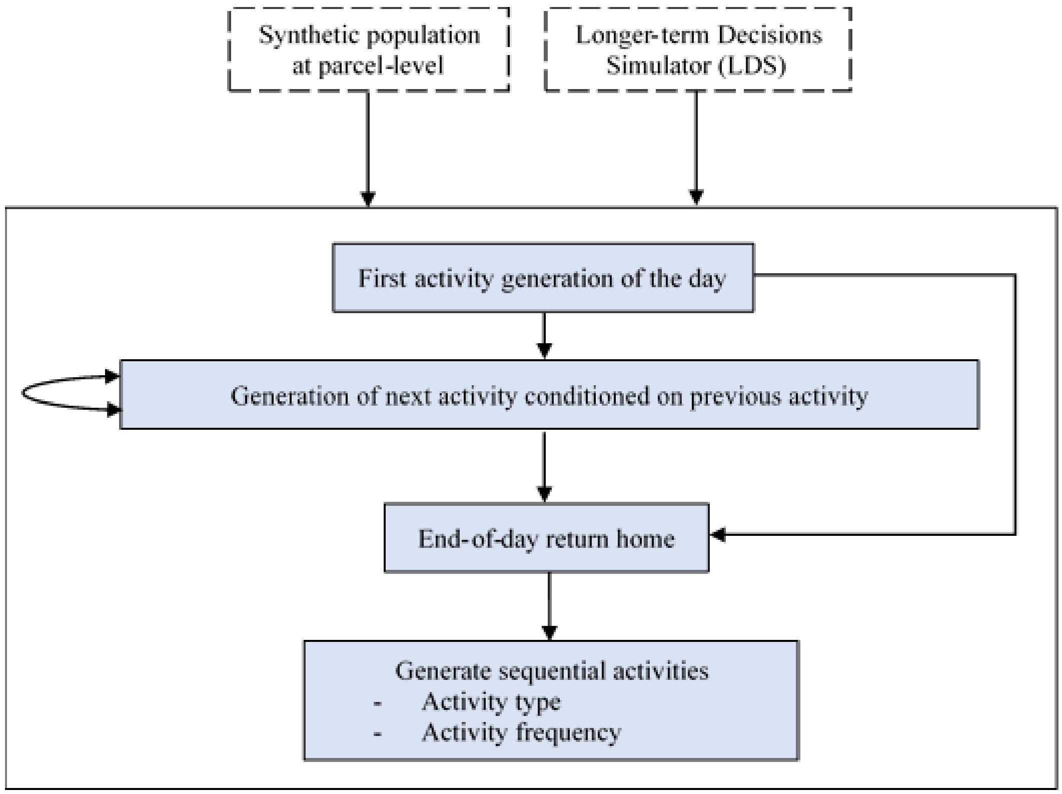


Figure 6-2 Process Diagram of Activity Generation

6.3.2 Activity Scheduling

Activity scheduling sub-module is implemented in this study as a process of activity agenda formation, destination location choice and shared travel choice decisions. The sub-module also includes an activity conflict resolution manager (A-CRM) that resolves any conflicts (e.g. overlapped activities, extended activities, etc.) that may have occurred while simulating different activity attributes and updates the activity plans accordingly. Figure 6-

3 presents the process diagram for the activity scheduling sub-module. Below is a brief discussion on the activity scheduling process of SDS.

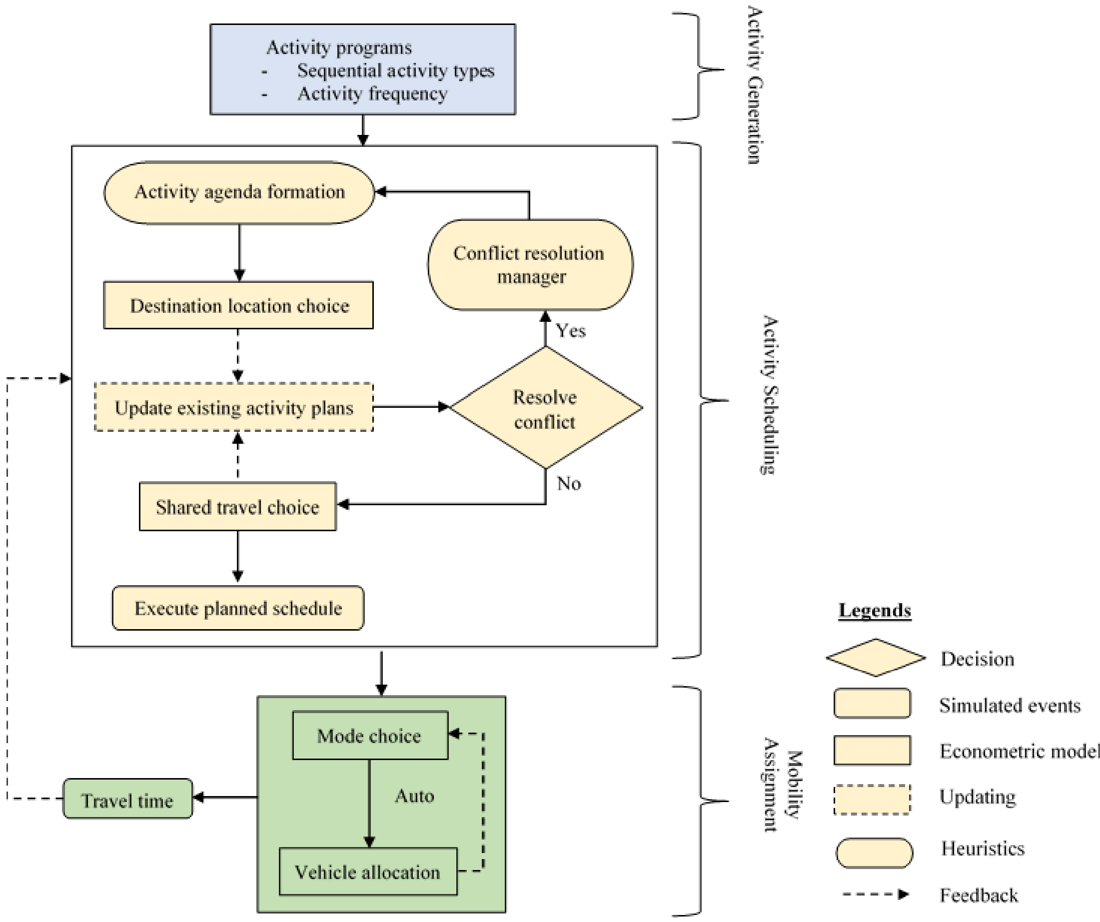


Figure 6-3 Process Diagram of Activity Scheduling

6.3.2.1 *Activity Agenda Formation*

Following the generation of activity programs, durations of the corresponding activities are simulated conditioned on activity frequency (i.e. total number of activities). Based on the assumption that a person's day starts at 3.00 am, the duration of each generated activity is randomly drawn from the joint frequency-duration distribution of the corresponding activities. Activity duration does not include travel time to or from the activity, instead it generates the time spent for the activity itself. After the simulation of activity durations, start times of each activity are chosen randomly from the joint distribution of duration-start time.

6.3.2.2 *Destination Location Choice*

The destination location choice component simulates appropriate locations for the generated activities utilizing a conditional multinomial logit model. The spatial unit of the simulation is at the dissemination area (DA) level. The utility function for the destination location choice can be written as:

$$U_{ij} = \beta_i X_{ij} + \alpha_i Z_i + \varepsilon_{ij} \tag{3}$$

Here, U_{ij} represents the utility of a location j that an individual i chooses for activity destination. X_{ij} denotes the attributes of the location j for individual i, Z_i is the characteristics of individual i, with the corresponding coefficients of the parameters to be estimated β and α. The probability function for the destination location choice model can be described as the following:

$$P_{ij} = \frac{exp[\beta_i X_{ij} + \alpha_i Z_i]}{\sum_{j=1}^{J} exp[\beta_i X_{ij} + \alpha_i Z_i]} \tag{4}$$

Equation 4 estimates the probability of choosing a destination location from a pool of randomly generated location alternatives. The destination location choice models are developed for six different activity types. Following is a brief discussion on the destination location choice mode results.

The parameter estimation results of destination location choice are reported in Appendix A (Table A-1 to Table A-6). All models exhibit acceptable goodness-of-fit and exhibit considerable improvement over null models as indicated by log-likelihood values at convergence and McFadden's pseudo R^2 values. Most of the variables retained in the final models turn out to be significant at 95% confidence level. Results suggest that individuals' choice of destination locations significantly depends on impedance variables, destination location characteristics and their socio-demographic characteristics, and majority of the parameters exhibit expected sign. For instance, the sign of impedance variable, travel time_auto, is found negative in work, shopping, recreation and personal business activity models. This suggests individuals' willingness to choose a destination that requires less time to travel. Travel distance also exhibits similar relationship in the school and dine out model. Individuals are willing to travel to shorter distance to get to school or dine out. Results suggest that individuals tend to travel to work in such locations where number of people working is higher. This is expected, since higher number of people working in an area indicates major employment concentration in the corresponding location. In case of destination location characteristics, this study found that people are likely to choose areas with prevalent urban characteristics (e.g. areas with higher mixed land-use and higher property values) for their work, shopping, recreation and dine out. This might be because urban areas are highly developed, have higher density of residential, cultural and entertainment facilities, and provide better accessibility through sustainable transportation alternatives. Interesting results are found when individuals' different socio-demographic characteristics were interacted with destination location's attributes. For example, older people exhibit a higher tendency to choose urban areas for shopping, recreation and personal business. They exhibit lower probability to choose urban areas for work. Full-time employees also exhibit similar results. They tend to travel to urban areas for dine out and shopping, instead of work and personal business.

Based on the probability estimation in equation 4, the SDS model assigns a destination location area to each activity. Home location of each person is taken from the residence information generated in LDS module. Consequently, travel time and distances are estimated between activity origin and destination pair. Travel distance is generated from an origin-destination travel distance matrix developed in ArcMap using the Network Analyst tool. Auto and transit travel time are drawn from the network skim matrices generated in EMME. Travel time by walk and bike are estimated using the travel distance by assuming a walking speed of 5 km/hour and a biking speed of 15 km/hour. These provide feedback to the existing generated activities that updates start time of each activity; thus, updates the existing activity programs accordingly. At this stage, temporal and institutional constraints are implemented, such as, 1) total time spent in a day never exceeds 1440 minutes (24 hour), 2) no out-of-home activities begin after midnight, and 3) no shopping activities begin after 9.00 pm. If any activity violates these constraints, the A-CRM heuristically reschedules the activities by removing them from daily activity programs based on an activity hierarchy until the corresponding activity plan (consists of activity program, duration, start time and destination) satisfies the constraints. The activity hierarchy is assumed as follows: work is given the highest priority if the individual is at least 18 years of age and a worker, otherwise school is given the highest priority, which is followed by escort and personal business. Shopping, dine out and recreational activities are given the same rank and the activity with the longest duration at the destination is considered to be the highest priority activity. In case of multiple activities with the same rank, the activity with longest duration at the destination is given the highest priority. When an activity is removed from the activity plan, the subsequent activity's origin location is updated with its new preceding activity, and the travel distance and travel time are updated to reflect the new origin-destination pair. Once the conflicts are resolved, activity-based tours are formed following the same activity hierarchy.

6.3.2.3 *Shared Travel Choice*

The next step is to determine the travel arrangements by accommodating individuals' social interactions with household and non-household members within the micro-behavioural modelling and simulation framework. Shared travel choice component is operated at the activity-based tour-level. Based on the activity hierarchy, three home-based activity-tours are formed which start and end at home: 1) mandatory activity-tours (work and school tours), 2) maintenance activity-tours (escort, personal business and shopping tours), and 3) discretionary activity-tours (dine out and recreational tours). To reduce the computational complexity, this research develops more simplified versions of previous shared travel choice models (reported in chapter four) that are compatible to the operational modelling framework of SDS (see Appendix A, Table A-7 to Table A-9 for simplified models).

The shared travel choices are simulated by using mixed logit (MXL) micro-behavioural models. Based on individuals' interactions with household and non-household members, five travel arrangements are considered as dependent variables: a) non-shared travel (i.e. travel alone), b) shared travel with partner/spouse, c) shared travel with children, d) shared travel with parents/other family members, and e) shared travel with roommates/friends/colleagues. The utility function for shared travel choice models can be described by the following equation:

$$V_{ij} = c_j + \lambda_i X_{ij} + \varepsilon_{ij} \tag{5}$$

Here, i is the individual, j is the travel arrangements, X is the observed attributes of individuals, c denotes the constant term, ε is the random error term and λ is the coefficient of the parameters to be estimated. Now, the probability that an individual i chooses a travel arrangement j from their available choice alternatives J_i can be written as:

$$R_{ij} = \int \frac{exp[c_j + \lambda_i X_{ij}]}{\sum_{j=1}^{J_i} exp[c_j + \lambda_i X_{ij}]} f(\lambda_i | m, \sigma)\, d\lambda_i \tag{6}$$

The variation in individuals' taste preferences across the sample population is accommodated by estimating the mean (m) and standard deviation (σ) of the λ parameter assuming a normal distribution of the density function f. Equation 6 is utilized to estimate the probability to choose travel arrangements. The micro-behavioural models create probability distributions over the possible shared travel choices for different activity-based tours. Then the computational procedure of SDS model assigns travel arrangements to individuals for their different activity-tours by comparing the estimated probabilities of shared travel choices against randomly generated probabilities using the Monte Carlo simulation technique. Once the model assigns travel arrangements to individuals' different activity-based tours, it couples the activity scheduling and generation sub-modules by providing feedback to update existing activity plans that consist of activity program, duration, start time, destination and skim travel time. Such feedback considers individuals' interactions with household and non-household members and joins the activity-based tours to handle the dynamic decision of mode choice and vehicle allocation. The model first searches for the matching tours with other individuals by utilizing certain criteria, such as 1) matching activity-based tours must be of same category, 2) estimated start time difference of work/school activity-based tours should be within 3 hours (not applicable for flexible maintenance and discretionary activities), and 3) made by an individual who matches the shared travel arrangement option. Once the activity-based tours are joined, a tour leader (i.e. household head) is identified based on participants' age and employment status. If no matching tours are found, individuals' tours are heuristically assigned as 'non-shared travel'. Finally, the planned activity schedules are executed for the individuals generated in the LDS module.

Following the activity scheduling, the mobility assignment sub-module simulates individuals' mode choice and vehicle allocation decisions for different activity-based tours as a two-stage dynamic decision process. Along with the information from activity scheduling sub-module, mobility assignment takes input from the mobility tool ownership of the LDS module for the year 2006 that provides information on driver's license ownership, transit pass ownership and the existing vehicle fleet in the households. Travel time by each mode is determined as a process of mobility assignment. It provides feedback to activity scheduling sub-module to update existing activity plans, and simulate the final activity schedules with modes and vehicles. Further discussion on the mobility assignment sub-module is reported in the next chapter. Once the baseline activity-travel information is generated, the SDS microsimulation model starts simulating the activity and travel information of all the individuals for the years 2007 to 2036. The model takes inputs (i.e. residence, household, individual and vehicle information) from the LDS module, and simulates various activity and travel attributes from 2007 to 2036.

6.4 Microsimulation Result Discussion

6.4.1 Validation of SDS Microsimulation Results

The SDS microsimulation model is implemented for Halifax region following the development of econometric micro-behavioural models and heuristics processes described in the previous sections. SDS is calibrated to the 2011 National Household Survey (NHS) data. Calibration is performed by adjusting heuristics rules that include applying and relaxing restrictions to several simulation parameters, such as activity start time and activity type choice, among others. While calibrating the SDS model, validations are conducted repeatedly until simulation year prediction closely matches the information from observed data. Since the sub-modules are interconnected and sequentially implemented, calibration is conducted simultaneously at all the steps of modelling process. This study compares the calibrated model data with the observed data based on the commute travel time. The comparison between observed NHS results and the calibrated SDS microsimulation model results in terms of commute travel time is shown in Figure 6-4.

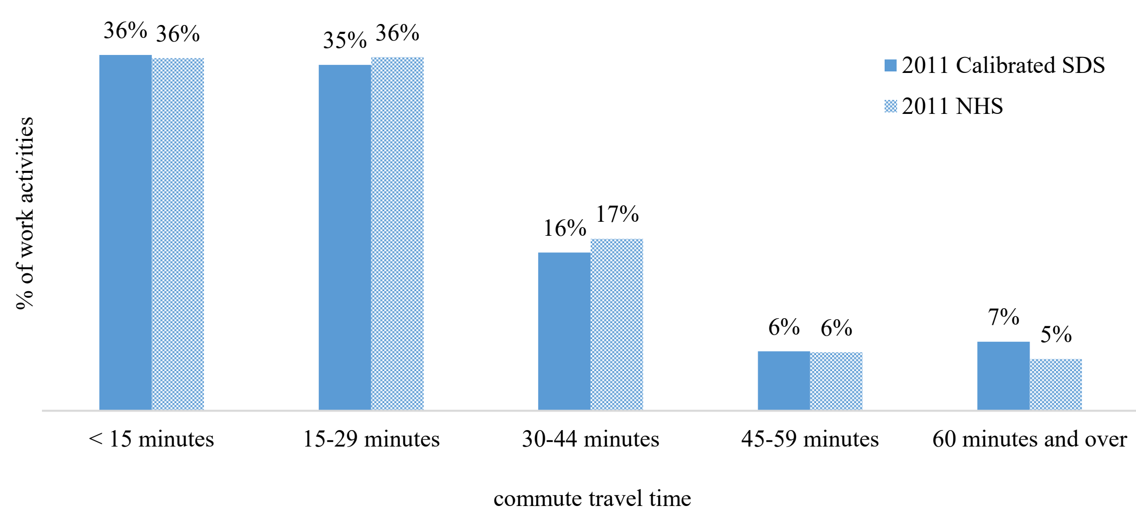


Figure 6-4 Comparison between Calibrated SDS Model Data and NHS Data

The performance of the SDS model is measured in this research by estimating a goodness-of-fit measure, called Absolute Percentage Error (APE) measure. It evaluates the performance of the spatial distribution of the simulated data in comparison to the observed data. The APE measure is estimated in this study based on the activity start time. APE measures can be calculated through the following equation:

$$APE = \left(\left|\frac{O_i - S_i}{O_i}\right|\right) * 100 \qquad (7)$$

Where, O_i is the observed percentage and S_i is the simulated percentage of commute start time in dissemination area *i.* APE measures range from 0% to 100%, where 0% represents a perfect fit. This thesis determines the APE values for three different commute start time categories (5am – 6.59am, 7am – 8.59am, and after 9am) at the DA-level utilizing simulated data of the year 2011 and observed data from 2011 NHS. The analysis suggests that approximately 90%, 85% and 91% of the DAs exhibit APE measure of less than 5% in case of the commute start time categories 5am to 6.59am, 7am to 8.59am and after 9am, respectively. Only around 3% of the DAs show an APE measure of above 15% in all cases. Figure 6-5 exhibits the APE measure of activity start time category 5am to 6.59am. APE measures for other start time categories can be found in Appendix C (Figure C-1 and Figure C-2).

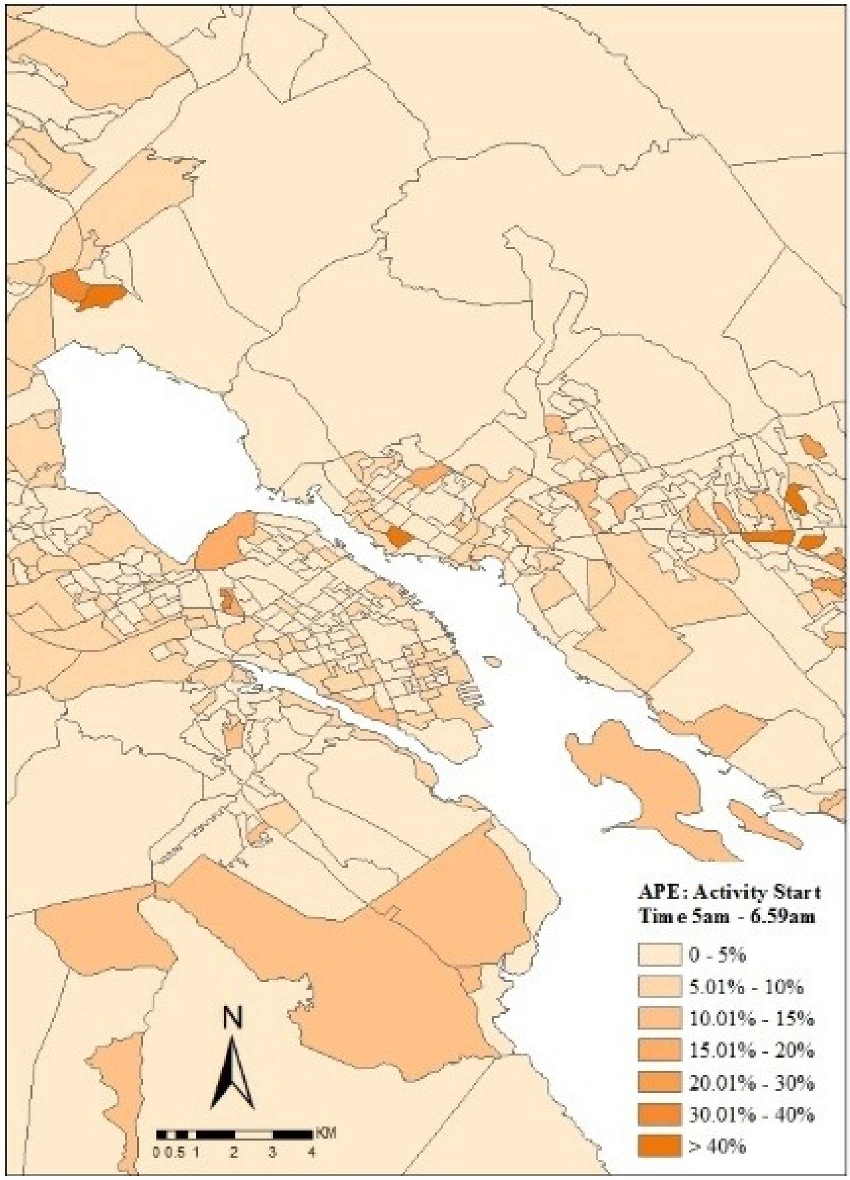
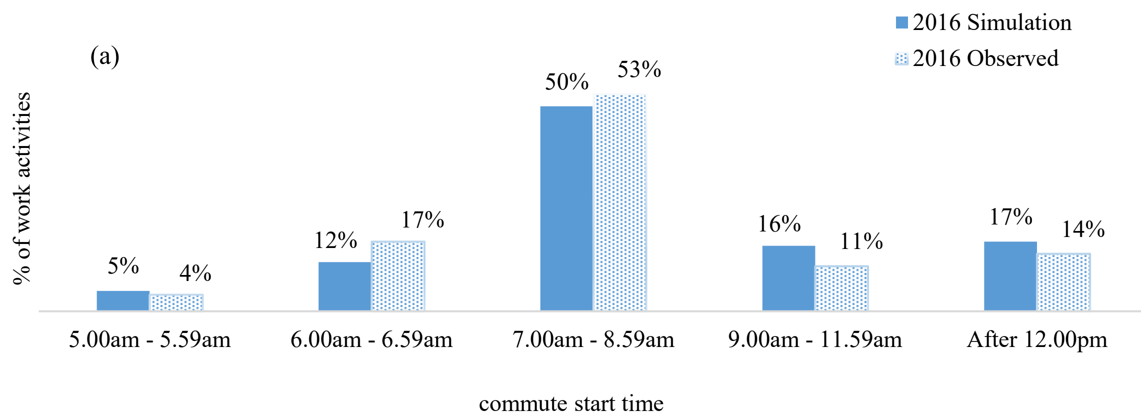


Figure 6-5 APE Measures based on Commute Start Time Category 5am to 6.59am

Validation of microsimulation results are performed by comparing 2016 simulated data with Canadian Census data in terms of commute start time and commute distance. The comparative analysis suggests that majority of the commuting activities start between 7 am - 8.59 am in 2016. A slight under-representation (3%) in this start time category is found in 2016 (Figure 6-6a). All other simulated start time categories exhibit less than 5%

difference with the observed distribution. In the case of commuting distance, results suggest that more than 50% of the work activities are performed within 10 km distance (Figure 6-6b). The commuting distance category 'less than 5 km' exhibits 32% simulated share in 2016, which is an approximately 7% under-representation of the observed data. Other distance categories exhibit less than 3% differences between the simulated and observed data. Therefore, based on the APE measures and comparative analysis, the microsimulation results of the SDS model can be considered satisfactory.



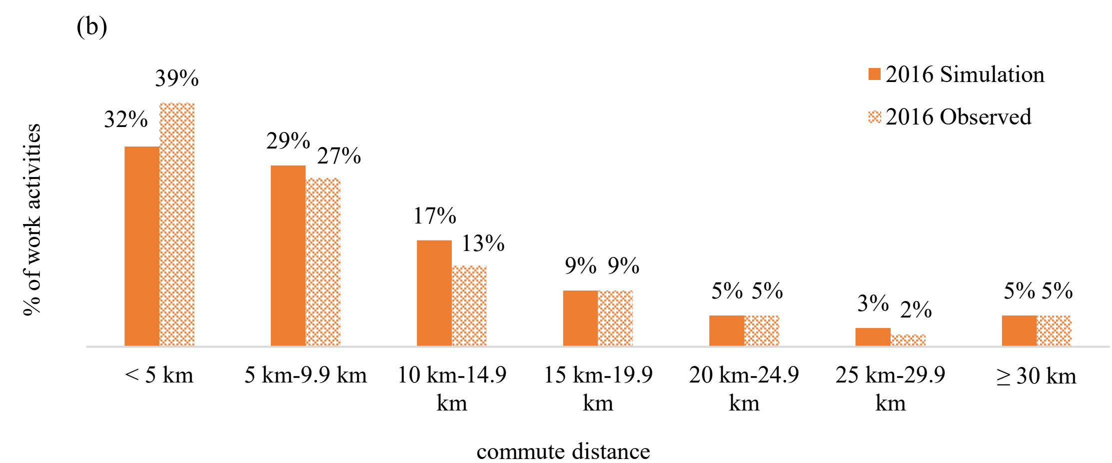


Figure 6-6 Validation of SDS Model Results in terms of a) Commute Start Time, b) Commute Distance

6.4.2 Predicted Changes in Activity Participation over the Years

The SDS model predicts a daily average of 2.84 out-of-home activities/person in the year 2036, which is 2.61 in the base year 2006. 10% of the predicted out-of-home activities in 2036 are work activities, 5% are school activities, 7% are escort activities, 7% are personal business activities, 15% are shopping activities, 4% are dine out activities and 12% are recreational activities. Among these activities, participation at school, personal business, dine out and escort activities exhibit stable trends from 2006 to 2036 (approximately 1% change over 30 years). Compared to the baseline information, work activities are predicted to decrease by 5% in 2036. Shopping and recreational activities are predicted to increase by 4% and 3%, respectively. Figure 6-7 exhibits the predicted changes in activity participation over the years.

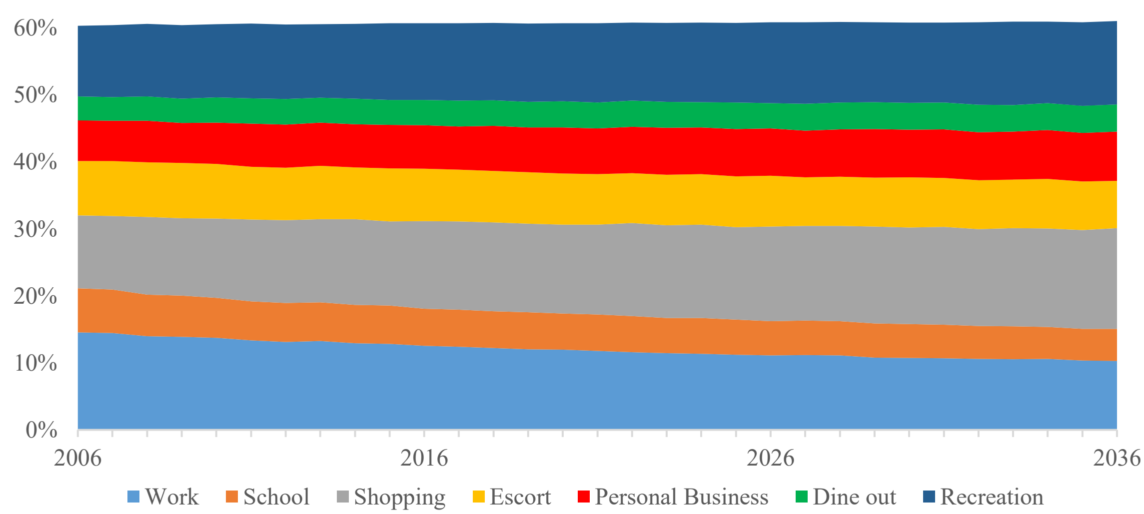


Figure 6-7 Predicted Changes in Activity Participation from 2006 to 2036

6.4.3 Predicted Activity Duration over the Years

Figure 6-8 exhibits the yearly distribution of agents' time spent at different out-of-home activities. Results suggest that the average time spent at an out-of-home work activity by an individual decrease over the 30-year period. The model predicts an average 18 minutes drop in out-of-home work activity duration per worker in 2036 compared to the base year 2006 (526 minutes). Average duration of both school activities and escort activities exhibit stable trends over the years. In the case of personal business activities, the mean value of average duration per individual is predicted to increase from 82 minutes (2006) to 87 minutes (2019), which is predicted to have a low variation over the next 17 years. Average time spent at shopping activities shows a 20-minutes drop from base year 2006 (60 minutes) to simulation year 2036 (40 minutes). Finally, the average time spent at recreational activities is also predicted to increase over the years (mean value is 121 minutes in 2006 and 148 minutes in 2036).

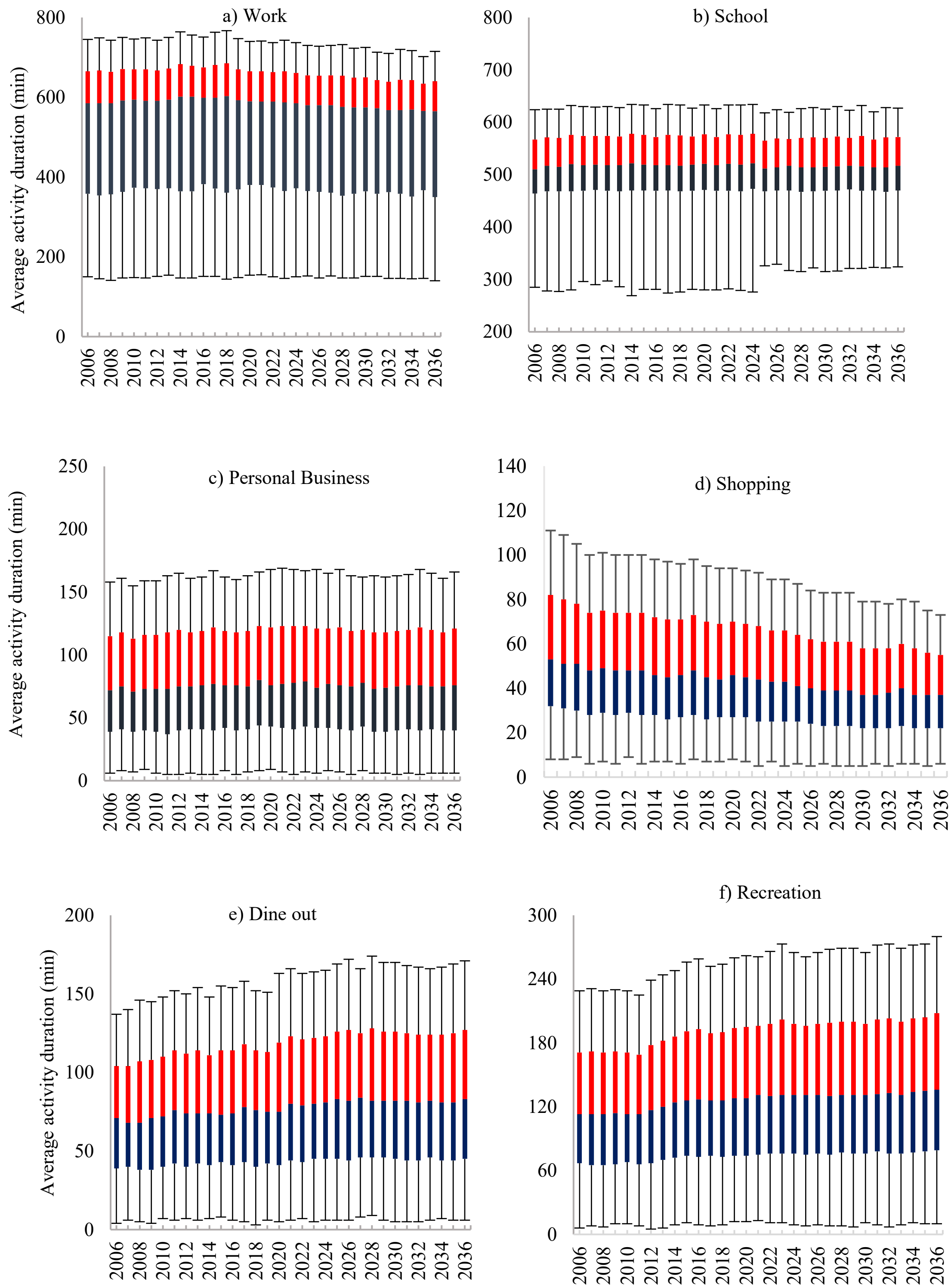


Figure 6-8 Predicted Durations over the Years for a) Work, b) School, c) Personal Business, d) Shopping, e) Dine out and f) Recreation Activities

6.4.4 Predicted Evolution of Spatial Distribution of the Activities

Figure 6-9 demonstrates the spatial distribution of different out-of-home activities over the 30-year period. The maps focus on urban areas in Halifax and Dartmouth, and their surrounding suburban areas. Results suggest that the percentage of work activities increase over the years in Halifax and Dartmouth urban core. Since urban core represents higher mixed land-use areas with more work opportunities, people may attract to such areas to perform work activities. Also, the destination location choice model for work activities demonstrates a positive coefficient value of the 'land-use index' parameter (Appendix A, Table A-1), which indicates individuals' higher probability to choose higher mixed land-use areas (i.e. urban areas) as their work location. This may attribute in increasing work activities in the Halifax and Dartmouth urban cores over the years. In addition, an increase in work activities from 2006 to 2036 is observed in some adjacent suburban areas (Clayton Park and Bedford). Interestingly, higher work activities are also predicted in the North End neighbourhoods of Halifax peninsula. The North End areas are experiencing gentrification as documented by Roth (2013), hence, may create more work opportunities. The LDS module of the iTLE urban model predicts higher density of employed population in Halifax and Dartmouth urban cores, adjacent suburban areas and North End areas in 2036 compared to the base year 2006 (Fatmi and Habib 2018a). In addition, the destination location choice model for work activities suggest that individuals tend to choose work location near their home location (Appendix A, Table A-1). Therefore, increase in work activities in such areas may be plausible. This may indicate individuals' likeness to work near their residential location.

In the case of school activities, core downtown areas and surrounding suburban areas in both Halifax and Dartmouth are predicted to increase from 2006 to 2036. Similarly, escort activities exhibit an increase in downtown areas and surrounding suburban areas. Shopping and personal business activities are predicted to increase primarily in Halifax and Dartmouth urban cores. In addition, an increase in shopping activities are predicted outside of the Dartmouth downtown (Burnside and Bedford Industrial Park), perhaps due to the shopping/industrial establishments in those areas. Some neighbourhoods in the Halifax North End also shows higher shopping activities over the years, which indicates gentrification process occurring in such areas as documented in Roth (2013). Dine out activities are predicted to increase in the core downtown areas and few surrounding suburban areas of Halifax and Dartmouth over the years. Recreational activities increase in some areas of Halifax and Dartmouth downtown; however, they increase more in suburban areas from 2006 to 2036. Figure 6-8 presents the spatial distributions of work, school, shopping and recreation activities. Evolution of spatial distribution of other activity types can be found in Appendix C (Figure C-3 to Figure C-5).

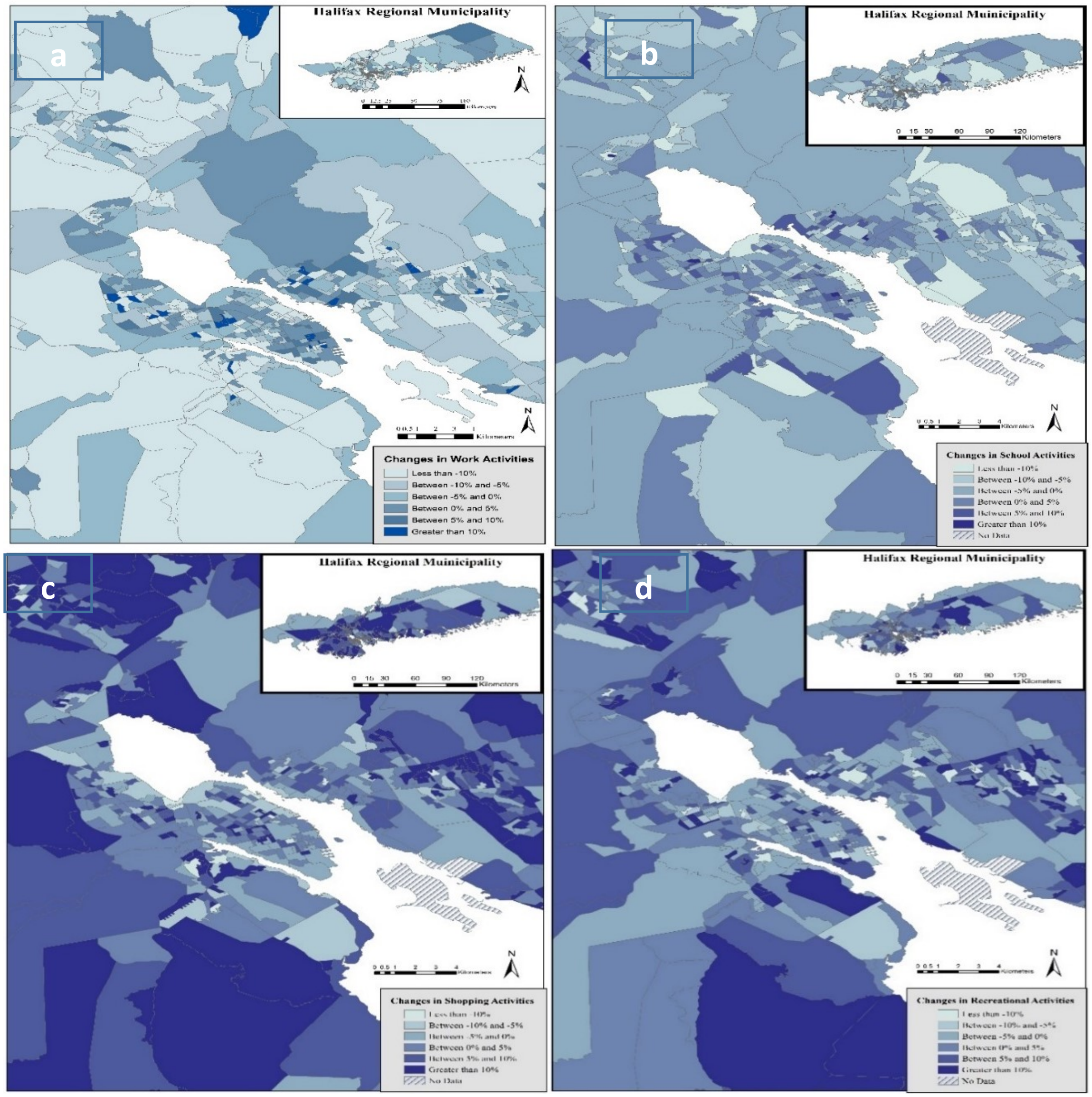


Figure 6-9 Predicted Spatial Distribution of Activities from 2006 to 2036 for a) Work, b) School, c) Shopping, and d) Recreation Activities

6.4.5 Predicted Evolution of Distances from Home to Activity Destination Locations

The microsimulation results of the destination location choice are presented in Figure 6-10. A kernel density is plotted against the activity destination location distance from home location for the simulation years. This study assumes a Gaussian kernel function for optimal bandwidth selection to estimate the kernel density. Six kernel densities are estimated for six types of out-of-home activities. All the plots in Figure 6-10 suggest that density is skewed to the left of approximately 10 km in the base year 2006 as well as other simulation years. Interestingly, the densities become more skewed to the left as the simulation years increase from 2006 to 2036. This might be attributed by the estimation results from the destination location choice models, where results suggest that people are more willing to travel to places that are of shorter distance and require less time (see Appendix A, Table A-1 to Table A-6). These prediction results are changing temporally because the SDS model utilizes individuals' home locations generated in LDS module to estimate the distance between activity location and home location. Microsimulation results from LDS module demonstrate that individuals' home locations are changing temporally from 2006 to 2036, and it found that the proportion of the population residing in high density neighbourhoods (i.e. urban cores with more activity opportunities) has increased over the 30 year periods.

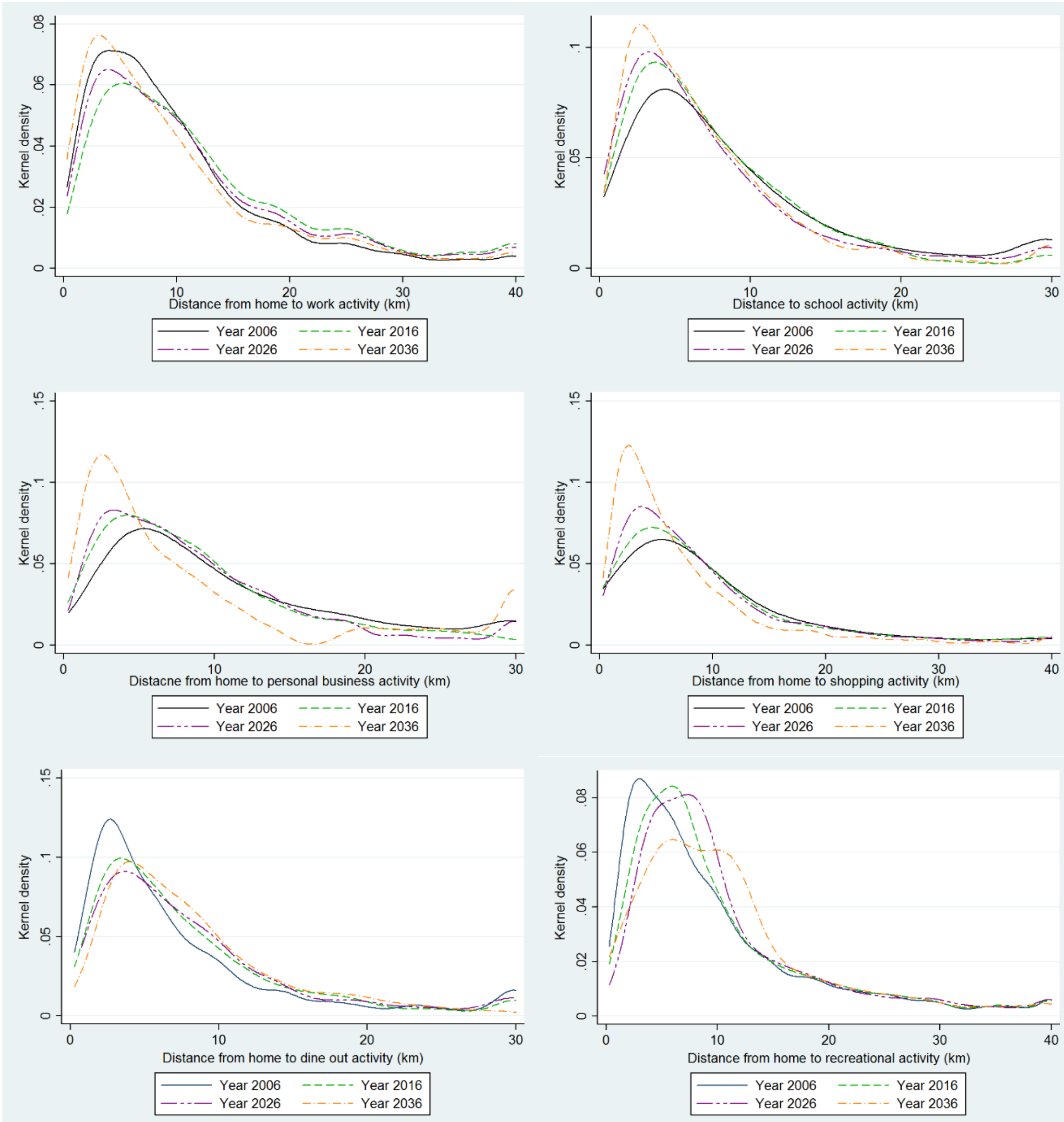


Figure 6-10 Predicted Distributions of Distances between Home Locations and Activity Destination Locations

6.4.6 Microsimulation Results of Shared Travel Choice

6.4.6.1 *Predicted Evolution of Shared Travel Choices*

Microsimulation results of shared travel choices predict that majority of the work-based tours are performed by traveling with partner/spouse. However, the percentage of shared travel with partner/spouse is predicted to drop over the years (from 52% in 2006 to 46% in 2036). Shared travel with children during work-based tours also decreases by 3% from 2006 to 2036. However, non-shared travel is predicted to increase in the case of work-based tours over the 30-year period. Lower percentage of work-based tours are predicted to be performed by sharing travel with parents/other family members (7%) and roommates (1%), which are predicted to remain stable over 30 years. Most of the school-based tours are predicted to be performed with parents/other family members, which are predicted to increase over years (73% in 2006 to 77% in 2036). Non-shared travel is predicted to increase slightly by 2% from 2006 to 2036. A comparatively smaller percentage of school-based tours are predicted to perform with roommates/friends/colleagues (9%) in the base year 2006, which decreases by 6% in 2036. This might be attributed by the living arrangements in the households simulated in the LDS module of iTLE, which predicts a lower proportion of students living with roommates/friends/colleagues in 2036 compared to the base year 2006. In the case of maintenance and discretionary activity-based tours, results indicate that higher percentages of the tours are performed alone. 45% of the total maintenance activity-based tours in 2006 are predicted to be performed by traveling alone, which increases to 66% in 2036. However, other shared travel alternatives during maintenance activity-based tours are predicted to decrease over 30 years. For example, 32% of the maintenance tours are performed with partner/spouse in 2006, which drops to

21% in 2036; 18% of such tours are performed with parents/other family members, which is predicted to decrease by 7% over the 30-year period. Percentage of discretionary activity-based tours in case of non-shared travel is predicted to decrease slightly by 2% from 2006 to 2036. Shared travel with children, parents/other family members and roommates are also predicted to decrease from 2006 to 2036. However, 33% of the discretionary activity-based tours are predicted to be performed with partner/spouse in 2036, which is a 11% increase from the base year 2006.

6.4.6.2 *Predicted Shared Travel Choices by Travel Length*

The analysis of shared travel choices by travel length reveals a similar trend in the base year as well as simulation years. Results suggest that the majority of activity-based tours are performed alone (non-shared travel) when travel length is shorter. However, higher percentages of travel shared with an accompanying person are predicted as the travel length increases. For example, in the simulation year 2036, the highest percentage of non-shared travel (32%) is predicted for a travel length of less than 5 km. The percentage decreases with the length and the lowest percentage (9%) is predicted for a travel length above 30 km. In contrast, 10% of the activity-based tours is predicted to be shared with children if the travel length is less than 5 km, which rises to 35% for a travel length greater than 30 km.

6.4.6.3 *Predicted Changes in Shared Travel Choices by Age Group*

Figure 6-11 exhibits the yearly evolution of shared travel choices by different age groups. Simulation results suggest that individuals who travel alone during different types of activity-based tours primarily belong to the older adult (41-64 years) and senior (above 64 years) age groups. 23% of the non-shared travel is performed by the senior individuals in

2006, which increases to 50% in simulation year 2036. 46% of the non-shared travel is performed by older adults that is predicted to drop by 13% in 30 years. In the case of traveling with partner/spouse, a higher percentage of individuals is also found to belong in the older adult and senior age groups. From the base year 2006, the percentage of older adults decreases from 56% to 44% in year 2036, however, this gradually increases from 16% to 41% for the senior age group.

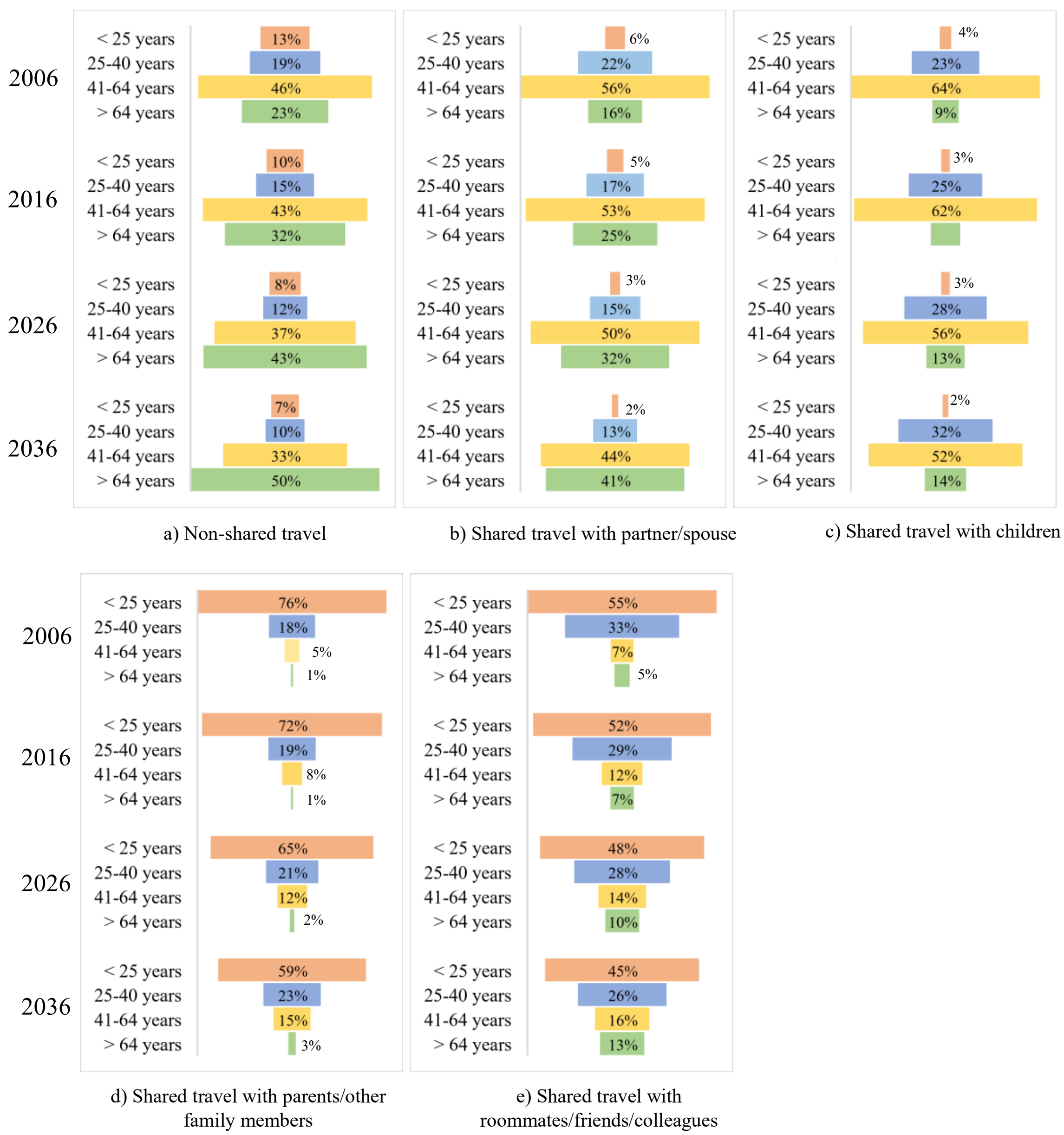


Figure 6-11 Predicted Changes in Shared Travel Choices by Age Groups

In the case of traveling with children, the model predicts that the majority of shared travel with children is performed by younger adults (25-40 years) and older adults in all simulation years. In 2006, 64% of shared travel with children is performed by the older adult group and 23% by the young adults. The percentage of young adults is predicted to increase by 9% over 30 years, however, the percentage of older adults drops to 52% in 2036. As expected, the majority of shared travel with parents/other family members is performed by young individuals (less than 25 years). In 2006, 76% of the shared travel with parents is performed by individuals who belong to the young age group. This percentage is predicted to drop by 17% in 2036. Shared travel with roommates/friends/colleagues also exhibits a similar trend over the years. 55% of the shared travel with roommates in the base year is performed by young individuals that reduces to 45% in the simulation year 2036.

6.5 Conclusions

This paper presents the simulation procedure and prediction results of activity generation and activity scheduling sub-modules within an activity-based shorter-term decisions simulator (SDS). The system is implemented within an agent-based integrated urban system simulation platform, iTLE. SDS is implemented in Halifax, Canada from the year 2006 to 2036. Activity generation sub-module simulates types and number of activities within the SDS modelling framework. One of the unique features of this sub-module is to implement a Markov Chain Monte Carlo method within the microsimulation framework to simulate sequential activities at a 24-hour temporal scale. Activity scheduling sub-module involves microsimulation of activity agenda formation, destination location choice and shared travel choice. Following a heuristics modelling approach, activity agenda formation component simulates duration and start time of each activity. Destination location component utilizes a conditional logit model to simulate the destination locations of the activities generated by the activity generation sub-module. Finally, shared travel choice component simulates the travel arrangements of the activities accommodating individuals' social interactions with household and non-household members. Shared travel choice component is implemented using a mixed logit modelling technique. The SDS microsimulation modelling framework addresses social interactions by implementing feedback mechanism within the activity scheduling process that contributes to reassess daily activity schedules.

The validation of the microsimulation results of activity generation and scheduling sub-modules suggest that SDS performs reasonably well in generating different activity attributes. This study performs the validation of SDS microsimulation by estimating APE values and by comparing simulated data with observed data. APE measures are calculated based on activity start time and using 2011 NHS and simulated data for three different activity start time category. Results suggest that around 90%, 85% and 91% of the DAs exhibit APE measure of less than 5% in case of the activity start time categories 5am to 6.59am, 7am to 8.59am and after 9am, respectively. While comparing the 2016 Census data with simulated data based on commute start time and commute distance, it is found that differences in the majority of the simulated and observed data are less than 3%. Based on such measures, the model is considered as performing considerably well. The simulation results predict the changes in activity participation over the years in Halifax, Canada.

Results predict a 5% decrease in work activities, and a 3% and 4% increase in recreational and shopping activities, respectively, from 2006 to 2036 in Halifax. Spatial distribution of different activities indicates that work activities increase over the years in the core downtown areas of Halifax. Maintenance (escort, shopping and personal business) and discretionary (dine out and recreational) activities are also predicted to increase in urban areas of Halifax and Dartmouth from 2006 to 2036. Results predict a decrease in home to activity destination location distances in the case of mandatory (work and school) and maintenance activities in the year 2036 compared to the base year 2006. In terms of average time spent at activities, individuals are predicted to decrease the time spent at work and shopping activities over 30 years. However, average time spent per person at recreational and dine out activities are predicted to increase from 2006 to 2036. In terms of shared travel choice decisions, the majority of work-based tours are predicted to be performed by traveling with a partner/spouse. However, this percentage is predicted to drop slightly by over the 30-year period. As expected, much of the school-based tours are predicted to be performed by traveling with parents/other family members, which exhibits an increasing trend over the years. Interestingly, in the case of maintenance and discretionary activity-based tours, a higher percentage of activity-based tours are predicted to be performed alone. In terms of travel length, individuals are predicted to travel alone when the travel length is shorter. However, with the increase in travel length, higher percentages of travel shared with an accompanying person are predicted. In terms of age groups, this research predicts that mostly older adult (41-64 years) and senior (above 64 years) people travel alone while performing different types of activity-based tours. Both shared travel with partner/spouse and shared travel with children also exhibit higher percentages in the age group 41-64 years. However, younger people (age below 25 years) are predicted to travel with parents/other family member and roommates/friends/colleagues more while performing different activity-based tours.

This study has certain drawbacks. For example, the current version of the SDS model assumes that shared travel choices only occur among the household and non-household members of the same households, meaning that different ride-sharing opportunities might not be possible to take into account within the mode choice modelling framework. Also, the model is validated utilizing only the commute data of Canadian Census tabulations due to unavailability of a comprehensive activity-travel survey. Since new NovaTRAC data will be available soon, one of the immediate future works should be performing an extensive validation procedure of microsimulation results based on multiple activity and travel attributes. Furthermore, the current prototype SDS model implements shared travel choice at activity-based tour-level. Future research should focus on simulating shared travel choices at stop-level in order to develop a more comprehensive activity-based travel demand model. Moreover, further analysis is necessary to reveal policy implications of the prediction results presented in this paper. Nevertheless, the SDS microsimulation results presented in this chapter offer critical insights on the yearly evolution of activity generation and activity scheduling decisions. Such outcomes provide inputs to a disaggregate-level dynamic traffic microsimulation process that can predict emission and energy consumption at a specific time-of-day in the traffic network. The simulation results can be used to test different travel demand management strategies and effective integrated transportation and land-use policies that aim at investigating behavioural changes with respect to activities and travel for achieving a sustainable transportation system.

Chapter 7

Microsimulation of Mobility Assignment

7.1 Introduction

This chapter presents the microsimulation framework and results of mobility assignment processes within the activity-based shorter-term decisions simulator (SDS). Mobility assignment is conceptualized as a dynamic two-stage process of mode choice and vehicle allocation in SDS. To implement such dynamic processes, this study applies both heuristics and econometric micro-behavioural modelling techniques. One of the key features of SDS is that it accounts for the social interactions within its modelling framework derived from individuals' shared travel choice decisions. The mobility assignment sub-module in SDS also accommodates social interactions within its micro-behavioural modelling and microsimulation frameworks. The micro-behavioural models are developed in this study following a mixed logit modelling approach. During the microsimulation process, mobility assignment decisions are simulated by addressing their multi-domain interactions with different short-term and long-term decision processes, such as activity scheduling and mobility tool ownership. This chapter presents the microsimulation processes and results of the mobility assignment sub-module of SDS from the year 2006 to 2036. Specifically,

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This chapter is derived from the following papers:

- Khan, N. A., & Habib, M. A. (2020). Modeling of Mode Choice and Vehicle Allocation within an Activity-based Shorter-term Decisions Simulator (SDS). Published in the *Proceedings of the 99th Annual Meeting of Transportation Research Board*. Washington, D. C., U.S.A., January 12-16, 2020.
- Khan, N. A., & Habib, M. A. (2020). Dynamic Mobility Assignment Microsimulation Processes in an Activity-based Travel Demand Microsimulation Model. *Transportmetrica A: Transport Science.* (Under review).

it presents the model estimation and simulation results of mode choice and vehicle allocation decisions.

The next section of this chapter describes the microsimulation procedure of mobility assignment. After that, section 7.3 briefly presents the microsimulation results that includes the validation process as well. Finally, section 7.4 presents a conclusion that includes summary of this chapter, limitations and future research directions.

7.2 Description of Mobility Assignment Microsimulation Process

The mobility assignment sub-module determines mode choice and vehicle allocation decisions for different types of activity-based tours. The microsimulation procedure in this sub-module is a simultaneous process in the sense that a decision to get a vehicle from a household's existing vehicle fleet depends on the household's long-term vehicle ownership decisions as well as vehicle availability at the time when a vehicle is required as a decision process of mode choice. Both micro-behavioural and heuristics models are utilized in the mobility assignment sub-module to simulate mode choice and vehicle allocation decisions. The mobility assignment micro-behavioural models are developed in chapter three and chapter five. However, to reduce computational complexity, this study develops more simplified version of mode choice and vehicle allocation micro-behavioural models, which are compatible to implement within the SDS modelling system (see Appendix A, Table A-10 to A-18). The operational framework of the mobility sub-module is presented in Figure 7-1. Below is a brief discussion of the microsimulation process.

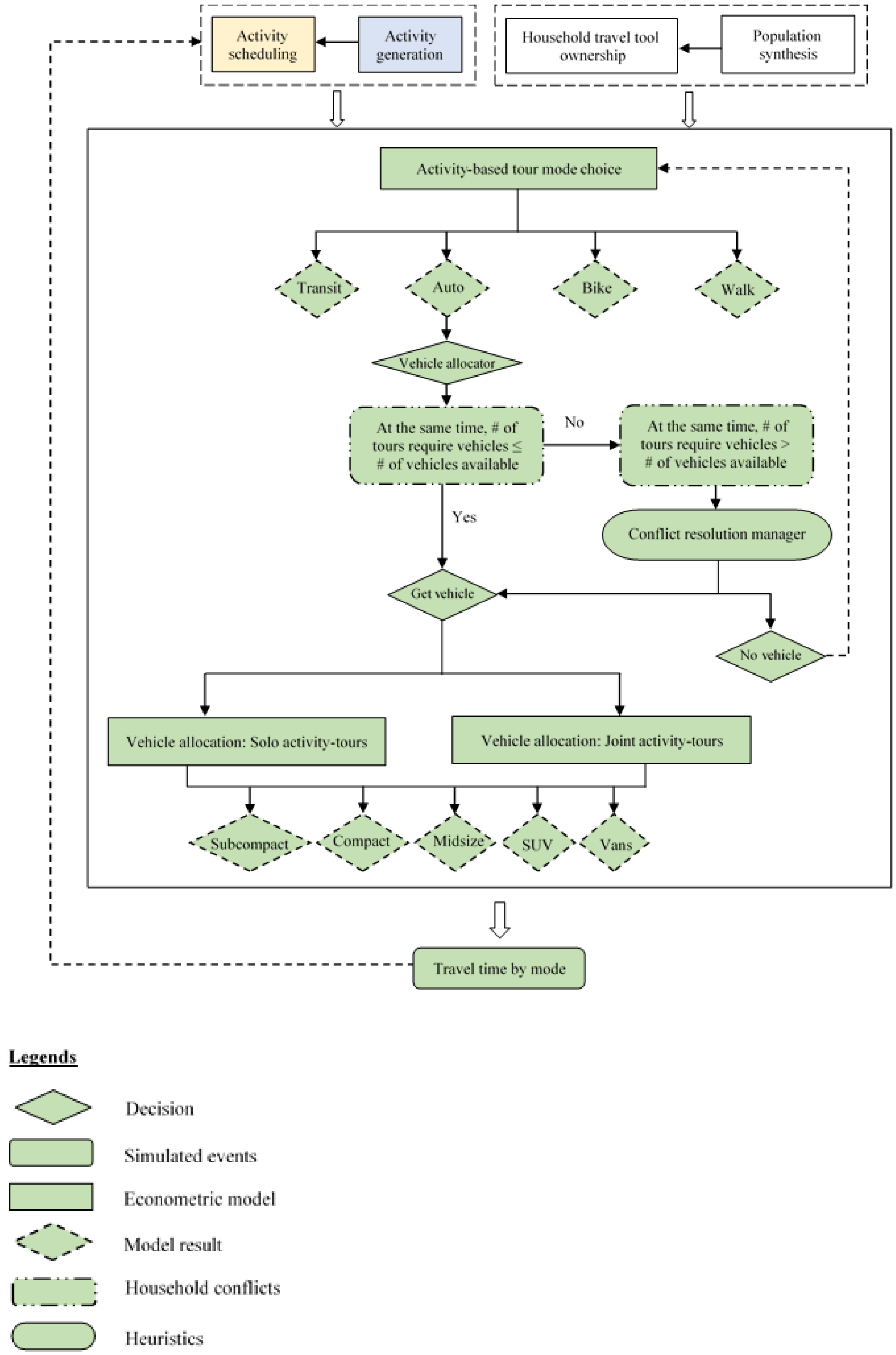

Figure 7-1 Operational Framework of the Mobility Assignment Process

7.2.1 Mode Choice

The microsimulation process in the mobility assignment sub-module starts with simulating the mode choice decisions in the base year 2006. Mixed logit (MXL) models are developed to determine the probability of choosing a mode for different activity-based tours. The mode choice models are developed for three broad categories of activity-based tours, namely mandatory activity-based tours (work and school tour), maintenance activity-based tours (escort, personal business and shopping tours), and discretionary activity-based tours (outside meal and recreational tours). All these tours are home-based, meaning that they start and end at home. Such activity-based tours are formed based on the primary activity within the activity chain. The activity with the highest priority is defined as the primary activity. Activity priority follows the activity hierarchy discussed in chapter three. Four types of modes are considered during micro-behavioural model development: auto, transit, walk and bike. While developing the micro-behavioural models, this study utilizes variable choice sets based on the availability of modes. For instance, transit mode is eliminated from the choice sets outside of the transit operating hours. Also, not owning a bike or auto results in eliminating such alternatives from the choice set of the corresponding individual. Utility function of the mode choice models can be written as:

$$U_{nj} = a_j + \beta_n X_{nj} + \varepsilon \qquad (1)$$

Here, n denotes the individual, j is the mode choice alternatives, X is the observed attributes, ε is the random error term and β is the coefficient vector of the parameters to be estimated. The probability of choosing a mode from a set of available mode choice alternatives J_n can be described as:

$$P_{nj} = \int \frac{exp[a_j+\beta_n X_{nj}]}{\sum_{j=1}^{J_n} exp[a_j+\beta_n X_{nj}]} f(\beta_n|q,\omega)d\beta_n \quad (2)$$

Here, q and ω are the mean and standard deviation of the predictor variables. The unobserved heterogeneity is captured by estimating the mean and standard deviation of random parameters assuming a normal distribution of the density function *f*. The effects of social interactions are accommodated through the shared travel arrangement variables (i.e. traveling alone, traveling with partner/spouse, traveling with children, traveling with parents/other family members, traveling with roommates/friends/colleagues) used in the micro-behavioural models. The mode choice models are utilized to determine probabilities to choose auto, transit, walk and bike modes. Individuals are assigned to a mode following the probability estimation.

7.2.2 Vehicle Allocation

Following the mode choice decisions, vehicle allocation component in SDS starts searching for a vehicle heuristically in the household that can be assigned to an individual's activity-based tour upon the choice of the auto mode. The vehicle allocation process also depends on households' long-term mobility tool ownership decisions, such as number of vehicles in the households, types of vehicles owned by the households and driver's license ownership. First, the vehicles which are available at the start of a person's activity-based tour is determined by consulting all household vehicles and identifying the ones with no conflicting tours. If the number of tours requires vehicles from a household's existing vehicle fleet is equal to or less than the number of vehicles available at that same time, the vehicle allocation component starts allocating different types of vehicles to different activity-based tours based on the travel arrangements. The vehicle allocation models also follow a mixed logit modelling technique (similar method to mode choice model) using the NovaTRAC data. Since households do not possess all types of vehicles, the vehicle allocation models are developed utilizing variable choice sets based on households' vehicle ownership level and types of vehicles they own. Five types of vehicles are considered during model development based on the vehicle body type, such as subcompact, compact, midsize, SUV and vans (passenger trucks, minivans, vans). Six vehicle allocation micro-behavioural models are developed based on shared travel arrangements (i.e. solo: traveling alone, and joint: traveling with partner/spouse, children, parents/other family members and roommates/friends/colleagues) and types of activity-based tours (i.e. mandatory, maintenance and discretionary activity-based tours). The vehicle allocation micro-behavioural models determine probabilities to assign different types of vehicles to specific activity-based tours. Based on the estimated probability, an individual's tour is assigned one of the five vehicle types that is available in his/her household's existing vehicle fleet at the time of the tour. Note that if multiple vehicles of the same type are available, each vehicle of the same type counts as a separate option, and two vehicles of the same type will have the same probability of being selected for the tour. Individuals' activity-based tours are assigned the vehicles by comparing model generated probabilities against randomly generated probabilities using the Monte Carlo Simulation technique.

However, conflicts may arise when 1) no vehicle is available during an activity-based tour, and 2) the number of tours require vehicles are more than the number of vehicles available at the same time. A vehicle conflict resolution manager (V-CRM) is implemented within the mobility assignment sub-module that resolves such conflicts and reassesses mode choice decisions. In the current version of SDS, the V-CRM utilizes activity-based tour priority and distance travelled to resolve the conflicts. In the case of such conflicts, V-CRM heuristically takes a vehicle away from the lowest priority activity-based tour which has a vehicle at that time. V-CRM assumes that the tours, where a person travels with partners/spouses, children, parents/other family members and roommates/friends/colleagues, have priority over the tours performed alone. In the case of the activity-based tours with same priority, tours with longer distance travelled are assumed as the highest priority tours. An activity-based tour with lowest priority gives up its vehicle for a higher priority tour and reassesses its mode choice options. The highest priority tour is assigned a vehicle based on the travel arrangement (solo or joint). Vehicles are allocated to different activity-based tours following the same procedure of non-conflicted vehicle allocation.

Once the model assigns modes and vehicles to each individual's activity-based tours, the mobility assignment sub-module generates travel time by each mode. This assists to couple the mobility assignment and activity scheduling sub-modules by providing feedback to daily activity plans in activity scheduling process, and updates start time of each tour and activity. Conflicts may arise at this stage due to the constraints implemented in activity scheduling process. These conflicts are resolved heuristically by the activity conflict resolution manager (A-CRM) within the activity scheduling sub-module. Thus, final activity schedules are formed with modes and vehicles for the base year 2006. Following the same procedure, SDS simulates activity schedules with modes and vehicles for the simulation years 2007 to 2036 utilizing dynamic inputs (i.e. residence, household, individual and vehicle information) from the LDS module.

7.3 Microsimulation Results of Mobility Assignment

7.3.1 Validation

Mobility assignment sub-module is implemented within the SDS microsimulation model for Halifax region. The SDS model is calibrated to the 2011 National Household Survey (NHS) data. The calibration procedure is involved adjusting heuristics rules that include applying and relaxing several constraints within the microsimulation modelling system. SDS model is calibrated by comparing simulated commute start time and mode share data with observed data from NHS. This chapter presents the comparison between calibrated SDS microsimulation model results and observed NHS results in terms of mode share in Figure 7-2. The detailed calibration process and comparison in terms of commute start time can be found in chapter six.

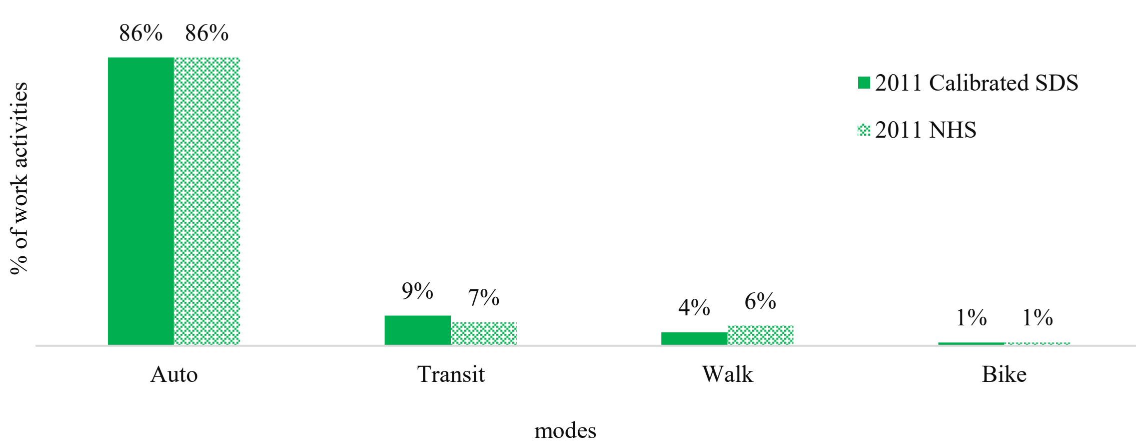

Figure 7-2 Comparison between Calibrated SDS Model Data and NHS Data

The simulation results of the mobility assignment sub-module are validated for two years: 2006 and 2016. Simulated data are validated with the observed data from 2006 and 2016 Canadian Census. A comparative analysis between simulated and observed mode choices is presented in Figure 7-3. According to the analysis, the majority of the work activities is performed using the auto mode in 2016. In 2016, simulation results suggest that 80% of the work activities is performed by using auto modes which is a 1% over-representation of the observed 2016 Census data. The bike mode is also over-represented by 1%, whereas the walk modes are under-represented by 2%. The transit mode exhibits no difference between simulated and observed data.

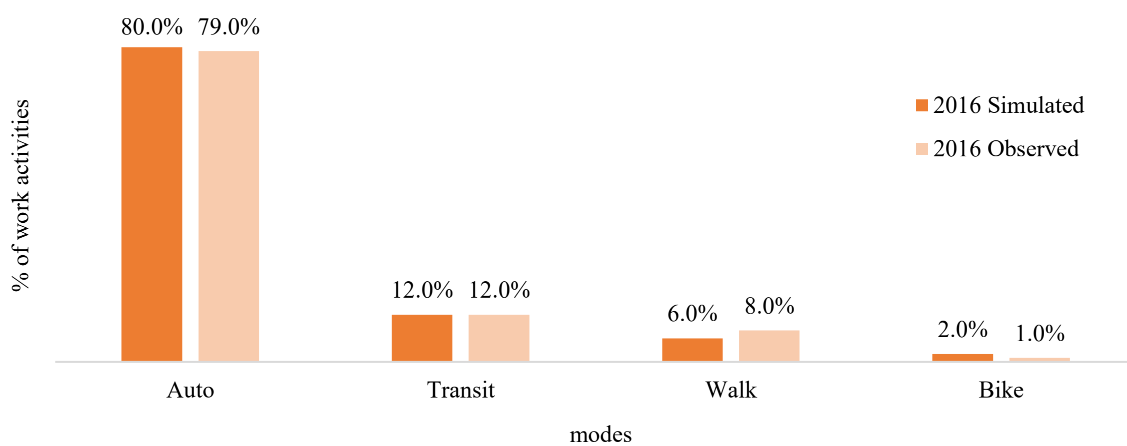

Figure 7-3 Validation of the Mode Choice Simulation Results

Furthermore, this research performs a validation analysis for spatial representation of mode share based on APE measures. It evaluates the performance of the spatial distribution of the simulated data in comparison to the observed data. The APE measures are estimated in this chapter using simulated commute mode choice data of the base year and 2006 Canadian Census data at DA-level. The proportion of commute modes (auto, transit and active transportation) in each DA is computed first for both simulated and observed data, and APE values are measured. Result analysis suggests that around 91% of the DAs show APE measure of less than 5% for commute auto mode share. Only 2% of the DAs exhibit an APE value of above 10% for auto mode share. In the case of transit and active transportation, 93% and 89% of the DAs show APE values of less than 5%, respectively. Therefore, based on the comparative analysis and APE measures, the microsimulation results of the mobility assignment sub-module can be considered satisfactory. Note that, although this chapter simulates multiple activity-based travel attributes, validation is performed based on mode choice only due to unavailability of observed data, specifically in Canadian Census. Figure 7-4 shows the APE measures based on auto mode share. APE measures for transit and active transportation can be found in Appendix C (Figure C-6 and Figure C-7).

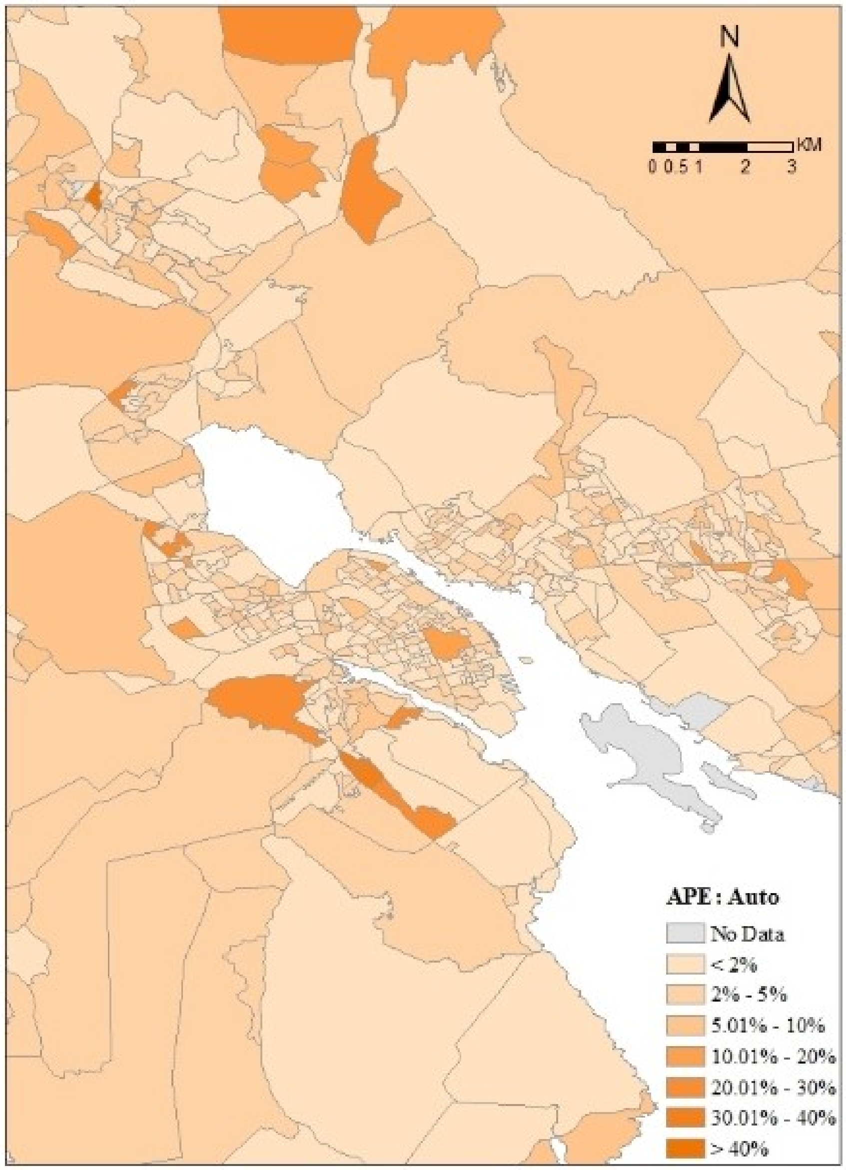

Figure 7-4 APE Measures of Auto Mode Share

7.3.2 Predicted Changes in Mode Choice from 2006 to 2036

Microsimulation of mobility assignment sub-module predicts the changes in mode choices from the base year 2006 to simulation year 2036. In each year, the majority of the activity-base tours are predicted to be made by the auto mode. More specifically, 85% of the total activity-based tours are performed by the auto mode in 2006. The share of the auto mode is predicted to drop to 81% in 2036. The percentage of transit mode choice is predicted to be 7.8% in 2036, which is a slight increase of 1.4% from the base year 2006. The walk mode share also increases from 7.1% in 2006 to 9.1% in 2036. Interestingly, the percentage of bike mode exhibits a stable trend over the years.

In terms of different types of activity-based tours, the SDS model predicts higher variations in mode choices during mandatory activity-based tours. For instance, 75% of mandatory activity-based tours are made by auto mode in 2036, which is a 11% drop from the base year 2006. The share of transit tours is predicted to increase from 8% in 2006 to 14% in 2036. The percentage of walk and bike modes in 2006 are 8% and 3% respectively, which increases by 4% and 1% over next 30 years. In the case of maintenance activity-based tours, 87% of the tours are predicted to be made by auto, 8% by transit, 4% by walk and 1% by bike in 2036, which are almost same as the mode choices in 2006. Mode choices of discretionary activity-based tours also exhibit similar stable trends over 30 years. 82% of the discretionary activity-based tours are made by auto, 16% by walk, 1% by transit and 1% by bike.

7.3.3 Predicted Changes in Mode Choices by Mobility Tool Ownership

Figure 7-5 exhibits the yearly evolution of mode choice by different mobility tool ownership, such as vehicle ownership, driver's license ownership and transit pass ownership. The implementation of mobility tool ownership sub-module within the iTLE urban model can be found in Fatmi and Habib (2018b). The sub-module is further improved in this version of the iTLE implementation, which can be found in Fatmi et al. (2019) and Khan et al. (2020).

The simulation results suggest that not owning any mobility tools results in a higher percentage of walk mode choice in 2006 (51%), which is predicted to drop to 45% in 2036. Interestingly, transit mode share is predicted to increase over the years in this case (42% in 2006 and 51% in 2036). With the increase in mobility tool ownership, the share of auto tours is found to increase in the same year. For example, individuals who own monthly transit passes, driver's licenses and at least 1 vehicle in the household, choose auto for 79% of their tours. However, a similar group of individuals who have multiple vehicles in the household, choose auto for 95% of their tours. Interestingly, such mode choices are predicted to decrease over the years. In 2036, for the above-mentioned group of individuals, the auto mode shares decrease by 5% and 1%, respectively. As expected, individuals who own monthly transit passes with different combinations of other mobility tools, exhibit a higher share of transit tours than the individuals with no monthly transit pass. For instance, in 2006, individuals who have driver's licenses and monthly transit passes but no vehicle in the household, choose transit mode for 36% of their activity-based tours, which is 33% for individuals who do not own a monthly transit pass with the rest of the mobility tool combination remaining same. For such groups of people, the transit tour share is predicted to increase over 30 years (47% and 37%, respectively). In addition, individuals who own driver's licenses and belong to the households with a higher number of vehicles demonstrate a higher percentage of activity-based auto tours; which is predicted to decrease over the 30-year simulation period.

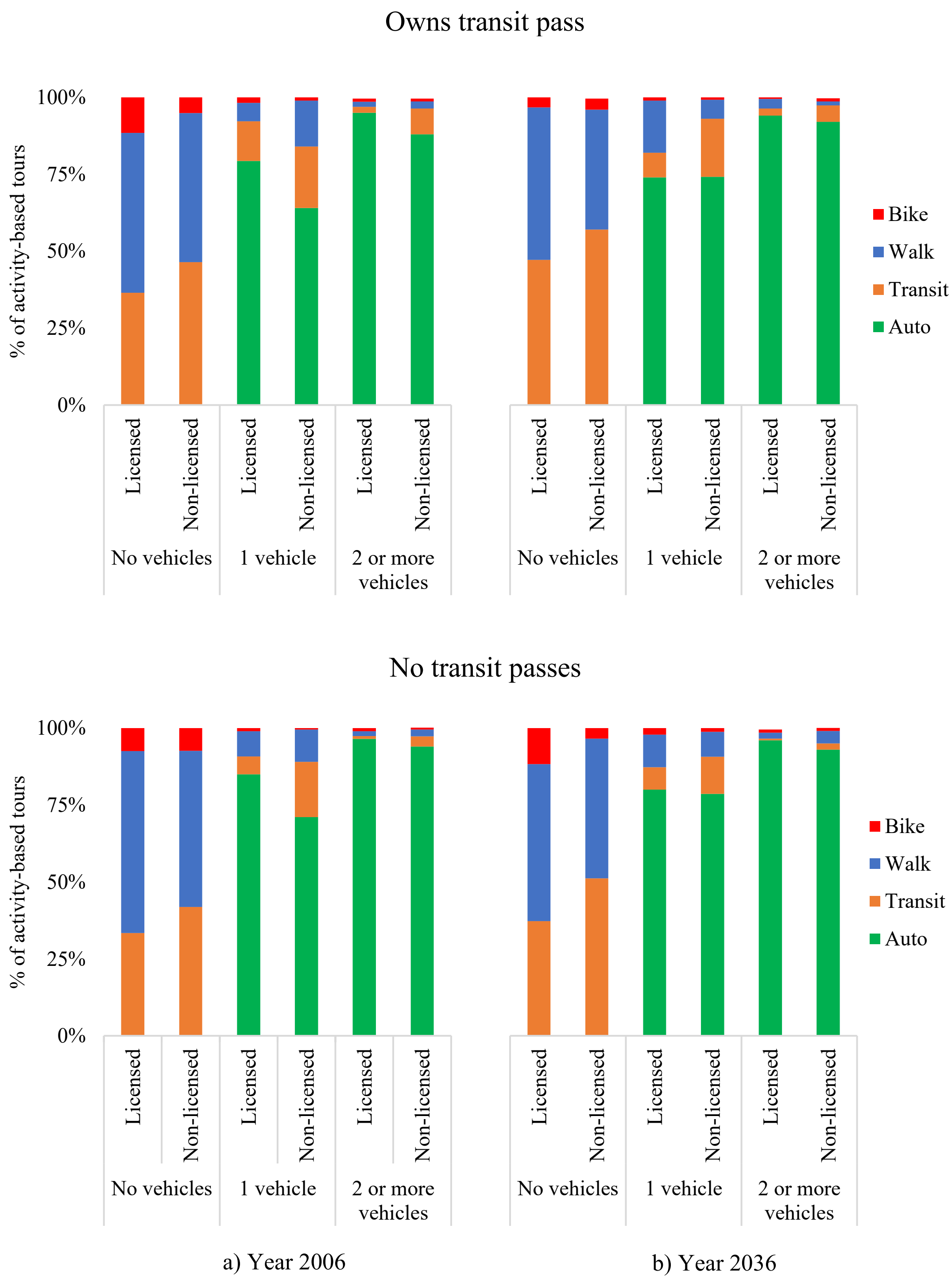

Figure 7-5 Predicted Mode Choices by Mobility Tool Ownership

7.3.4 Predicted Changes in Mode Choices by Shared Travel Choice Decisions

Auto mode choice for individuals' shared travel decisions exhibit interesting results for different types of activity-based tours. In the case of mandatory activity-based tours, the percentage of auto mode choice is predicted to decrease over the years for all types of shared travel arrangements. For example, in 2006, individuals' 81% of the mandatory tours with roommates are predicted to be made by auto mode which decreases to 47% in 2036. However, transit and active mode (walk and bike) shares are predicted to increase over 30-year period for all shared travel arrangements of mandatory activity-based tours. In the case of maintenance activity-based tours, auto mode share increases from 2006 to 2036 for the non-shared travel arrangement (i.e. travel alone); however, a slight decrease in auto mode choice is predicted for the other shared travel arrangements. For example, in 2006, individuals' 85% of the maintenance tours are predicted to be made by auto modes while traveling alone, which increases by 3% over the next 30 years. Transit and active mode shares are predicted to be stable over the years for all types of shared travel arrangements in case of maintenance activity-based tours. In the case of discretionary activity-based tours, auto mode share is predicted to increase for shared travel arrangements with children and decrease for shared travel arrangements with roommates/friends/colleagues. Auto mode share of other travel arrangements, such as travel alone, travel with a partner/spouse and travel with parents/other family members, are predicted to be stable from 2006 to 2036.

7.3.5 Predicted Mode Choices by Home to CBD Distance

Figure 7-6 presents the kernel density of home to CBD distance by mode choice for different activity types. This study assumes a Gaussian kernel function for optimal bandwidth selection to estimate the kernel density. The analysis reveals that in the base year 2006, the density for auto mode is skewed left of about 15 km for mandatory activity-base tours. The density for transit mode is skewed left of 12 km. The kernel density for active modes (walk and bike) is skewed left of 5 km. Such analysis suggests that individuals who live in distant places (mainly suburban areas, since locations 10 km away from the CBD are suburban areas in the context of Halifax) mostly use autos and transit for their mandatory activity-based tours. In addition, locations within 5 km from CBD are core downtown areas and such areas offer better active travel infrastructures, individuals live in those areas are predicted to use active modes mostly for their mandatory activity-based tours. For the maintenance and discretionary activity-based tours, distribution of active transportation modes indicates similar distributions to that of mandatory activity-based tours. However, for both maintenance and discretionary tours, density of auto mode shows more variability and is skewed to the left of 20 km. Interestingly, over the years, the kernel densities exhibit such left skewness in the higher distance region. For instance, in 2036, densities for auto, transit, walk and bike modes are skewed left of about 22 km, 18 km, 10 km and 15 km, respectively (Figure 7-6) in the case of mandatory activity-based tours.

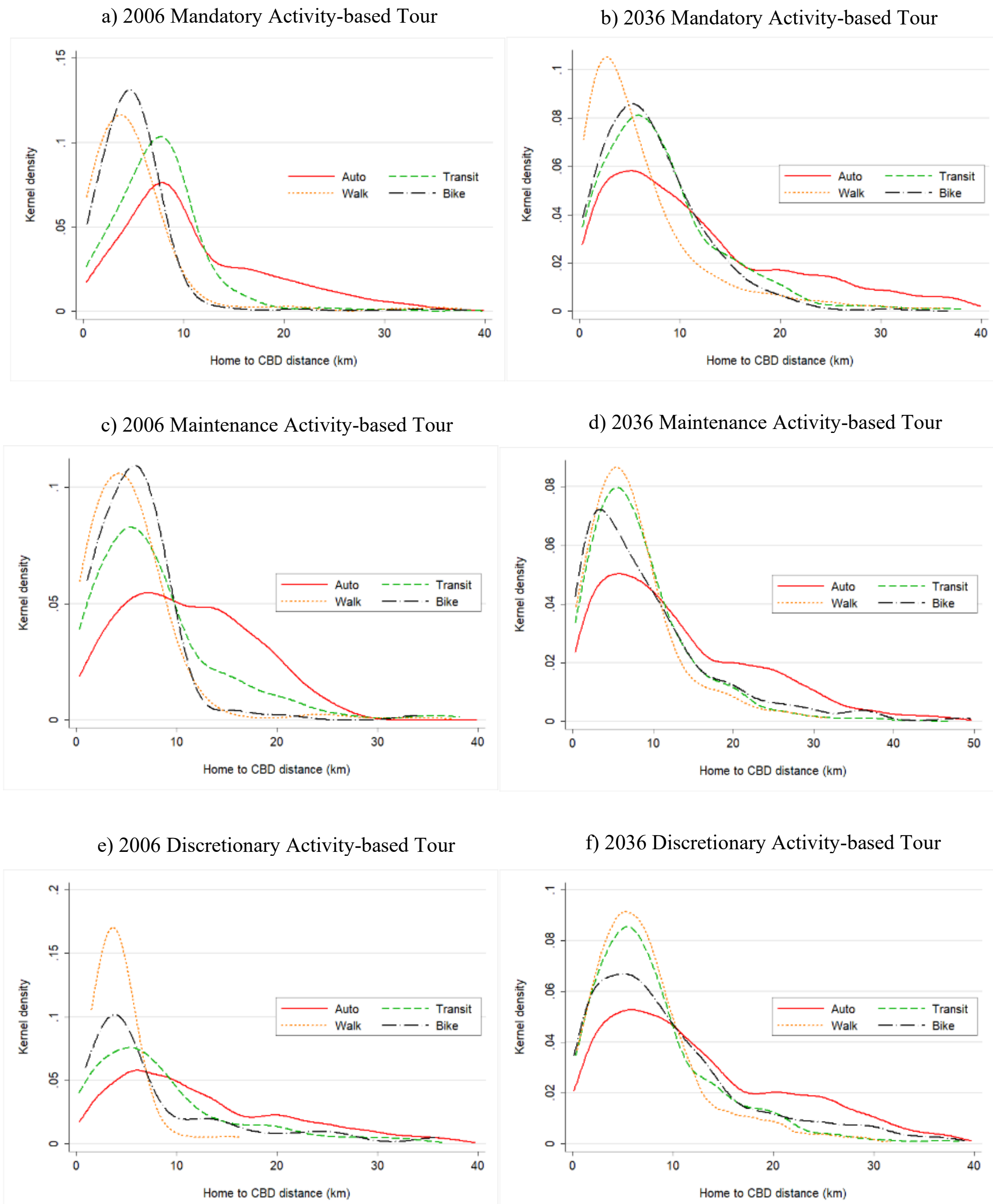

Figure 7-6 Predicted Distribution of Mode Choices by Home to CBD Distance

7.3.6 Predicted Changes in Vehicle Allocation from 2006 to 2036

The vehicle allocation component is implemented in this study for each year, starting from the base year 2006 to the simulation year 2036. Analysis of the microsimulation results suggest that higher proportion of the mandatory activity-based tours are performed by utilizing SUVs in 2006, whereas, smaller-sized vehicles (i.e. subcompact and compact) are allocated to majority of the maintenance and discretionary activity-based tours. In particular, 32% of the mandatory activity-based tours are performed by using SUVs in 2006; 29% of the maintenance activity-based tours are performed by using subcompact vehicles; and 36% of the discretionary activity-based tours are performed by using compact vehicles. Interestingly, the proportion of smaller-sized vehicles allocated to different activity-based tours are predicted to decrease in each year from 2006 to 2036. For instance, percentage of subcompact vehicles allocated to maintenance and discretionary activity-based tours are predicted to decrease by 23% in 2036. However, the model predicts an increase in larger-sized vehicle allocation over 30 years for all types of activity-based tours. For example, 44% of the mandatory activity-based tours are performed by using SUVs in 2036, which is a 12% increase from 2006. Figure 7-7 exhibits the predicted vehicle allocation for 2006 and 2036.

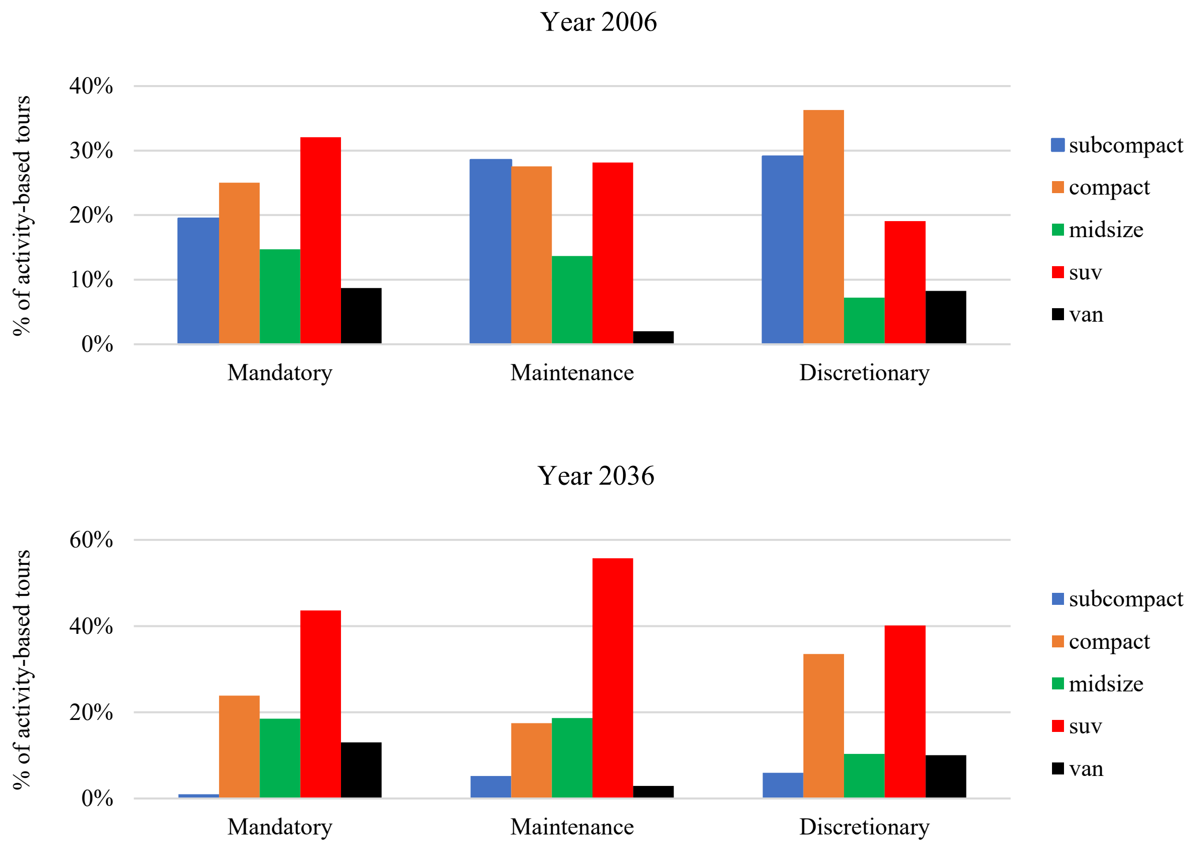

Figure 7-7 Predicted Vehicle Allocation in 2006 and 2036

7.3.7 Predicted Vehicle Allocation by Shared Travel Arrangements

Figure 7-8 exhibits predicted changes in vehicle allocation by shared travel arrangements. In 2006, higher proportion of subcompact vehicles (28%) are allocated to the non-shared travel arrangement. While traveling with a companion (i.e. partner/spouse, children, parents/other family members, roommates), the proportion of subcompact vehicles is predicted to be lower than that of traveling alone. Instead, the percentage of compact vehicles and SUVs are predicted to increase, with the compact vehicle percentage being the highest. For example, 33% of the shared travel with parents/other family members are predicted to be performed by using compact vehicles; 29% by SUVs and 24% by subcompact vehicles. However, over the 30-year period, the proportion of smaller vehicle (e.g. subcompact vehicle) allocation decreases in the case of all travel arrangements. Larger vehicles such as SUVs are predicted to be allocated for different activity-based tours in 2036 for all shared travel arrangements. Such prediction results might be attributed by the vehicle allocation model estimation results, where the joint activity-based tour models exhibit positive parametric values for joint shared travel choices with household and non-household members in case of larger vehicle allocation, and negative values for smaller vehicle allocation.

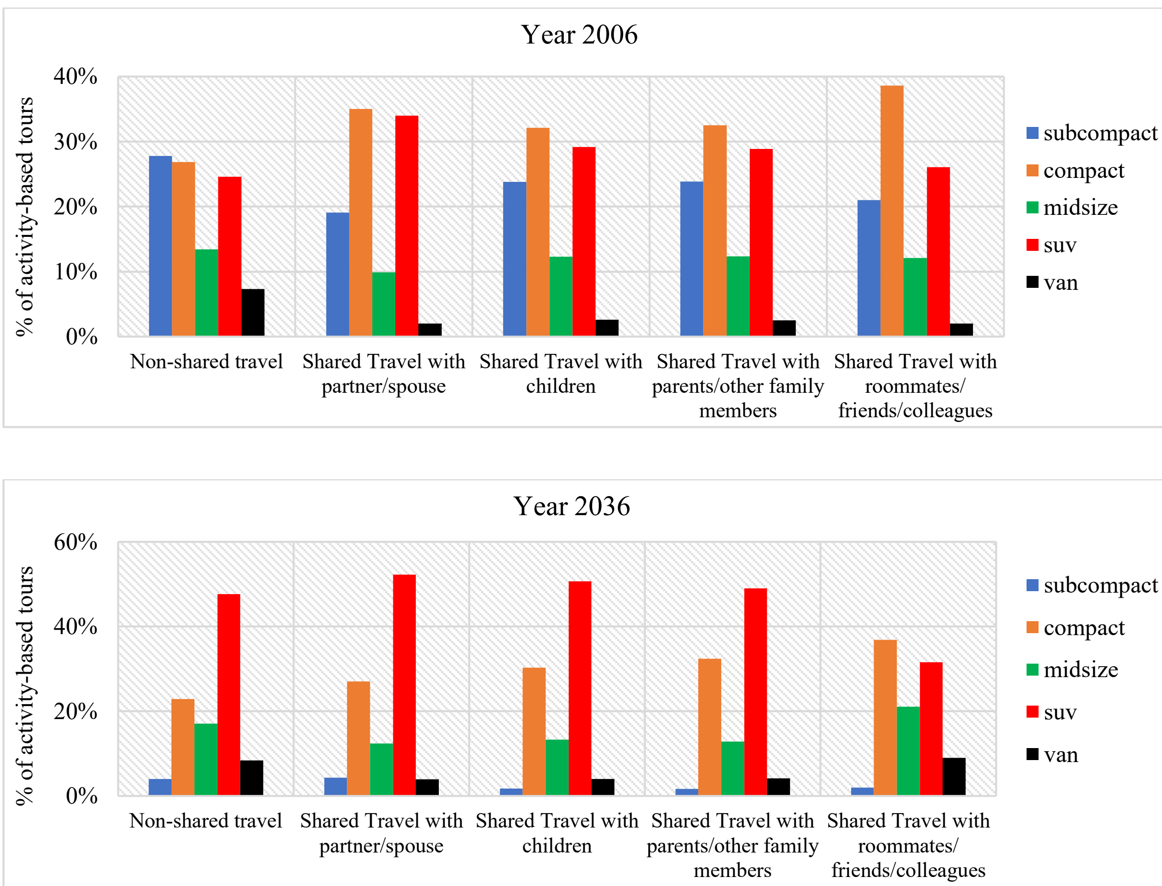

Figure 7-8 Predicted Vehicle Allocation by Shared Travel Arrangements

7.4 Conclusions

This chapter presents the findings of microsimulating a mobility assignment sub-module of the activity-based shorter-term decisions simulator (SDS). The model is implemented within an agent-based urban microsimulation system platform, iTLE. This research particularly presents the micro-behavioural model estimation, microsimulation procedure, and microsimulation results of mobility assignment, which is a two-stage dynamic process of mode choice and vehicle allocation. The micro-behavioural models are developed utilizing a mixed logit modelling technique. Estimation results of the micro-behavioural models confirm that individuals' interactions with household and non-household members via their shared travel choices have considerable effects on mode choice and vehicle allocation decisions. The model generates the baseline mode choice and vehicle allocation information for the year 2006 and simulates agents' mobility decisions from 2007 to 2036 in each year.

The validation results of the mobility assignment sub-module suggest that the SDS model performs quite well in predicting the mode choice and vehicle allocation decisions. The model is calibrated to the 2011 National Household Survey data, and microsimulation results are validated with 2006 and 2016 Canadian Census information. The validation for spatial representation of mode choice is performed based on absolute percentage error (APE) measures, which is estimated using simulated commute mode share data of the base year and 2006 Canadian Census at dissemination area (DA)-level. Majority of the dissemination areas exhibit APE values less than 5% for each mode. Also, maximum difference between simulated and observed commute mode categories from 2016 Canadian Census is found 2%. Based on the APE measures and comparative analysis, SDS is considered to generate satisfactory mode choice and vehicle allocation estimates for the Halifax population. The microsimulation results of the mode choice component suggest that the majority of the tours are predicted to be made by auto mode in the base year as well as in all of the simulation years. This proportion is predicted to decrease over the 30-year periods, whereas, transit and walk mode shares are predicted to increase. In terms of the long-term mobility tool ownership, the model provides interesting insights. Individuals' zero mobility tool ownership results in higher walk mode share in the base year. Over the years, transit mode share is predicted to increase, and the proportion becomes highest among all mode share in 2036. With the increase in number of mobility tools, this model predicts a higher auto mode share over 30 years. In terms of shared travel arrangements, the proportion of auto mode is predicted to decrease from 2006 to 2036. The vehicle allocation microsimulation results suggest that majority of the mandatory activity-based tours are performed by using SUVs in 2006, however, the percentage is higher for subcompact and compact vehicles during maintenance activity-based tours and discretionary activity-based tours, respectively. The proportion of smaller-sized vehicles allocated to different activity-based tours are predicted to decrease in each year from 2006 to 2036, whereas, SUV is predicted to be allocated to much of the activity-based tours in 2036. Results also suggest that non-shared travel is predicted to be performed mostly by subcompact vehicles in 2006. During joint travel, percentage of subcompact vehicle allocation is found to be lower than that of traveling alone. Interestingly, in 2036, SUVs are predicted to be the highest allocated vehicle for all types of travel arrangements.

This study has certain limitations. For instance, it simulates the mobility assignment sub-module based on broad activity-based tour categories due to data limitation. Immediate future work includes analysing mode choice and vehicle allocation components within the mobility assignment sub-module based on more disaggregate-level tours once data will be available from the new NovaTRAC survey. Also, the stop-level modelling and microsimulation of such components have not occurred in this study. Future research should focus on implementing mode choice and vehicle allocation at stop-level in order to develop a more comprehensive activity-based travel demand model. The current prototype SDS model considers only four types of modes (auto, transit, walk and bike) during the empirical and computational procedures of mobility assignment. Based on data availability, future research should consider alternative modes while estimating and simulating mode choice decisions. Furthermore, in this study, vehicle allocation component assumes that all vehicles are equally likely to be used by any member of the household. Due to data unavailability, it overlooks the fact that vehicles often belong to or are usually used by a specific household member. Therefore, a primary driver allocation model should be implemented, which would assign a specific type of vehicle from the households' existing vehicle fleet to a specific person in the household. Finally, the microsimulation results of the sub-module are validated on the basis of only work-based tours' modal share due to the absence of a comprehensive activity-travel survey. Future research should aim at conducting a large-scale NovaTRAC survey that could provide more information for validating the mobility assignment sub-module. Note that the predicted behaviour presented in this chapter is based on the models developed for the base year. It does not account for fundamental changes in future years with respect to activity needs and travel arrangements (e.g. post COVID-19 years). Nevertheless, this research shows the predictive capacity of the model, which can be used as a decision support tool to accommodate major shifts in behaviour over the years within the modelling system, if necessary.

In summary, this research contributes to the current travel demand modelling literature by implementing the dynamic mobility assignment decision procedures within an activity-based shorter-term decisions simulator (SDS). Implementation of mode choice and vehicle allocation process mechanisms within a multi-year travel demand forecasting tool that addresses social interactions in both empirical and computational settings assist to predict travel demand in a more behaviourally consistent way. In particular, explicit estimation and simulation of the underlying behavioural process mechanisms of vehicle allocation within the SDS microsimulation model enhance the capacity of the iTLE urban model to estimate future network-level emission and energy consumption in a more improved way. This research would help to develop and test alternative transportation and land use policy interventions that support to develop sustainable, safe and convenient transportation infrastructures as well as create viable and diverse neighbourhoods.

Chapter 8

Conclusions

8.1 Summary of the Modelling and Microsimulation Framework

The primary reason to shift from trip-based analysis of travel demand to the activity-based analysis is due to the notion that individuals' travel decisions are derived from their desire to participate in activities. Motivations behind travel are being ignored in trip-based analysis that results in behaviourally unrealistic travel pattern. An activity-based analysis recognizes travel as the outcome of daily needs, which are fulfilled by undertaking activities. Such approach captures underlying decision processes of activity and travel behaviour that assists to model individuals' travel demand more realistically and improve forecasting ability. Moreover, the need for testing new and emerging travel demand management strategies, and alternative land use and transportation policy interventions lead to the development of activity-based travel demand microsimulation model. An activity-based travel model simulates the process mechanisms of a wide range disaggregate individual-level activity and travel decisions. Activity generation, activity scheduling and mobility decisions are the major critical elements of an activity-based travel demand model. This thesis contributes to the current activity-based modelling and microsimulation research by representing disaggregate individual-level activity and travel behaviour in a more behaviourally plausible way. In particular, this thesis presents the development of alternative econometric modelling approaches of individuals' activity and travel decisions, as well as implementation of the components of activity generation, activity scheduling and mobility assignment within an activity-based shorter-term decisions simulator (SDS).

The research in this thesis provides a review of the existing activity-based literature to identify multiple research gaps. First, there is a gap in understanding the influence of modal accessibility on individuals' daily activity engagement. Investigation of such relationship is important due to its direct implications in the transportation network. Secondly, the underlying behavioural mechanism of individuals' shared travel choices that accommodate their social interactions with household and non-household members is not well addressed in the existing activity-based research. In addition, how such shared travel choices influence individuals' daily activity engagement, is not evident. The relationship between individuals' social utilities (derived from shared travel choices) and activity engagement is critical to explore since it accommodates both the needs of travellers and the companions. Thirdly, evaluation of vehicle allocation decisions in the households for different activity purposes is limited in the existing activity-based literature. Such decisions are crucial in a household decision process since they not only address various interactions among household and non-household members, but also may influence the estimation of emission and energy consumption in transportation networks. Finally, the existing activity-based travel demand microsimulation models do not address the process mechanisms of sequential activity generation, shared travel choices and vehicle allocation decisions. Based on the research gaps, this thesis develops alternative econometric models to investigate different activity and travel attributes, namely activity participation, time allocation, mode choice, shared travel choice and vehicle allocation at activity-based tour-level. Activity participation and time allocation decisions are modelled as a joint decision. The impacts of modal accessibility and social utility on activity participation is estimated by implementing coupling mechanisms that provide logsum-based feedbacks to the activity engagement decisions . Such mechanisms carry all information (socio-demographic characteristics, activity-travel attributes, neighbourhood characteristics and accessibility measures) made during the mode choice or shared travel choice decisions, hence, provide behaviourally consistent interdependencies among activity and travel components.

This research proposes a novel framework to develop a prototype activity-based travel demand microsimulation model, namely shorter-term decisions simulator (SDS). The SDS model is implemented within the agent-based integrated Transportation, Land use and Energy (iTLE) modelling system. iTLE consists of three modules: longer-term decisions simulator (LDS), shorter-term decisions simulator (SDS) and traffic flow simulator (TFS). SDS takes inputs from the LDS module and simulates various activity and travel decisions at each simulation time-step by considering individuals' social interactions within the modelling framework. The model has three major sub-modules: activity generation, activity scheduling and mobility decisions. Each sub-module consists of multiple activity and travel components, which are implemented following various heuristics and econometric modelling methodologies. Activity generation sub-module involves simulating types and number of activities to form an activity program that an individual performs in a day. Activity scheduling is conceptualized as a three-stage process of activity agenda formation, destination location choices and shared travel choices. Activity agenda formation involves generating durations and start times of the activities. Destination location choice component simulates the locations for each activity. Activity plans are formed at this step that consists of activity program, duration, start time and destination location. At the final stage, shared travel choice component simulates shared travel arrangements by recognizing individuals' social interactions with household and non-household members within the empirical and computational processes of the component. This component assists to couple the activity scheduling and generation sub-modules by providing social interaction-based feedbacks to the activity plans to execute planned activity schedules. Mobility assignment sub-module is a two-stage dynamic procedure of mode choice and vehicle allocation. Both components of mobility assignment are implemented by considering social interactions within their micro-behavioural as well as microsimulation framework. Mode choice component simulates different types of modes for different activity-based tours. Vehicle allocation component simulates the type of vehicle from households' existing vehicle fleet available during different auto-based activity-tours. Travel times by each mode are generated at the end of the process, which assist to couple the mobility assignment and activity scheduling sub-modules by giving feedback to daily activity plans in activity scheduling process. Finally, activity schedules with modes and vehicles are formed by the SDS microsimulation model.

This thesis utilizes multiple data sources to develop the alternative econometric modelling approaches of estimating activity and travel decisions, and the activity-based SDS microsimulation model. The primary data source is a cross-sectional Nova Scotia Travel Activity (NovaTRAC) survey conducted in Halifax, Nova Scotia, Canada. The survey collected various household- and individual-level information, and each household member's activity and travel information. A 24-hour travel log was included in the survey that collected each household member's information on activity location, purpose, arrival and departure time, mode of travel, vehicle used for the activity and travel companion. In addition, secondary data sources include Canadian Census, National Household Survey (NHS), Halifax Regional Municipality (HRM) land use database, Desktop Mapping and Technologies Inc. (DMTI) database, HRM road network, transportation network-level skim datasets, Info Canada Business Establishment dataset, and households' long-term decisions datasets. Independent variables such as socio-demographic characteristics, activity and travel attributes, neighbourhood characteristics and accessibility measures are derived from the primary and secondary data sources, which are tested during the micro-behavioural model estimation procedure. In addition, the simulation procedure utilizes data from the households' long-term decisions datasets that provide input information for the SDS microsimulation model. A summary of the micro-behavioural model estimation and microsimulation model results is presented below.

8.2 Summary of Results

The research develops an alternative micro-behavioural modelling approach to investigate different activity-based tour-level attributes, namely activity participation, time allocation and mode choice decisions and interdependencies among them. The modelling methods and estimation results are discussed in chapter three. The activity-based tours are home-based, which start and end at home. Such tours are formed based on primary activities of the activity chains. To develop the econometric micro-behavioural models, activities are categorized as: mandatory activities (work, school), maintenance activities (shopping, escorting, personal business, etc.) and discretionary activities (dine out, recreation, etc.). The activity-based tour-level mode choice models are developed for mandatory activities and non-mandatory activities (maintenance and discretionary activities) following mixed logit (MXL) modelling technique that capture unobserved heterogeneity for repeated observations from same individual. The tour-level participation and time allocation decisions into mandatory, maintenance and discretionary activities (in addition to an 'at-home' alternative) are estimated jointly by developing a multiple discrete-continuous extreme value (MDCEV) model in this research. In order to ensure the model integration and capture the influence of the transportation network level modal accessibility on the activity engagement decisions, logsum values calculated from mode choice models are incorporated into the joint model that provides behavioural consistency within the modelling framework. The model estimation results suggest that a number of socio-demographic characteristics, activity-travel attributes, neighbourhood characteristics and accessibility measures are found to affect individuals' mode choice decisions at tour-level. For instance, older individuals tend to choose auto as their primary mode during a mandatory activity-tour. Land-use index shows positive coefficient values for transit, bike and auto, although higher coefficient value for transit indicates individuals' higher preference for transit during mandatory activity-tours. However, significant standard deviation of land-use index for auto mode reveals some individuals' behavioural variation of auto preference while living in mixed land-use areas. In case of non-mandatory activity-tour, female respondents are found to choose auto rather than bike as their primary mode. Also, individuals tend to prefer auto in a non-mandatory activity-tour while traveling with partner/spouse. The mixed logit (MXL) model of mode choice revealed extensive heterogeneity of modal preference among the population for both the mandatory and non-mandatory activity-tour types. The standard deviations of the modal constants indicates significant variability in the modal preference among the individuals of the region. The activity-based tour participation and time allocation model also exhibit reasonable estimation results. For example, individuals belonging into 18 to 24 years age group are highly likely to participate in mandatory and discretionary activity-based tours, and less likely to participate in maintenance activity-tour. However, this age group are more likely to spend less time on their mandatory activity-tour compared to the old individuals. The coefficients to the mode choice logsum values are found positive, which suggests that higher modal accessibility in the transportation network increases individuals' probability to engage in more activity-based tours.

The findings of a tour-level activity participation, time allocation and shared travel choices model are presented in chapter four. The shared travel choice decisions for different activity-based tours are estimated by developing MXL models. Participation and time allocation in different activity-tours are modelled jointly following a MDCEV model, where the temporal constraint of a 24-hour time limit is accommodated within the modelling framework. One of the unique features of this research is to implement coupling mechanism between the shared travel choice and activity participation decisions that explore how social utility, which accounts for individuals' social interactions while traveling, influences the daily activity-based tour participation decisions. Model estimation results suggest that the social utility parameters, derived from mandatory, maintenance and discretionary activity-tour shared travel choice decisions via logsum values, are found positive and statistically significant for all types of activity-based tour participation. This indicates individuals' higher propensity to participate in more activity-tours due to the social utility that arises from individuals' desire to fulfil self-needs and needs-of-others during their travel. Model results also offer interesting insights. For instance, individuals exhibit higher probability to participate in mandatory activity-based tours instead of participating in other activity-tours in a one-vehicle household. However, with the number of vehicles in the households, an individuals' tendency to participate in different activity-tours increases. In case of the time allocation, young individuals who are less than 25 years old tend to spend more time on mandatory activity-based tours and less time on discretionary activity-tours. An opposite relationship is found for the individuals who are 25 to 34 years old. The shared travel choice model results suggest that a higher travel time increases individuals' probability to travel with a companion rather than traveling alone. They are more likely to travel with a partner/spouse, children and roommates/friends/colleagues during their mandatory activity-tours. However, a higher standard deviation of travel time in the case of traveling with children indicates some individuals' tendency to travel less with children if travel time is higher. In case of maintenance activity-tours, higher travel time increases individuals' propensity to travel with a partner/spouse. Furthermore, individuals from zero-vehicle households are more inclined to travel with a partner/spouse and roommates/friends/colleagues during their discretionary activity-tours. Participating in discretionary activity-based tours at late morning and afternoon is found to increase individuals' probability to travel with a partner/spouse.

The vehicle allocation decisions for different activity-based tours are estimated by developing latent segmentation-based random parameter logit (LSRPL) models in chapter five. This research offers insights on the behavioural variations of activity-based vehicle allocation decisions, while incorporating individuals' social interactions within the modelling frameworks through their shared travel choices, namely traveling alone (i.e. solo travel) or traveling with partner/spouse, children, parents/other family members, and roommates/friends/colleagues (i.e. joint travel). Four LSRPL models are developed in this research for solo mandatory activity-based tours, joint mandatory activity-based tours, solo non-mandatory activity-based tours and joint non-mandatory activity-based tours. The models capture taste preference heterogeneity across individuals by implicitly sorting them into two discrete latent segments. Results of the latent segment allocation components of all four vehicle allocation models suggest that segment one can be probabilistically identified as the segment of older-higher income individuals, whereas, segment two as the segment of younger-lower income individuals based on their socio-demographic characteristics. In addition, individuals' unobserved preference heterogeneity within each latent segment are also captured during model estimation by introducing random parameters within the modelling process. The model results suggest that individuals' activity and travel characteristics, attitudinal variables, neighbourhood characteristics and accessibility measures have considerable impacts on vehicle allocation decisions in multi-car households. For instance, during joint mandatory and non-mandatory activity-tours, individuals' probability of getting SUVs is found higher in the presence of children within the tours. Interestingly, positive attitude towards active transportation decreases the probability of getting vehicles from household's available existing vehicle fleet during both solo and joint mandatory activity-tours. Nevertheless, in case of non-mandatory activity-tours, individuals tend to prefer subcompact vehicles despite being positive towards active transportation. 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. Findings of the vehicle allocation models demonstrate the existence of substantial heterogeneity 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' behavioural preference heterogeneity within each segment during joint mandatory activity-tour by showing significant standard deviations.

In the case of developing an activity-based travel demand microsimulation model, this thesis implements the prototype version of the activity-based shorter-term decisions simulator (SDS) in Halifax, Canada. The model implements activity generation, activity scheduling, and mobility assignment sub-modules within an agent-based microsimulation platform called 'iTLE Sim'. iTLE Sim is programmed using C# language under the .NET framework. iTLE generates a 100% synthetic population of Halifax is generated in iTLE for the base year 2006. However, 10% synthesized population sample is considered for the 30-year simulation run. The SDS microsimulation model takes input from the LDS module of the iTLE urban model that provides longitudinal information on residences, households, individuals and vehicles from 2006 to 2036. Based on this, SDS simulates individuals' activity-travel decisions for a typical weekday in each yearly time-step for the 30-year period. The SDS modelling codebase is established as a model-view-viewmodel (MVVM) framework, which separates user interface from the back-end program logic. Such framework allows for cleaner and more efficient implementation. Microsimulation of SDS for each time-step takes about 15 minutes on a computer with Core i7-4770 processor and

16 GB of RAM, running on a 64-bit Windows 7 operating system. In chapter six, the SDS microsimulation model first develops the activity generation sub-module that implements a Markov Chain Monte Carlo modelling technique within the microsimulation framework to simulate sequential activities at a 24-hour temporal scale. Activity generation sub-module simulates daily activity programs that includes different types and number of activities. After that, activity scheduling sub-module is implemented that involves microsimulation of activity agenda, destination location and shared travel choices. Following a heuristics modelling approach, activity agenda component simulates duration and start time of each activity. Destination location choice component utilizes a conditional logit model to simulate the destination locations of the activities generated by the activity generation sub-module. Finally, shared travel choice component simulates the shared travel arrangements accommodating individuals' social interactions with household and non-household members. Shared travel choice component is implemented using a mixed logit modelling technique. The SDS microsimulation modelling framework addresses social interactions by implementing a feedback mechanism within the activity scheduling process that contributes to reassess daily activity plans. The validation of the microsimulation results of activity generation and scheduling sub-modules suggest that SDS performs reasonably well in generating different activity attributes. This study performs the validation of SDS microsimulation model by estimating absolute percentage error (APE) values and by comparing simulated data with observed data. The simulation results predict the changes in activity participation over the years in Halifax, Canada. Results predict a 5% decrease in work activities, and a 3% and 4% increase in recreational and shopping activities, respectively, from 2006 to 2036 in Halifax. Spatial distribution of different

activities indicates that work activities increase over the years in the core downtown areas of Halifax and Dartmouth. Maintenance (shopping and personal business) and discretionary (dine out and recreational) activities are also predicted to increase in urban areas of Halifax and Dartmouth from 2006 to 2036. Results predict a decrease in home to activity destination location distances in the case of mandatory (work and school) and maintenance (shopping and personal business) activities in the year 2036 compared to the base year 2006. In terms of average time spent at activities, individuals are predicted to decrease the time spent at work and shopping activities over 30 years. However, average time spent per person at recreational and dine out activities are predicted to increase from 2006 to 2036. In terms of shared travel choice decisions, the majority of work-based tours are predicted to be performed by traveling with a partner/spouse that is predicted to drop slightly over the 30-year period. As expected, much of the school-based tours are predicted to be performed by traveling with parents/other family members, which exhibits an increasing trend from 2006 to 2036. Interestingly, in the case of maintenance and discretionary activity-based tours, a higher percentage of activity-based tours are predicted to be performed alone. In terms of travel length, individuals are predicted to travel alone when the travel length is shorter. However, higher percentages of travel shared with an accompanying person are predicted as the travel length increases. In terms of age groups, this research predicts that mostly older adult (41-64 years) and senior (above 64 years) people travel alone while performing different types of activity-based tours. However, younger people (age below 25 years) are predicted to travel with parents/other family member and roommates/friends/colleagues more while performing different activity-based tours.

Finally, the mobility assignment sub-module is implemented within the SDS microsimulation model in chapter seven. Mobility assignment is a two-stage dynamic process of mode choice and vehicle allocation. The micro-behavioural models are developed utilizing a mixed logit modelling technique. Estimation results of the micro-behavioural models confirm that individuals' interactions with household and non-household members via their shared travel choices have considerable effects on mode choice and vehicle allocation decisions. The model generates the baseline mode choice and vehicle allocation information for the year 2006 and simulates individuals' mobility decisions from 2007 to 2036 in each year. The validation results of the mobility assignment sub-module suggest that the SDS model performs quite well in predicting the mode choice and vehicle allocation decisions. Similar to the activity generation and scheduling sub-modules, the microsimulation results of mobility assignment are validated by comparing simulated data with observed data and by estimating dissemination area-level APE values. The microsimulation results of the mode choice component suggest that the majority of the activity-based tours are predicted to be made by auto mode in the base year as well as in all of the simulation years. However, the proportion of auto mode is predicted to decrease over the years. In contrast, transit and walk mode shares exhibit an increase from 2006 to 2036. The model predicts that zero mobility tool ownership results in a higher percentage of transit mode choice in 2036. However, higher auto mode share is predicted with the increase in the number of mobility tool ownerships. In terms of mandatory activity-based tours shared travel arrangements, the percentage of auto mode choice is predicted to decrease over the years for all types of shared travel arrangements. Vehicle allocation microsimulation results suggest that majority of the mandatory activity-based tours are predicted to be performed by using SUVs in 2006, however, the percentage is higher for subcompact and compact vehicles during maintenance activity-based tours and discretionary activity-based tours, respectively. The proportions of smaller-sized vehicles allocated to different activity-based tours are predicted to decrease in each year, and majority of the activity-tours are predicted to be performed by SUVs. Interestingly, the model predicts that in 2036, SUVs will be the highest allocated vehicle for all types of activity-based tours and shared travel arrangements.

8.3 Contributions of the Thesis

This thesis contributes in the activity-based travel demand research in terms of both micro-behavioural and microsimulation modelling perspective. It attempts to estimate and simulate agents' multiple activity and travel decisions in a behaviourally plausible way by addressing social interactions within the empirical and computation procedures. Alternative econometric modelling-based methods are developed in this thesis to investigate agents' activity and travel decisions. An activity-based travel demand microsimulation model – shorter-term decisions simulator (SDS) is conceptualized and prototype model is implemented in this thesis that recognizes various process mechanisms during the model estimation and simulation procedure. Following is a brief discussion on the major contributions of this research.

1. **Develops advanced and innovative alternative econometric modelling-based methodologies to model activity and travel decisions.**

- A multiple discrete-continuous extreme value (MDCEV) model is developed in this thesis to estimate the joint decisions of activity participation and time allocation, where 'time' is considered as a continuous component. The model has the ability to tackle multiple activity type choice and time allocation decisions simultaneously in a single framework.
- Advanced econometric models are developed to address the repeated choices and capture unobserved heterogeneity. For instance, this thesis develops mixed logit models to explore mode choice and shared travel choice decisions. The research also develops latent segmentation-based random parameter logit models to investigate the vehicle allocation decisions for different activity-based tours. The LSRPL models capture two layers of heterogeneity in the case of vehicle allocation – first, by allocating individuals probabilistically into multiple latent segments; second, introducing random parameters to capture unobserved heterogeneity within each latent segment.

2. **Advances methods for coupling mechanisms within activity-based models.** This thesis implements activity-based feedback mechanisms within the econometric modelling framework that not only couple different activity and travel components, but also ensure the integration and behavioural consistency among different activity and travel decisions. For example, a feedback mechanism from mode choice decisions is implemented in the tour-level activity participation and time allocation model via logsum values that carry information about the decisions made on mode choices; thus, explore the modal accessibility in the transportation network for multiple activity-based tours. This thesis also implements a feedback mechanism from shared travel choices to

the tour-level activity participation and time allocation model in the form of social utility, which is estimated through logsum measures from shared travel choices. This social utility explores individuals' desire to fulfil self-needs and needs-of-others while participating in different activity-based tours. Furthermore, this thesis estimates activity-based accessibility measures to use in the LDS module of iTLE modelling system that provide a mechanism for full integration of land use and transportation models.

3. **Develops shared travel choice micro-behavioural models coupled with activity decisions.** This research develops shared travel choice models that address individuals' social interactions with partner/spouse, children, parents/other family members and roommates/friends/colleagues. Investigation of such choice decisions for different activity-tours in terms of socio-demographic, neighbourhood and activity-travel characteristics provide a better understanding of the underlying behavioural process of individuals' interactions with household and non-household members.

4. **Develops conceptual and computational framework of an activity-based travel demand microsimulation model, known as shorter-term decisions simulator (SDS).** The microsimulation model consists of following sub-module: activity generation, activity scheduling and mobility assignment. Multiple activity and travel related decision components are implemented within the computational framework of SDS model, such as activity types, frequencies, durations, start times, destination location choices, shared travel choices, mode choices and vehicle allocation. The model simulates activity and travel decisions for a 30-year period, starting from the base year

2006 to 2036. The model contributes in the activity-based research paradigm in following ways:

- A Markov Chain Monte Carlo method is implemented within the microsimulation modelling framework to develop the activity generation sub-module of the SDS model. In this process, instead of random generation, activities are generated sequentially where occurrence of next potential activity depends on the occurrence of current activity. Implementation of such process to predict multi-year activity participation within a microsimulation framework provides a behaviourally plausible way of generating activities.
- Shared travel choice models are implemented within the activity scheduling process of SDS model that explicitly recognize individuals' social interactions with household and non-household members. Microsimulation of the underlying behavioural processes of shared travel choices is critical since it contributes in reassessing daily activity plans.
- Finally, this thesis implements activity-based tour vehicle allocation decisions within the mobility assignment sub-module of the SDS model. In this process, different types of vehicles (categorized based on the body types) are allocated to different activity-based tours on the basis of households' existing vehicle fleet as well as availability of vehicles during the time of the tour. The process of vehicle allocation accommodates individuals' social interactions within its empirical and computational settings.

8.4 Policy Implications

The activity-based travel demand research presented in this thesis has important implications in integrated transportation land use and land use planning. The proposed prototype SDS microsimulation model as well as the findings obtained from this thesis can be used to test policy scenarios and develop critical policy interventions. Emerging policy scenarios can be evaluated within the SDS microsimulation tool by controlling multiple simulation and modelling parameters, and running the SDS model to predict the evolution of activity and travel decisions under those scenarios. Following is a brief discussion on the policy implications based on this thesis.

1. This thesis offers an operational activity-based shorter-term decisions simulator (SDS) for Halifax, Canada, which has multi-year prediction capability. Therefore, transportation planners and policymakers in Halifax can utilize this model for alternative policy testing. For example, Halifax Regional Council has recently introduced an Integrated Mobility Plan (IMP) (2017) to reduce vehicle usage and traffic congestion, and increase active transportation and transit usage and more efficient use of road capacity by 2031. To achieve such targets, IMP has suggested multiple strategies such as congestion pricing, incentive to own transit pass, promoting alternatives for single-occupant trips, alternative work schedules, and telecommuting, among others. The proposed SDS microsimulation model in this thesis can be used to examine such policy scenarios and inform the policymakers whether to achieve the goals set by the integrated mobility plan.

2. Predicted activity and travel patterns offer important insights about how the city will evolve in terms of activity density, shared travel demand, modal share and vehicle usage. This would assist to develop policy interventions, for instance, what types of shared mobility opportunities may work in Halifax and where it may have the highest impact.
3. The SDS microsimulation model complements the development of the iTLE urban model. Since iTLE provides multi-year prediction of land use and transportation, various alternative policy scenarios can be examined utilizing the model. For instance, the Halifax Centre Plan (2019) aims a 40% growth in the regional centre by the year 2031. This includes well-designed and high-density developments in mixed land-use areas, compact and walkable neighbourhoods, and more residential density to well-served biking areas, among others. Policy scenarios can be developed that reflect such land use plans. Then the iTLE model can be run to understand impacts of these land use plans on the activity patterns and transportation networks.

Furthermore, the findings from the activity participation, time allocation and mode choice analysis indicate positive and significant impacts of modal accessibility on individuals' activity engagement decisions. This suggests that higher accessibility in transportation network via multiple modal alternatives increase individuals' probability to perform more activity-based tours on a daily basis. Such modelling methodology can be used to test the sensitivity of the activity engagement decisions in response to the policies related to the variations in the network-level accessibility (e.g. congestion pricing) as manifested by the changes in the mode choice logsum values. Moreover, parameter estimation results of the vehicle allocation models have critical policy implications. For instance, people living in higher mixed land-use areas are more likely to get smaller subcompact vehicles than midsize vehicles and SUVs in suburban areas for solo mandatory activity-tours. This suggests that a better designed neighbourhood with diverse land uses and sustainable transportation options may encourage individuals to decrease their usage of larger vehicles, thus reducing daily fuel consumption.

The microsimulation results of the activity-based SDS model offer interesting insights. For instance, compared to the baseline information, out-of-home work activities and time spent at such activities are predicted to decrease over the years. Such prediction could be useful to promote telecommuting and alternate work schedules. Also, mode choice microsimulation process predicts a reduction in auto mode share over the years, whereas, transit and walk mode shares are predicted to increase. These prediction results can be used by the transportation planners and policy makers to encourage using emerging travel alternatives, such as shared mobility, carpooling, ridesharing, demand responsive service, etc. Since transit and walk mode shares are predicted to increase over the years, policy makers should concentrate not only to examine various sustainable transportation options, but also to develop strategies to create mixed designed neighbourhoods with improved transit and active transportation infrastructure. The shared travel choice component (that anticipates extensive social interactions among individuals) in SDS microsimulation model suggest that majority of the work-based tours are predicted to be performed by traveling with a partner/spouse, and much of the school-based tours are predicted to be performed by traveling with parents/other family members. Therefore, policy strategies that provide travel time incentives for sharing travel during a specific time-of-day, such as high occupancy vehicle lane and high occupancy toll roads, can be implemented to support shared travel that is manifested by the social interactions among individuals. Finally, SDS implements a vehicle allocation component that predicts types of vehicles assigned for different activity-based tours at specific time-of-day. Such information can be used as inputs in the traffic microsimulation model, where dynamic traffic assignment method can track specific types of vehicles present in the transportation network. Thus, network-level congestion, emission and energy consumption can be estimated in a more improved way, which in turn would assist to develop alternative policy interventions such as carbon pricing, and incentives on zero-emission vehicles and cleaner fuels for vehicles.

8.5 Future Research

This thesis presents a novel framework to develop the state-of-the-art prototype activity-based shorter-term decisions simulator (SDS) that specifically focuses on modelling and microsimulating various activity and travel decisions. However, the current prototype version of the model has certain limitations, hence, require some future research. Following is a brief summary of the future directions of this thesis:

1. Since SDS is designed as an integral part of the iTLE modelling system, an immediate future work should be running the SDS module with the LDS module of iTLE to predict the evolution of an urban region. The activity-based accessibility measures (i.e. logsum values) estimated in the mobility assignment sub-module will be used provide feedback to the long-term location choices. Such mechanism will assist to develop the behaviourally consistent iTLE urban model.
2. The SDS microsimulation model not only depends greatly on the inputs from origin-destination travel time matrices from a traffic microsimulation model, but also it can

provide necessary inputs to the traffic model. Therefore, an integration between SDS and traffic flow simulator (TFS) of iTLE model needs to be conceptualized to improve the activity scheduling process of SDS as well as provide better inputs to the traffic microsimulation model.

3. The current prototype SDS model implements shared travel choice, mode choice and vehicle allocation decisions at activity-based tour-level. The stop-level modelling and microsimulation of such components have not been attempted in this thesis. Future research should focus on implementing these components at the intermediate stops of an activity-based tour in order to develop a more comprehensive activity-based travel demand model.

4. The 30-year microsimulation results of the SDS modelling system offer critical insights towards the long-range evolution of different activity and travel decisions. However, such microsimulation results are validated in this thesis based on commute data only. Since new NovaTRAC data will be available soon, one of the immediate future works should be performing an extensive validation procedure of microsimulation results based on multiple activity and travel attributes, such as types of activities, shared travel arrangements, and vehicle allocation to skeleton and flexible activities, among others.

5. Another future direction of this research should be the development of other critical components of the SDS microsimulation model. For instance, in the current prototype SDS model, vehicle allocation component assumes that all vehicles are equally likely to be used by any member of the household. Due to data unavailability, the SDS model disregards the fact that vehicles often belong to or are usually used by a specific household member. Therefore, a primary driver allocation model should be

implemented, which would assign a specific type of vehicle from the households' existing vehicle fleet to a specific person in the household; thus, develop a more behaviourally robust vehicle allocation process within the microsimulation procedure.

6. The current prototype SDS model considers only four types of modes (auto, transit, walk and bike) during the empirical and computational procedure of mobility assignment. Based on data availability, future research should consider alternative modes such as taxi, schoolbus, carsharing, paratransit, etc. while developing the mode choice models.

8.6 Concluding Remarks

This research advances the activity-based travel demand modelling literature by developing alternative econometric modelling-based methodologies as well as a microsimulation model that addresses individuals' social interactions with household and non-household members within its empirical and computational procedure. The alternative modelling structures provide an improved behavioural understanding of analysing multiple activity and travel components and the influence of modal accessibility and social utility on activity engagement decisions through coupling mechanisms. A new methodology is implemented in this research to generate daily activities within the multi-year SDS microsimulation tool that offers critical insights towards the daily activity-based travel demand analysis. Investigation of the behavioural basis of shared travel choices within micro-behavioural and microsimulation modelling framework disentangle social interactions among individuals in case of daily activity scheduling as well as mobility assignment processes. Implementing vehicle allocation process mechanisms within a multi-year travel demand forecasting tool informs the presence of a specific type of vehicle in a transportation network, which assists to better estimate the network-level emission and energy consumption. The disaggregate-level activity and travel information generated in this thesis will be used to operationalize a fully integrated iTLE urban modelling system. Integration of short-term decision components with iTLE's long-term decision components and traffic microsimulation modelling components will enhance the capacity of the urban modelling system to forecast the evolution of a region's land use, transportation and environment. The research presented in this thesis contributes significantly in existing activity-travel modelling and microsimulation paradigm that will assist to develop effective land use and transportation policies to promote environmental sustainability, vibrant and liveable neighbourhoods, and enhance the quality of life.

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Appendix A: Parameter Estimation Results of the Micro-behavioural Models used in SDS Microsimulation Model

Table A-1 Parameter Estimation Results of Work Location Choice Model

Variables	Coefficient	*t*-stat
Travel time_auto (in min)	-0.090	-2.89
Log sales volume of destination (sales volume in 1000s of $)	-0.00009	-1.96
Number of employees working at destination	0.002	2.15
Land use index of destination DA	1.407	3.67
Average property value in destination DA (in 1000s of $)	0.0006	1.59
Proportion of property owned in destination DA	-0.850	-3.70
Destination is urban (population density > 400 people/km^2) × Individual's age	-0.0032	-2.84
Destination is urban × Household income under $50k	0.105	1.69
Destination is urban × Individual is full-time employed	-0.276	-1.99
Goodness-of-fit		
Log-likelihood (constant)	-3737.76	
Log-likelihood (convergence)	-691.486	
McFadden's Pseudo R^2	0.815	

Table A-2 Parameter Estimation Results of School Location Choice Model

Variables	Coefficient	*t*-stat
Travel Distance (in km)	-0.331	-1.82
Land use index of destination DA	-1.016	-2.36
Average property value in destination DA (in 1000s of $)	0.0019	3.95
Destination is urban × Household income over $100k	-1.569	-4.80
Destination is urban × Individual is part-time employed	0.744	1.94
Destination is urban × Individual is student	0.298	2.44
Goodness-of-fit		
Log-likelihood (constant)	-1927.191	
Log-likelihood (convergence)	-427.836	
McFadden's Pseudo R^2	0.778	

Table A-3 Parameter Estimation Results of Shopping Location Choice Model

Variables	Coefficient	*t*-stat
Travel time_auto (in min)	-0.167	-4.16
Number of vehicles owned by household	0.002	2.43
Log sales volume of destination (sales volume in 1000s of $)	0.0002	1.51
Land use index of destination DA	0.836	5.44
Average property value in destination DA (in 1000s of $)	0.0007	6.85
Proportion of property owned in destination DA	0.782	3.91
Destination is urban (population density > 400 people/km^2) × Individual's age	0.0001	1.69
Destination is urban × Household income over $100k	-0.294	-1.95
Destination is urban × Individual is full-time employed	0.059	1.98
Destination is urban × Individual is part-time employed	-0.373	-2.24
Goodness-of-fit		
Log-likelihood (constant)	-2298.435	
Log-likelihood (convergence)	-452.792	
McFadden's Pseudo R^2	0.803	

Table A-4 Parameter Estimation Results of Personal Business Location Choice Model

Variables	Coefficient	*t*-stat
Travel time_auto (in min)	-0.123	-5.08
Log sales volume of destination (sales volume in 1000s of $)	0.00006	2.98
Average property value in destination DA (in 1000s of $)	-0.0009	-6.17
Population density in destination DA (in people/km^2)	-0.00003	-1.73
Destination is urban (population density > 400 people/km^2) × Individual's age	0.006	2.29
Destination is urban × Household income over $100k	-0.308	-1.61
Destination is urban × Individual is full-time employed	-0.395	-4.12
Goodness-of-fit		
Log-likelihood (constant)	-1521.59	
Log-likelihood (convergence)	-575.161	
McFadden's Pseudo R^2	0.622	

Table A-5 Parameter Estimation Results of Recreation Location Choice Model

Variables	Coefficient	*t*-stat
Travel time_auto (in min)	-0.147	-3.62
Number of vehicles owned by household	0.004	6.19
Log sales volume of destination (sales volume in 1000s of $)	0.00004	2.51
Land use index of destination DA	0.844	2.10
Average property value in destination DA (in 1000s of $)	0.0009	1.66
Proportion of property owned in destination DA	1.704	1.91
4.81Destination is urban (population density > 400 people/km^2) × Individual's age	0.018	2.43
Destination is urban × Household income over $100k	-0.405	-2.03
Destination is urban × Individual is student	1.063	1.75
Destination is urban × Individual is retired	0.564	4.81
Goodness-of-fit		
Log-likelihood (constant)	-1059.188	
Log-likelihood (convergence)	-409.906	
McFadden's Pseudo R^2	0.613	

Table A-6 Parameter Estimation Results of Dine out Location Choice Model

Variables	Coefficient	*t*-stat
Travel Distance (in km)	-0.295	-3.13
Log sales volume of destination (sales volume in 1000s of $)	0.0002	1.69
Land use index of destination DA	1.080	2.16
Proportion of property owned in destination DA	1.379	1.83
Destination is urban × Household income under $50k	-0.221	-4.92
Destination is urban × Household income over $100k	-0.767	-2.30
Destination is urban × Individual is full-time employed	0.103	1.99
Destination is urban × Individual is retired	-0.512	-1.66
Goodness-of-fit		
Log-likelihood (constant)	-1817.907	
Log-likelihood (convergence)	-381.76	
McFadden's Pseudo R^2	0.790	

Table A-7 Parameter Estimation Results of Mandatory Activity-tour Shared Travel Choice

Variables	Coefficient	*t*-stat
Non-shared travel	-5.400	-3.16
Individual age (mean)	-1.039	-1.66
Individual age (standard deviation)	1.096	4.52
Household income C$55-75K	-3.292	-1.60
Number of activities within the tour	0.256	2.22
Living in urban areas (density > 400ppl/km^2) x individual is retired	-4.391	-2.94
Shared travel with partner/spouse	-0.477	-2.45
Individual age	0.052	1.69
Individual age above 65 years × Household size	0.181	1.78
Number of vehicles in household	-0.641	-1.98
Living in urban areas	-0.645	-4.21
Shared travel with children	-1.250	-3.33
Individual age x Household size	0.011	1.71
Individual is full-time employed (mean)	-0.553	-1.49
Individual is full-time employed (standard deviation)	0.622	2.67
Number of vehicles in household	-0.605	-1.82
Living in urban areas	-0.742	-2.89
Shared travel with parents/other family members	*Reference*	*Reference*
Individual age	-0.044	-1.70
Individual age 25-40 years (mean)	-0.283	-1.82
Individual age 25-40 years (standard deviation)	0.209	2.95
Individual age above 65 years x Household size	0.576	2.41
Individual is full-time employed	-0.441	-1.64
Number of activities within the tour	0.249	1.05
Living in urban areas	0.516	4.08
Shared travel with roommates/friends/colleagues	4.937	5.10
Household income below C$50K	3.498	1.73
Individual age 25-40 years x Household size	0.674	1.66
Individual age 41-64 years x Household size	-0.202	-0.91
Individual is full-time employed	-0.624	-1.06
Number of activities within the tour	3.334	1.89
Living in urban areas x Individual age 25-40 years	3.087	3.85
Goodness-of-fit		
Log-likelihood (constant)	-959.321	
Log-likelihood (convergence)	-330.964	
McFadden's Pseudo R^2	0.654	

Table A-8 Parameter Estimation Results of Maintenance Activity-tour Shared Travel Choice

Variables	Coefficient	*t*-stat
Non-shared travel	-5.910	-4.22
Individual age	2.455	1.84
Household income C$55-75K	2.210	2.22
Household vehicle ownership: at least 1 vehicle	-1.110	-3.96
Number of activities within the tour	4.069	1.66
Living in urban areas x individual is retired	0.641	1.99
Shared travel with partner/spouse	2.288	6.51
Individual age x Household size	1.013	1.92
Individual is full-time employed	3.359	1.87
Number of vehicles in household	-0.093	-1.90
Living in urban areas x individual age	-0.007	-2.55
Shared travel with children	*Reference*	*Reference*
Individual age	2.054	1.78
Individual age above 65 years x Household size (mean)	3.113	1.73
Individual age above 65 years x Household size (standard deviation)	3.359	2.19
Number of vehicles in household	2.436	1.60
Living in urban areas x Household income above C$100K	4.320	6.66
Shared travel with parents/other family members	-2.821	-1.71
Individual age	-0.031	-2.64
Individual age x Household size	3.634	1.75
Individual age 25-40 years x Household size (mean)	4.419	1.42
Individual age 25-40 years x Household size (standard deviation)	5.291	4.44
Individual is full-time employed	-0.056	-1.88
Living in urban areas x Household income under C$50K	2.080	1.98
Shared travel with roommates/friends/colleagues	2.843	2.39
Household income below $50K	0.468	2.47
Individual age 25-40 years x Household size	0.518	1.68
Individual age 41-64 years x Household size	-0.641	-4.80
Household vehicle ownership: at least 1 vehicle	-1.552	-1.67
Number of activities within the tour	0.143	1.31
Living in urban areas x Household income above C$100K	-0.893	-3.30
Goodness-of-fit		
Log-likelihood (constant)	-591.086	
Log-likelihood (convergence)	-174.961	
McFadden's Pseudo R^2	0.704	

Table A-9 Parameter Estimation Results of Discretionary Activity-tour Shared Travel Choice

Variables	Coefficient	*t*-stat
Non-shared travel	6.175	1.72
Individual age	-0.053	-3.04
Number of vehicles in household > 0	-1.134	-1.81
Number of activities within the tour	-0.156	-1.06
Living in urban areas (density > 400ppl/km^2) x individual age above 65 years	0.951	1.37
Living in urban areas x individual is retired	-0.267	-5.20
Shared travel with partner/spouse	*Reference*	*Reference*
Individual age	0.072	2.51
Individual age above 65 years × Household size	0.445	2.49
Land-use index (mean)	-1.874	-4.73
Land-use index (standard deviation)	2.382	5.17
Living in urban areas x Household income above $100K	0.646	2.45
Shared travel with children	2.659	4.32
Individual age x Household size	0.012	1.69
Individual is full-time employed (mean)	0.534	1.73
Number of vehicles in household > 0	-1.423	-2.22
Living in urban areas x Individual's age	-0.025	-2.39
Shared travel with parents/other family members	4.621	1.83
Individual age 25-40 years x Household size (mean)	-0.707	-3.67
Individual age 25-40 years x Household size (standard deviation)	0.828	4.10
Individual age above 65 years x Household size	-0.485	-1.66
Individual is part-time employed	-0.828	-2.00
Individual is student	1.024	2.93
Number of vehicles in household > 0	-1.762	-1.80
Living in urban areas x Household income $50-75K	-0.946	-1.49
Shared travel with roommates/friends/colleagues	2.158	1.75
Individual age	0.257	1.59
Individual age 41-64 years x Household size	-0.246	-2.78
Individual is student	1.102	1.70
Living in urban areas x Individual age	0.017	2.18
Goodness-of-fit		
Log-likelihood (constant)	-1008.320	
Log-likelihood (convergence)	-372.176	
McFadden's Pseudo R^2	0.629	

Table A-10 Parameter Estimation Results of Mandatory Activity-tour Mode Choice

Variables	Coefficient	*t*-stat
Auto	1.123	1.67
Annual household income between C$50K-C$75K	0.635	4.66
Number of vehicles in household x age 25 to 40 years	1.485	0.34
Number of vehicles in household x age 41-64 years	2.198	1.77
Travel with partner/spouse	-0.087	-2.38
Travel with roommates/friends/colleagues	-2.260	-4.97
Interaction variable: Female x travel with children	0.075	1.19
Travel time	-0.260	-4.11
Driver's licesne_yes	0.482	1.89
Home to CBD distance	1.279	2.88
Land-use index	-0.172	-3.60
Transit	-0.224	-3.26
Annual household income less than C$25K	1.049	4.46
Travel with partner/spouse	-1.185	-4.88
travel with other family members	-0.662	-2.48
Number of vehicles x age 25 to 40 years	0.719	4.08
Interaction variable: Female x travel with partner/spouse	2.439	2.44
Travel time	-0.622	-1.77
Driver's licesne_yes	-0.194	-2.05
Home to CBD distance	0.735	2.88
Home to nearest transit stop distance	-0.264	-2.09
Bike	0.327	1.34
Age 41-64 years	-1.480	-3.51
Travel alone	1.547	3.55
Travel with roommates/friends/colleagues	-0.021	-3.14
Travel time	-1.156	-2.52
Home to CBD distance	0.981	1.05
Land-use index	0.256	2.22
Walk	*Reference*	*Reference*
Age 25-40 year	-1.246	-1.03
Age above 64 years	2.769	3.06
Travel with children	0.572	2.49
Travel with roommates/friends/colleagues	0.068	1.08
Land-use index	0.207	2.56
Standard Deviation		
Auto_land-use index	0.694	1.88
Transit_household income less than C$25K	1.907	3.83
Walk_age above 64 years	2.145	2.72
Goodness-of-fit		
Log-likelihood (constant)	-1132.142	
Log-likelihood (convergence)	-293.650	
McFadden's Pseudo R^2	0.741	

Table A-11 Parameter Estimation Results of Maintenance Activity-tour Mode Choice

Variables	Coefficient	*t*-stat
Auto	1.575	3.25
Age 25-40 years	0.239	1.14
Travel alone	1.438	2.51
Travel with partner/spouse	0.004	1.69
Travel with children	-0.001	-2.95
Travel with roommates/friends/colleagues	-0.927	-3.57
Number of vehicles in the household	0.047	2.12
Travel time	-0.165	-1.01
Driving license_yes	1.667	1.88
Dwelling density	-1.417	-2.47
Home to CBD distance	0.002	1.43
Home to closest shopping center distance	0.444	2.08
Transit	-0.295	-1.26
Age 41-60 years	-1.587	-2.98
Driving license_yes	-0.220	-2.04
Travel with children	-0.001	-1.61
Travel with parents/other family members	0.0003	0.99
Travel time	-1.129	-1.94
Home to CBD distance	-0.862	-1.71
Home to closest transit stop distance	-0.628	-0.31
Bike	*Reference*	*Reference*
Household income less than C$25K	0.715	3.43
Number of vehicles in HH	-0.707	-3.58
Travel alone	0.001	2.68
Travel with partner/spouse	-0.003	-1.71
Land use index	1.373	3.99
Home to closest shopping center distance	-0.814	-1.18
Walk	-0.201	-1.79
Age above 64 years	1.479	2.48
Travel alone	0.016	1.09
Travel with roommates/friends/colleagues	-0.117	-2.27
Travel time	-0.229	-2.83
Land use index	0.367	1.54
Home to CBD distance	0.047	2.81
Standard Deviation		
Walk_travel with roommates/friends/colleagues	0.842	4.22
Bike_household income less than C$25K	1.288	4.35
Goodness-of-fit		
Log-likelihood (constant)	-849.74	
Log-likelihood (convergence)	-186.29	
McFadden's Pseudo R^2	0.780	

Table A-12 Parameter Estimation Results of Discretionary Activity-tour Mode Choice

Variables	Coefficient	*t*-stat
Auto	1.092	3.26
Household income less than C$25K	-0.543	-1.03
Travel alone	0.001	1.48
Travel with children	1.882	3.99
Travel with roommates/friends/colleagues	-1.084	-1.97
Number of vehicles in the household	0.735	2.55
Travel time	-1.446	-3.84
Driving license_yes	0.530	3.17
Land use index	-1.615	-1.07
Home to CBD distance	0.267	3.18
Transit	0.147	4.65
Age above 64 years	-0.246	-2.26
Travel alone	0.194	4.92
Travel with parents/other family members	-0.004	-1.60
Travel with roommates/friends/colleagues	-0.893	-2.08
Travel distance	-0.122	-4.58
Home to CBD distance	-0.143	-1.59
Home to closest transit stop distance	-0.359	-2.20
Bike	*Reference*	*Reference*
Age 25-40 years	0.528	1.32
Travel alone	0.108	2.97
Travel with partner/spouse	0.061	1.27
Home to closest park distance	1.470	2.09
Land use index	0.833	1.71
Walk	-1.404	-2.09
Household income C55K-C$75K	-0.564	-5.19
Travel alone	0.390	4.73
Travel with parents/other family members	0.009	1.68
Travel time	-1.170	-4.62
Land use index	1.478	3.24
Home to closest park distance	0.570	3.82
Standard Deviation		
Auto_number of vehicles in the household	0.873	2.71
Transit_travel alone	1.247	1.71
Walk_land use index	2.079	1.88
Goodness-of-fit		
Log-likelihood (constant)	-982.95	
Log-likelihood (convergence)	-347.2	
McFadden's Pseudo R^2	0.657	

Table A-13 Parameter Estimation Results of Solo Mandatory Activity-tour Vehicle Allocation

Variables	Coefficient	*t*-stat
Subcompact	-0.942	-5.31
Age 25-40 years	-0.439	-5.05
Household income below C$50K	-0.816	-1.31
Travel distance	-0.072	-1.98
Tour start time: Morning (7am - 9am)	-0.179	-3.72
Land-use index	0.381	1.52
Compact	1.404	4.54
Female	1.321	3.85
Household income $50K-$75K	1.214	1.38
Tour start time: Late morning (9am - 12pm)	-1.133	-4.01
Travel time	-0.676	-3.72
Home to CBD distance	-0.938	-1.68
Land-use index	0.322	1.04
Midsize	-0.127	-2.32
Female	-0.041	-0.82
Age 41-64 years	0.445	1.46
Travel distance	1.131	2.34
Tour start time: Late morning (9am - 12pm)	0.401	4.67
Population density	-0.023	-4.99
Home to closest transit stop distance	-0.578	-2.79
SUV	1.066	4.42
Age 25-40 years	0.091	3.21
Age above 64 years	0.029	1.66
Travel time	0.158	2.60
Tour start time: Morning (7am - 9am)	0.097	2.72
tour start time: Evening (4pm - 7pm)	-0.847	-1.03
Land-use index	-0.450	-2.94
Home to CBD distance	0.817	3.93
Vans	*Reference*	*Reference*
Female	-0.144	-3.46
Travel distance	0.927	1.98
Tour start time: Afternoon (12pm - 4pm)	-0.214	-3.31
Population density	0.024	1.53
Standard Deviation		
Subcompact_housheold income below C$50K	1.484	2.11
Compact_land-use index	0.843	1.69
SUV_tour start time: Evening (4pm - 7pm)	1.295	2.78
Goodness-of-fit		
Log-likelihood (constant)	-1352.246	
Log-likelihood (convergence)	-445.981	
McFadden's Pseudo R^2	0.695	

Table A-14 Parameter Estimation Results of Joint Mandatory Activity-tour Vehicle Allocation

Variables	Coefficient	*t*-stat
Subcompact	2.148	3.32
Age 25-40 years	0.024	0.93
Travel with partner/spouse	-1.861	-2.11
Travel with parents/other family members	-1.933	-2.63
Travel with roommates/friends/colleagues	-2.004	-1.65
Tour start time: Morning (7am – 9am)	-0.954	-3.04
Travel distance	-0.315	-2.33
Dwelling density	0.134	2.67
Compact	0.443	3.33
Male	-1.447	-1.38
Age above 64 years	-0.074	-1.86
Household income below C$50K	0.110	3.45
Travel time	-0.244	-1.62
Travel with partner/spouse	-0.181	-1.58
Tour start time: Late morning (9am - 12pm)	-1.225	-3.40
Travel with roommates/friends/colleagues	-0.005	-4.19
Land-use index	0.533	3.89
Midsize	-0.283	-2.64
Female	-0.032	-2.97
Age 25-40 years	0.064	2.38
Travel distance	0.286	1.39
Travel with children	-0.069	-1.95
Travel with roommates/friends/colleagues	2.244	1.26
Tour start time: Afternoon (12pm – 4pm)	-0.833	-4.11
Land-use index	-0.323	-0.94
Home to closest school distance	0.171	3.63
SUV	1.109	3.52
Age 41-64 years	0.507	2.87
Male	0.430	1.42
Travel time	0.665	3.49
Tour start time: Morning (7am - 9am)	0.091	3.43
Travel with partner/spouse	1.701	2.10
Travel with children	0.965	3.97
Travel with roommates/friends/colleagues	0.013	2.44
Travel with parents/other family members	1.201	2.31
Land-use index	-0.185	-1.71
Home to CBD distance	0.575	2.50
Home to closest school distance	0.606	2.66
Vans	*Reference*	*Reference*
Age above 64 years	-0.005	-1.33
Tour start time: Afternoon (12pm - 4pm)	0.109	1.03
Tour start time: Morning (7am - 9am)	0.392	1.89
Travel distance	1.053	2.14
Travel with roommates/friends/colleagues	0.925	2.23
Dwelling density	-0.327	-1.39
Standard Deviation		
Compact_male	1.655	1.79
Vans_age above 64 years	0.015	1.99
Midsize_travel with children	0.140	2.27
Goodness-of-fit		
Log-likelihood (constant)	-510.839	
Log-likelihood (convergence)	-124.237	
McFadden's Pseudo R^2	0.776	

Table A-15 Parameter Estimation Results of Solo Maintenance Activity-tour Vehicle Allocation

Variables	Coefficient	*t*-stat
Subcompact	0.296	2.71
Age 41-64 years	-0.625	-3.77
Household income below C$50K	0.994	3.03
Tour start time: Afternoon (12pm – 4pm)	0.513	1.89
Travel time	-0.092	-4.25
Dwelling density	0.029	0.78
Home to closest businesspark distance	-1.437	-2.96
Compact	*Reference*	*Reference*
Male	-1.651	-2.08
Tour start time: Afternoon (12pm - 4pm)	0.180	3.86
Tour start time: Evening (4pm - 7pm)	0.137	1.81
Land-use index	-1.111	-2.46
Home to CBD distance	-0.852	-3.69
Midsize	-0.045	-3.08
Age 25-40 years	1.295	0.84
Travel time	-0.481	-2.84
Tour start time: Late morning (9am - 12pm)	0.377	3.00
Tour start time: Evening (4pm - 7pm)	-0.409	-1.65
Land-use index	-0.246	-2.96
SUV	-0.514	-2.12
Age 41-64 years	0.070	1.39
Female	-0.230	-2.04
travel time	0.400	1.46
Tour start time: Afternoon (12pm - 4 pm)	-0.308	-3.48
tour start time: Late morning (9 am - 12 pm)	0.013	3.99
Land-use index	-2.234	-2.19
Distance from home to closest businesspark	0.159	1.53
Van	0.412	2.98
Female	-0.245	-3.81
Household income C$50K-C$75K	0.546	1.76
Travel distance	-0.019	-1.98
Tour start time: Evening (4pm - 7pm)	0.187	0.72
Population density	-2.635	-1.08
Home to CBD distance	0.137	1.40
Standard Deviation		
Compact_male	1.115	1.87
Midsize_travel time	1.057	2.20
Goodness-of-fit		
Log-likelihood (constant)	-951.243	
Log-likelihood (convergence)	-314.73	
McFadden's Pseudo R^2	0.703	

Table A-16 Parameter Estimation Results of Joint Maintenance Activity-tour Vehicle Allocation

Variables	Coefficient	*t*-stat
Subcompact	-0.014	-0.72
Female	-0.348	-3.05
Female x Travel with children	-0.867	-5.22
Tour start time: Late morning (9am - 12pm)	-0.839	-3.50
Travel with partner/spouse	-1.114	-2.63
Travel with children	-0.954	-1.53
Travel with parents/other family members	-1.024	-2.01
Travel time	-0.624	-1.99
Population density	1.229	2.46
Compact	-0.629	-1.96
Age 25-40 years	-0.306	-1.01
Household income below C$50K	1.051	3.47
Travel distance	-0.354	-2.19
Travel with partner/spouse	-1.003	-2.94
Tour start time: Afternoon (12pm - 4pm)	0.011	4.19
Land-use index	1.930	3.47
Home to businesspark distance	-0.960	-0.88
Midsize	0.017	3.52
Age above 64 years	0.752	0.09
Travel with partner/spouse x Tour start time: Evening (4pm - 7pm)	-0.145	-2.03
Travel with parents/other family members	0.278	3.72
Tour start time: Late morning (9am - 12pm)	0.138	1.22
Travel with roommates/friends/colleagues	0.222	1.91
Travel distance	0.004	1.29
Land-use index	-0.881	-1.42
SUV	0.208	3.56
Age 41-64 years	0.813	2.95
Travel time	0.168	3.70
Travel with partner/spouse	0.141	2.40
Travel with children	0.518	1.66
Female x Travel with children	1.231	0.48
Travel with roommates/friends/colleagues	1.355	1.94
Tour start time: Morning (7am – 9am)	0.888	1.61
Land-use index	-1.013	-2.11
Home to closest businesspark distance	0.972	3.28
Vans	*Reference*	*Reference*
Travel time	-0.144	-4.19
Tour start time: Evening (4pm - 7pm)	-0.541	-1.87
Travel with roommates/friends/colleagues	1.537	1.58
Dwelling density	-0.144	-0.32
Home to closest businesspark distance	0.287	4.17
Standard Deviation		
Midsize_land-use index	1.115	2.89
Vans_travel time	0.442	1.68
Goodness-of-fit		
Log-likelihood (constant)	-1036.924	
Log-likelihood (convergence)	-214.351	
McFadden's Pseudo R^2	0.793	

Table A-17 Parameter Estimation Results of Solo Discretionary Activity-tour Vehicle Allocation

Variables	Coefficient	*t*-stat
Subcompact	*Reference*	*Reference*
Male	-0.115	-2.08
Age 41-64 years	-0.048	-1.98
Tour start time: Afternoon (12pm - 4pm)	-0.548	-3.13
Travel time	-1.024	-2.36
Home to closest park distance	1.579	4.81
Compact	0.772	1.99
Age 25-40 years	-0.107	-1.15
Household income below C$50K	-0.116	-3.24
Tour start time: Evening (4pm - 7pm)	0.275	1.24
Travel distance	-0.960	-3.70
Land-use index	0.378	3.49
Home to closest transit stop distance	-0.409	-3.65
Midsize	0.201	0.71
Female	0.797	3.26
Travel time	-1.475	-1.38
Tour start time: Late morning (9am - 12pm)	0.014	1.94
Tour start time: Evening (4pm - 7pm)	0.329	3.18
Land-use index	-0.028	-2.92
SUV	-1.548	-4.10
Age above 64 years	-0.195	-1.65
Household income above C$100K	0.969	1.06
Travel time	0.492	4.04
Tour start time: Afternoon (12pm - 4pm)	1.513	1.30
Tour start time: Late morning (9am - 12pm)	1.786	4.29
Dwelling density	-0.076	-4.24
Home to closest park distance	0.251	0.43
Vans	0.319	3.36
Female	-0.121	-1.53
Travel distance	-0.082	-2.91
Tour start time: Evening (4pm - 7pm)	-1.290	-2.60
Land-use index	-0.138	-1.18
Home to closest transit stop distance	0.395	1.43
Standard Deviation		
Compact_age 25-40 years	0.517	2.09
Midsize_female	1.005	1.98
SUV_dwelling density	0.831	1.64
Goodness-of-fit		
Log-likelihood (constant)	-1058.193	
Log-likelihood (convergence)	-337.218	
McFadden's Pseudo R^2	0.663	

Table A-18 Parameter Estimation Results of Joint Discretionary Activity-tour Vehicle Allocation

Variables	Coefficient	*t*-stat
Subcompact	0.475	1.88
Age 25-40 years	-0.435	-2.83
Travel with partner/spouse	-0.535	-2.04
Travel with roommates/friends/colleagues	-0.931	-2.56
Travel with parents/other family members	-1.046	-1.63
Tour start time: Evening (4pm – 7pm)	-0.237	-3.46
Travel time	-0.401	-1.58
Land-use index	0.273	4.78
Compact	0.109	3.33
Age 41-64 years	-0.020	-3.91
Male x Travel with roommates/friends/colleagues	0.294	2.54
Travel with partner/spouse	-0.487	-3.11
Tour start time: Morning (7am - 9am)	0.026	2.36
Dwelling density	0.093	3.39
Home to closest park distance	-0.794	-0.66
Midsize	*Reference*	*Reference*
Age 25-40 years	0.054	1.28
Male x Travel with roommates/friends/colleagues	1.033	2.08
Travel with children	0.062	2.32
Tour start time: Afternoon (12pm - 4pm)	1.025	1.42
Travel time	1.310	4.29
Land-use index	0.318	2.67
SUV	1.355	2.49
Travel time	0.497	1.08
Travel with partner/spouse	0.031	4.25
Travel with children	0.060	0.65
Travel with parents/other family members	0.015	4.49
Travel with roommates/friends/colleagues	1.555	2.10
Tour start time: Late morning (9am - 12pm)	1.225	2.54
Land-use index	-0.367	-4.96
Home to closest park distance	0.329	3.83
Vans	-1.194	-0.58
Age above 64 years	-0.617	-1.97
Travel with roommates/friends/colleagues	0.124	1.82
Tour start time: Morning (7am - 9am)	-0.054	-2.41
Dwelling density	-1.056	-5.09
Home to closest park distance	0.091	1.12
Standard Deviation		
Subcompact_land-use index	0.842	1.95
Midsize_age 25-40 years	0.093	2.01
Goodness-of-fit		
Log-likelihood (constant)	-649.760	
Log-likelihood (convergence)	-216.343	
McFadden's Pseudo R^2	0.659	

Appendix B: Transition Probability Matrices

a) Markov transition probabilities: Full-time live alone

Current activities	Next activity probabilities								
	Dine out	Escort	Intermediate home return	Personal business	Recreation	School	Shopping	Work	End-of-day return home
In-home activity	0.06	0.04	0.04	0.07	0.08	-	0.06	0.57	0.08
Dine out	-	-	-	0.03	0.02	-	0.12	0.47	0.36
Escort	-	0.32	0.31	-	-	-	-	0.33	0.04
Intermediate home return	0.14	0.04	0.04	0.10	0.31	-	0.12	0.20	0.05
Personal business	0.03	-	0.08	0.17	0.13	-	0.04	0.25	0.30
Recreation	-	-	0.35	0.07	-	-	0.09	0.03	0.46
School	-	-	-	-	-	-	-	-	-
Shopping	0.03	-	0.16	0.01	0.01	-	0.10	0.03	0.65
Work	0.03	0.02	0.20	0.06	0.05	-	0.14	0.16	0.34

b) Markov transition probabilities: Full-time live with children

Current activities	Next activity probabilities								
	Dine out	Escort	Intermediate home return	Personal business	Recreation	School	Shopping	Work	End-of-day return home
In-home activity	0.03	0.20	0.02	0.03	0.05	0.01	0.02	0.55	0.07
Dine out	-	0.12	0.04	0.01	0.05	-	0.05	0.47	0.26
Escort	0.01	0.14	0.18	0.03	0.02	-	0.09	0.27	0.26
Intermediate home return	0.06	0.23	0.03	0.07	0.24	0.01	0.18	0.13	0.05
Personal business	0.03	0.03	0.15	0.20	0.08	-	0.09	0.17	0.25
Recreation	0.04	0.02	0.16	0.02	0.08	-	0.11	0.10	0.47
School	-	-	0.20	-	0.32	-	-	0.28	0.20
Shopping	0.04	0.08	0.18	0.04	0.03	-	0.09	0.08	0.46
Work	0.05	0.11	0.21	0.07	0.03	-	0.06	0.09	0.38

c) Markov transition probabilities: Full-time live with parents/other family members

Current activities	Next activity probabilities								
	Dine out	Escort	Intermediate home return	Personal business	Recreation	School	Shopping	Work	End-of-day return home
In-home activity	0.02	0.05	0.03	0.01	0.02	0.01	0.03	0.70	0.13
Dine out	-	-	-	-	-	-	-	0.54	0.46
Escort	0.03	-	0.23	-	0.19	-	0.07	0.15	0.33
Intermediate home return	0.03	0.09	0.01	0.06	0.49	0.02	0.17	0.10	0.03
Personal business	-	0.06	0.12	0.18	-	-	-	0.11	0.53
Recreation	0.02	0.09	0.11	-	0.06	-	-	0.01	0.71
School	-	-	0.47	-	-	-	-	-	0.53
Shopping	0.04	0.07	0.24	0.01	-	-	0.09	-	0.55
Work	0.03	0.01	0.23	0.02	0.06	-	0.05	0.07	0.53

d) Markov transition probabilities: Full-time live with partner/spouse

Current activities	Next activity probabilities								
	Dine out	Escort	Intermediate home return	Personal business	Recreation	School	Shopping	Work	End-of-day return home
In-home activity	0.03	0.05	0.02	0.07	0.06	-	0.08	0.60	0.09
Dine out	0.09	0.03	0.06	0.08	0.09	-	0.05	0.25	0.35
Escort	0.04	0.03	0.14	0.11	0.02	-	0.14	0.25	0.27
Intermediate home return	0.12	0.12	-	0.13	0.26	-	0.27	0.09	0.01
Personal business	0.04	0.02	0.19	0.17	0.02	-	0.06	0.24	0.26
Recreation	0.03	0.03	0.16	0.02	0.12	-	0.17	0.10	0.37
School	-	-	-	-	-	-	-	-	-
Shopping	0.02	0.03	0.15	0.01	0.04	-	0.22	0.08	0.45
Work	0.03	0.02	0.17	0.07	0.03	-	0.11	0.17	0.40

e) Markov transition probabilities: Full-time live with roommates/friends/colleagues

Current activities	Next activity probabilities								
	Dine out	Escort	Intermediate home return	Personal business	Recreation	School	Shopping	Work	End-of-day return home
In-home activity	0.03	-	0.04	0.03	0.08	-	0.09	0.71	0.02
Dine out	-	-	0.11	-	-	-	0.07	0.60	0.22
Escort	0.27	0.10	0.28	-	-	-	-	-	0.35
Intermediate home return	0.03	0.13	0.05	0.03	0.35	-	0.20	0.21	-
Personal business	0.12	0.01	0.17	0.09	-	-	0.12	0.38	0.11
Recreation	-	-	0.20	-	0.02	-	0.13	0.09	0.56
School	-	-	-	-	-	-	-	-	-
Shopping	0.02	-	0.09	0.04	0.09	-	0.11	0.17	0.48
Work	0.07	-	0.16	0.09	0.03	-	0.10	0.10	0.45

f) Markov transition probabilities: Retired live alone

Current activities	Next activity probabilities								
	Dine out	Escort	Intermediate home return	Personal business	Recreation	School	Shopping	Work	End-of-day return home
In-home activity	0.05	0.03	0.02	0.15	0.20	-	0.21	0.00	0.35
Dine out	-	0.12	0.09	0.10	0.08	-	0.19	-	0.41
Escort	0.13	0.13	0.20	0.05	0.09	-	0.21	-	0.19
Intermediate home return	0.05	0.05	0.03	0.17	0.36	-	0.26	0.02	0.06
Personal business	0.05	0.04	0.14	0.10	0.07	-	0.28	-	0.32
Recreation	0.05	0.03	0.18	0.03	0.11	-	0.14	-	0.45
School	-	-	-	-	-	-	-	-	-
Shopping	0.03	0.03	0.16	0.06	0.04	-	0.25	0.01	0.41
Work	0.17	0.17	0.17	0.17	-	-	0.17	-	0.17

g) Markov transition probabilities: Retired live with children

Current activities	Next activity probabilities								
	Dine out	Escort	Intermediate home return	Personal business	Recreation	School	Shopping	Work	End-of-day return home
In-home activity	0.03	0.20	0.01	0.13	0.14	0.03	0.24	0.02	0.20
Dine out	0.03	0.05	0.21	0.04	-	-	0.15	-	0.52
Escort	0.04	0.16	0.26	0.03	0.12	-	0.14	-	0.26
Intermediate home return	0.06	0.25	0.03	0.06	0.33	-	0.17	0.02	0.08
Personal business	-	0.06	0.19	0.14	0.04	0.01	0.26	0.07	0.22
Recreation	0.02	0.03	0.27	0.02	0.05	-	0.11	-	0.50
School	-	-	-	0.65	-	0.11	-	-	0.24
Shopping	0.07	0.01	0.31	0.05	0.03	0.01	0.20	0.01	0.32
Work	-	0.11	0.15	-	0.12	-	0.11	0.09	0.42

h) Markov transition probabilities: Retired live with parents/other family members

Current activities	Next activity probabilities								
	Dine out	Escort	Intermediate home return	Personal business	Recreation	School	Shopping	Work	End-of-day return home
In-home activity	0.03	0.09	0.09	0.02	0.12	0.15	0.04	-	0.47
Dine out	-	0.17	-	-	0.02	-	-	-	0.81
Escort	-	0.11	0.23	0.03	0.11	-	0.10	-	0.41
Intermediate home return	0.13	0.14	-	0.07	0.42	0.07	0.12	-	0.06
Personal business	0.04	0.11	0.11	-	0.17	-	0.45	-	0.12
Recreation	0.08	0.06	0.20	-	0.01	-	0.09	-	0.56
School	-	-	0.31	-	0.09	-	0.13	-	0.47
Shopping	-	0.04	0.35	0.01	-	-	0.07	-	0.52
Work	-	-	-	-	-	-	-	-	-

i) Markov transition probabilities: Retired live with partner/spouse

Current activities	Next activity probabilities								
	Dine out	Escort	Intermediate home return	Personal business	Recreation	School	Shopping	Work	End-of-day return home
In-home activity	0.03	0.04	0.04	0.14	0.23	0.00	0.22	0.03	0.28
Dine out	-	0.05	0.19	0.02	0.10	-	0.21	0.00	0.42
Escort	0.08	0.12	0.21	0.07	0.09	-	0.13	0.01	0.30
Intermediate home return	0.14	0.12	0.03	0.11	0.29	0.00	0.25	0.01	0.05
Personal business	0.05	0.02	0.20	0.12	0.03	-	0.26	0.02	0.30
Recreation	0.05	0.03	0.24	0.03	0.10	-	0.13	0.00	0.43
School	-	-	-	-	-	-	-	-	1.00
Shopping	0.03	0.01	0.17	0.05	0.05	-	0.24	0.01	0.44
Work	0.03	0.01	0.17	0.09	0.06	-	0.07	0.09	0.47

j) Markov transition probabilities: Retired live with roommates/friends/colleagues

Current activities	Next activity probabilities								
	Dine out	Escort	Intermediate home return	Personal business	Recreation	School	Shopping	Work	End-of-day return home
In-home activity	0.05	0.03	0.02	0.15	0.25	-	0.24	0.06	0.20
Dine out	0.04	0.10	0.15	-	0.04	-	0.20	0.11	0.35
Escort	0.09	0.24	0.18	-	0.12	-	0.06	-	0.30
Intermediate home return	0.11	0.03	-	0.13	0.32	-	0.34	0.03	0.04
Personal business	0.02	-	0.31	0.03	0.13	-	0.25	0.06	0.19
Recreation	0.04	0.05	0.24	0.04	0.04	-	0.05	0.02	0.52
School	-	-	-	-	-	-	-	-	-
Shopping	0.01	0.01	0.13	0.04	0.05	-	0.17	-	0.58
Work	0.14	-	0.15	0.21	0.08	-	0.05	0.08	0.29

k) Markov transition probabilities: Part-time live with household members (partner/spouse, children)

Current activities	Next activity probabilities								
	Dine out	Escort	Intermediate home return	Personal business	Recreation	School	Shopping	Work	End-of-day return home
In-home activity	0.02	0.08	0.02	0.07	0.10	0.04	0.09	0.42	0.15
Dine out	-	0.16	-	0.08	-	-	0.25	0.18	0.33
Escort	0.09	0.11	0.17	0.02	0.10	-	0.17	-	0.35
Intermediate home return	0.06	0.23	-	0.14	0.27	-	0.13	0.17	-
Personal business	0.04	-	0.12	0.22	0.11	-	0.23	-	0.27
Recreation	0.02	0.02	0.25	-	0.07	-	0.09	0.07	0.48
School	-	-	0.22	0.32	-	-	-	-	0.46
Shopping	0.03	0.01	0.24	0.02	0.04	0.05	0.15	0.08	0.39
Work	0.01	0.06	0.22	0.01	0.06	-	0.03	0.14	0.47

l) Markov transition probabilities: Part-time live alone and/or with non-household members (parents/other family members, roommates/friends/colleagues)

Current activities	Next activity probabilities								
	Dine out	Escort	Intermediate home return	Personal business	Recreation	School	Shopping	Work	End-of-day return home
In-home activity	0.04	0.03	0.03	0.03	0.09	0.15	0.04	0.41	0.18
Dine out	-	0.02	0.29	-	0.12	-	0.10	0.14	0.32
Escort	0.04	0.06	0.27	0.26	0.29	-	0.02	-	0.06
Intermediate home return	0.04	0.07	-	0.07	0.45	0.02	0.18	0.16	0.00
Personal business	-	-	0.19	0.20	0.09	-	0.22	0.03	0.27
Recreation	0.03	0.01	0.25	-	0.09	0.03	0.01	0.01	0.58
School	-	-	0.45	-	0.05	0.06	0.12	0.06	0.26
Shopping	0.07	-	0.27	0.02	0.08	-	0.09	-	0.47
Work	-	0.02	0.17	0.02	0.07	-	0.07	0.03	0.63

m) Markov transition probabilities: Students living alone and/or with non-household members (parents/other family members, roommates/friends/colleagues)

Current activities	Next activity probabilities								
	Dine out	Escort	Intermediate home return	Personal business	Recreation	School	Shopping	Work	End-of-day return home
In-home activity	0.01	0.03	0.00	0.02	0.11	0.61	0.03	0.03	0.17
Dine out	-	-	-	0.06	0.05	0.24	0.14	-	0.51
Escort	0.08	0.03	0.11	-	0.08	0.14	0.12	-	0.44
Intermediate home return	0.02	0.04	0.02	0.08	0.49	0.12	0.15	-	0.06
Personal business	0.04	-	0.13	0.09	0.05	0.05	0.22	0.07	0.36
Recreation	0.01	0.05	0.12	-	0.05	0.03	0.04	-	0.72
School	0.02	0.03	0.24	0.02	0.11	0.01	0.02	0.01	0.54
Shopping	0.07	-	0.08	-	-	-	0.19	-	0.66
Work	-	-	0.43	0.12	-	-	-	-	0.45

n) Markov transition probabilities: Unemployed living alone, with household and/or non-household members

Current activities	Next activity probabilities								
	Dine out	Escort	Intermediate home return	Personal business	Recreation	School	Shopping	Work	End-of-day return home
In-home activity	0.05	0.07	0.02	0.08	0.18	0.10	0.09	-	0.40
Dine out	0.11	0.12	-	0.17	0.37	-	0.17	-	0.06
Escort	-	0.11	0.43	0.03	-	0.06	-	-	0.37
Intermediate home return	0.08	0.32	0.04	-	0.25	0.05	0.21	-	0.05
Personal business	-	-	0.20	0.21	0.08	-	0.19	-	0.32
Recreation	-	0.04	0.19	0.04	0.12	-	-	-	0.62
School	-	-	0.33	-	-	-	-	-	0.67
Shopping	0.03	0.03	0.18	0.02	-	-	0.17	-	0.58
Work	-	-	-	-	-	-	-	-	-

Appendix C: Microsimulation Results

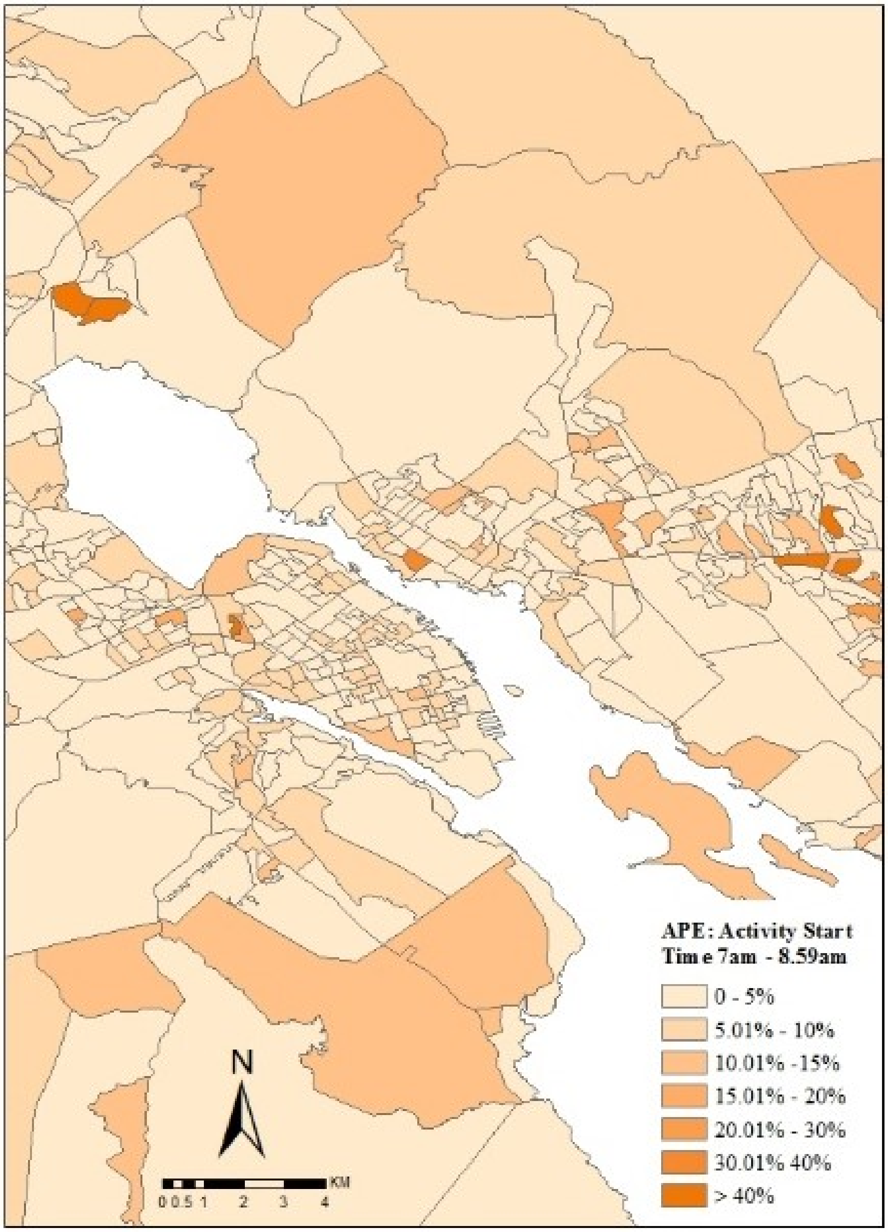

Figure C-1 APE Measure for Commute Start Time Category 7am to 8.59am

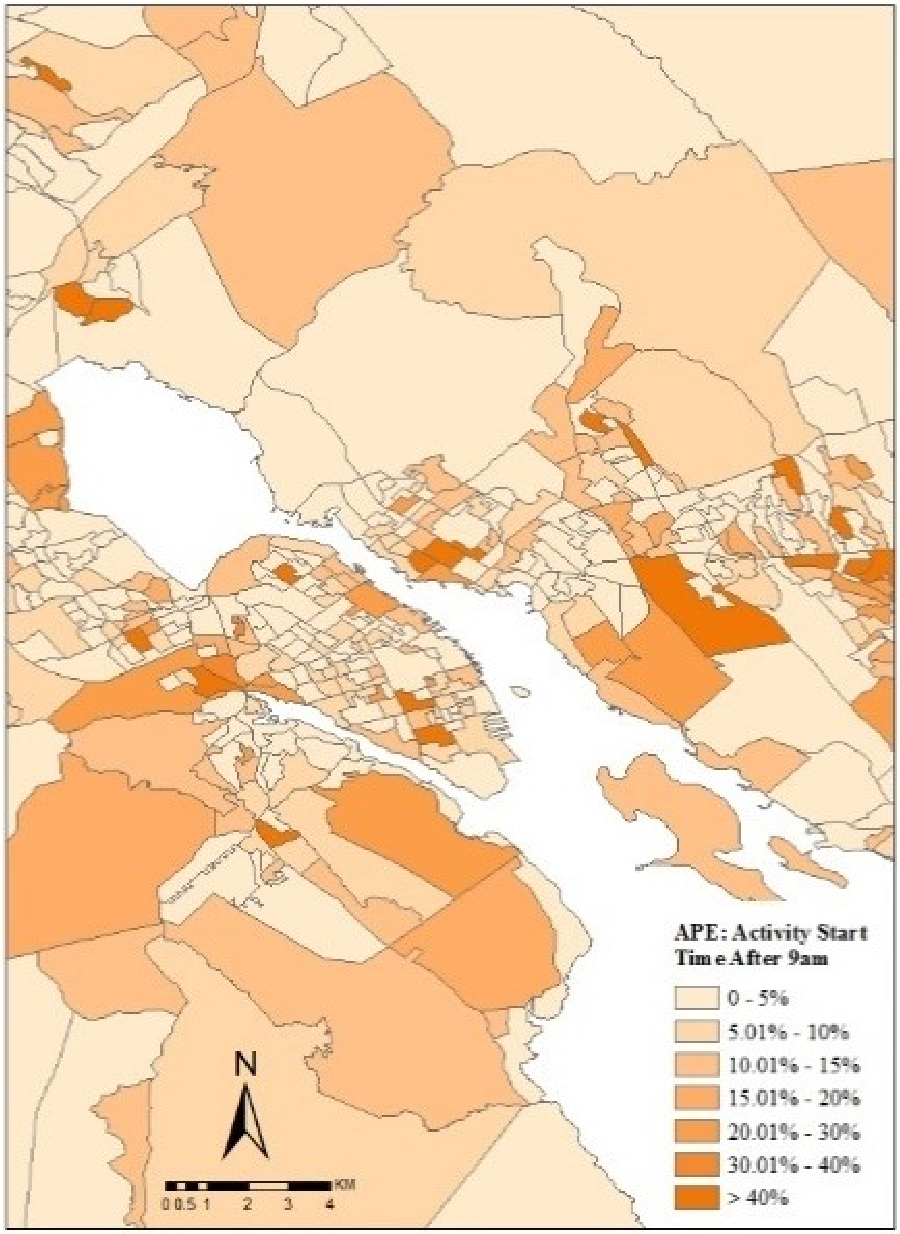

Figure C-2 APE Measures for Commute Start Time Category After 9am

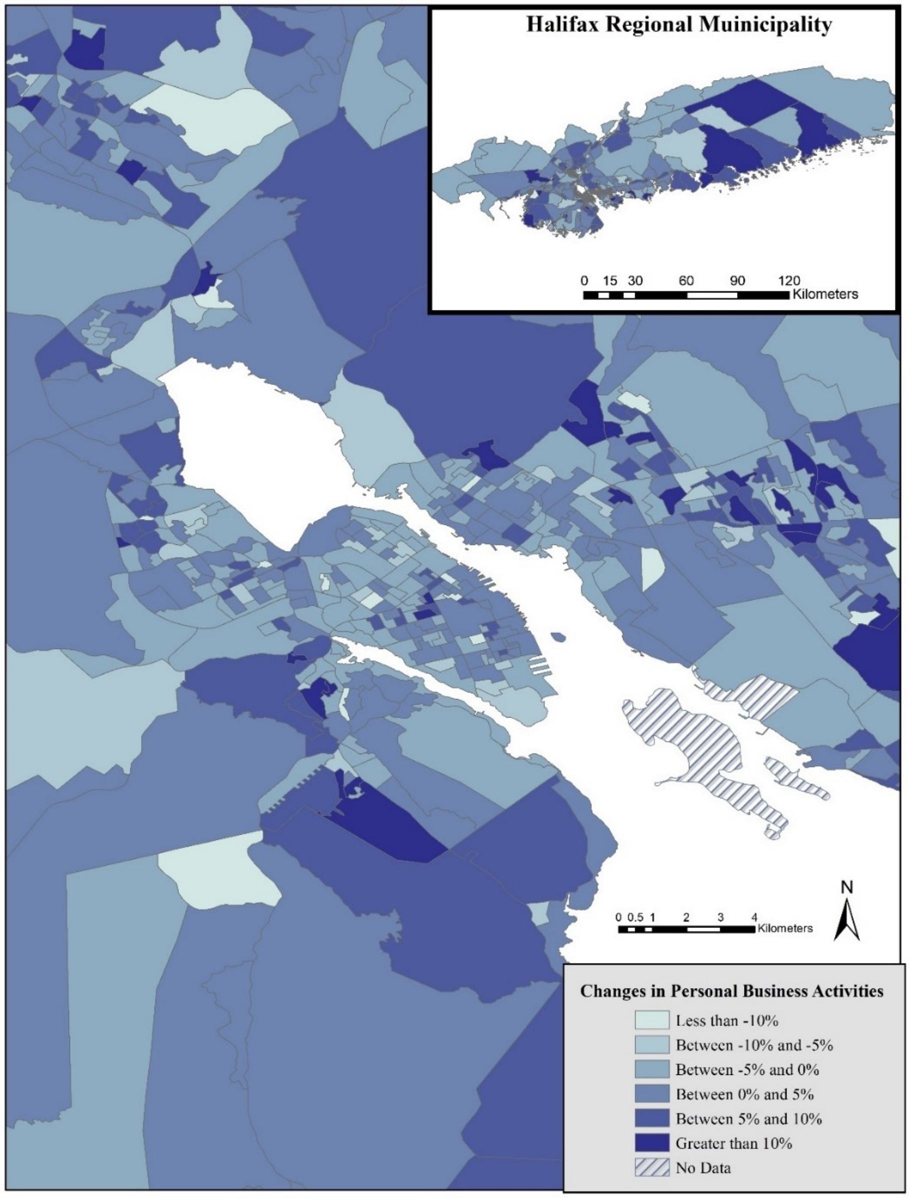

Figure C-3 Predicted Spatial Distribution of Personal Business Activities

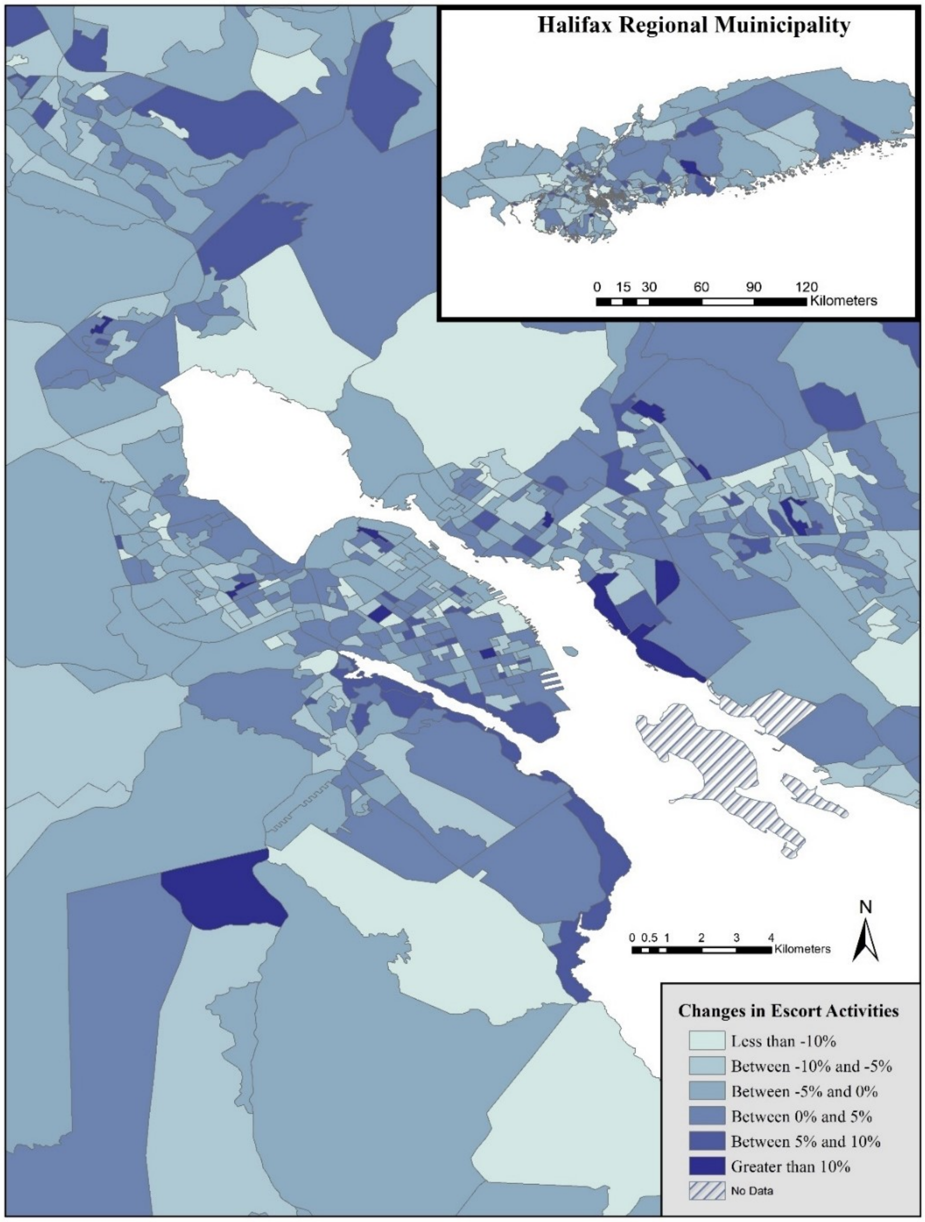

Figure C-4 Predicted Spatial Distribution of Escort Activities

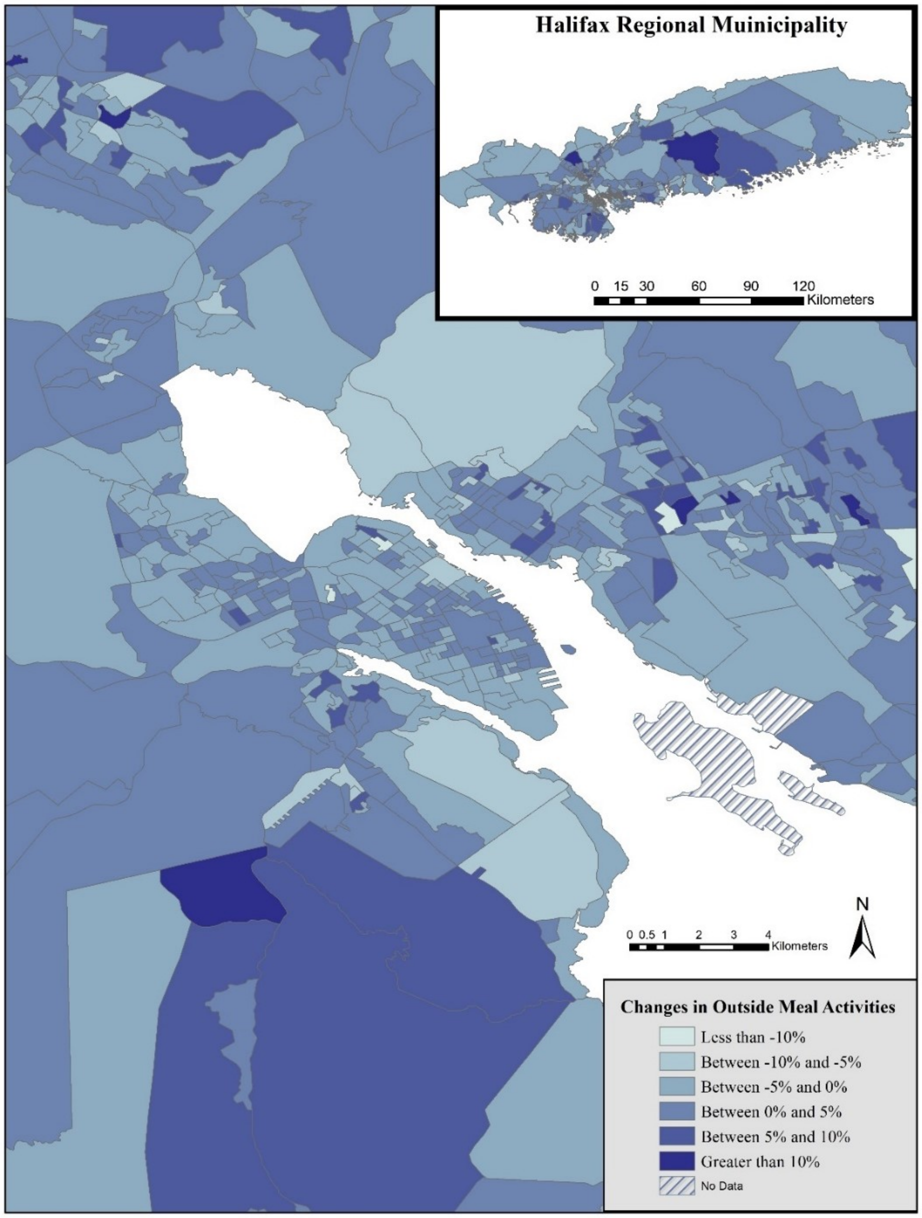

Figure C-5 Predicted Spatial Distribution of Dine out Activities

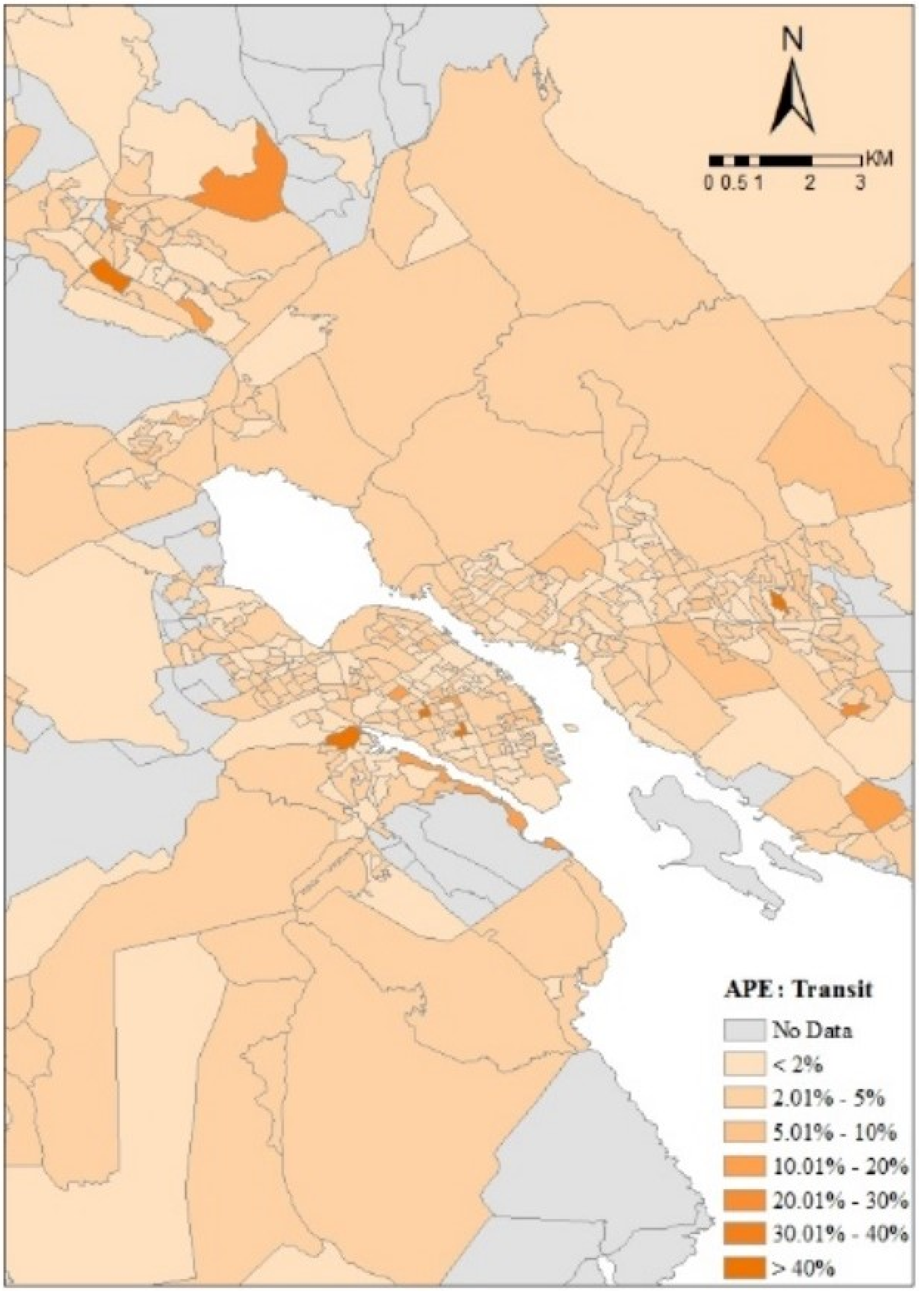

Figure C-6 APE Measures for Transit Mode Share

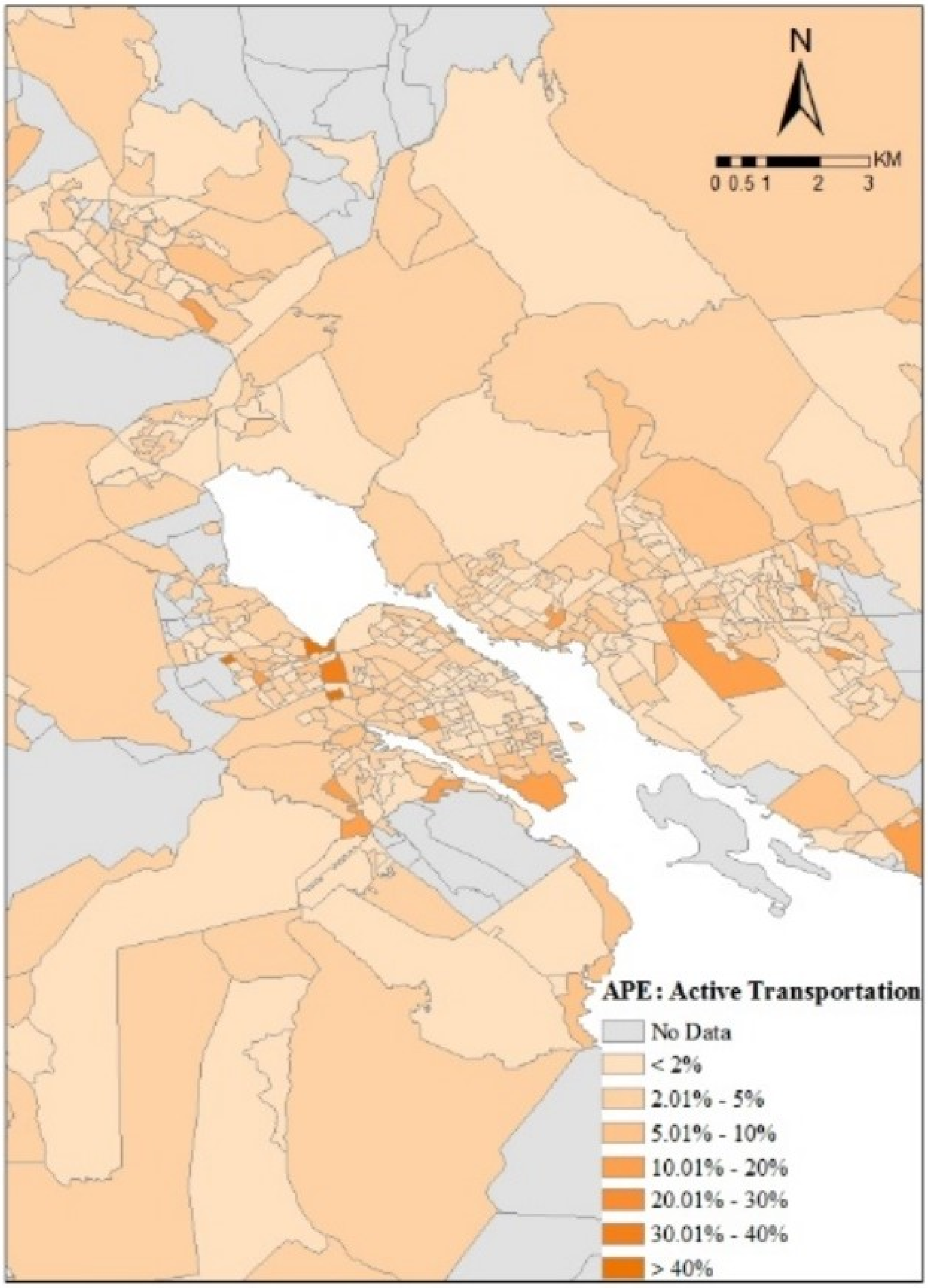

Figure C-7 APE Measures for Active Transportation Mode Share