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# Modelling the dynamics between tour-based mode choices and tour-timing choices in daily activity scheduling

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## Abstract

The paper presents a dynamic discrete–continuous modelling approach to capture individuals' tour-based mode choices and continuous time expenditure choices tradeoffs in a 24-h time frame. The analysis of traditional activity-based models are typically limited to activity-type, location and time expenditure choices. Besides, mode choice is often simplified to fit in a pre-defined activity schedule. However, decisions of tour departure time, tour mode choice and time expenditure choice for out-of-home activities are intricately inter-related, and common unobserved attributes influence these choices. This paper proposes a random utility maximization based dynamic discrete–continuous model for joint tour based mode and tour timing choices. Tour timing choice is modelled as continuous time allocation/consumption choice under 24-h time-budget. In the case of the tour-based mode choice component, it uses a modelling structure which harnesses the power of dynamic programming and discrete choice. A cross-sectional household travel survey dataset collected in the Greater Toronto and Hamilton Area in 2016 is employed for the empirical investigation in this study. Empirical model shows the capability of handling all possible mode combinations within a tour including ride-hailing services (e.g., Uber, Lyft). Empirical results reveal that individuals variations in time expenditure choice are defined by activity type, employment status, and vehicle ownership. In terms of mode choice, it is clear the emerging transportation service users have different travel pattern than conventional mode users. This modelling framework has the potential to test a wide range of policies.

**Keywords** Dynamic discrete–continuous modelling · Time expenditure choice · Tour-based mode choice · Tour departure time · Uber · Ride-hailing

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## Introduction

In the context of an activity-based modelling (ABM) system, the time constraint is shaped by depleting time budget with increasing number of activities and the space constraint is defined by activity locations and work/home locations. Such dynamic time–space constraint is a fundamental tenet of the ABM system; however, most of the operational ABM tend to simplify the scheduling process that may force to overlook the dynamics of scheduling behaviour. In particular, in the case of out-of-home activities, tour departure time, tour-based mode choice and time expenditure choice need to comply with the time–space constraint and these elements are inter-related as well (Jara-Díaz 2003). A tour refers to a chain of trips that starts from a point (e.g., home) and return to the same point (e.g., home) at the end the trip-chain. Tour-based mode refers to the combinations of all trip-modes within a tour. For example, in a three-trip tour the mode for the first trip is walk, second trip is public transit and the last trip is Uber. Therefore, the tour-based mode choice will be "walk-public transit-Uber". The analysis of traditional activity-based models (ABM) are preliminarily focused on activity types, location and time expenditure choices. Mode choice component is often simplified to fit in the operational activity-based models superficially. As a result, dealing with tour departure time, tour-based mode choice and time expenditure choice comprehensively within a unified econometric modelling framework is rare in the literature.

To address this issue, a few studies employed activity time expenditure as an exogenous input to jointly model trip departure time and mode choice (Shabanpour et al. 2017; Habib 2013). A few other studies only modelled trip-based mode choice and work activity time expenditure without incorporating departure time in the modelling framework (Munizaga et al. 2006). Another interesting study used mode choice as an exogenous input to tour-departure time and activity duration model (Vovsha and Bradley 2004). There are three limitations to these approaches. First, a majority of this studies are trip-based and focused only on commuting trip and work duration which are not compatible with most of the operational ABM systems. Second, the analysis of traditional ABMs are primarily focused on activity-type, location and time expenditure choices. Mode choice component is often simplified to fit in the operational activity-based models superficially. The majority of the operational ABMs use the main tour-mode, and each trip has a different mode, conditional on the main tour-mode, location and previous trip's mode choice (Bradley et al. 2010; Davidson et al. 2010). This main tour-mode assumption apparently converts the tour-based mode choice paradigm into the trip-based mode choice system and hence loses the dynamics of inter-dependence among various aspects of mode choices. Third, there are obvious tradeoffs between the tour departure time, tour mode choice and time expenditure choice which are overlooked in the conventional approach. Despite the importance of jointly modelling the tour departure time, tour-based mode choice, and time expenditure of the out-of-home activities, which are well-established in the literature, methodological limitations made it difficult to address such issues.

From the methodological perspective, to capture the inter-relationship between tour departure time, tour-based mode choice and time expenditure choice, a robust modelling technique is warranted which considers a dynamic time–space constrained scheduling process and will avoid the arbitrary discretization of tour departure time. This paper presents a dynamic discrete–continuous modelling approach to capture individuals' tour-based mode choices, tour departure time, and continuous time expenditure choices tradeoffs in a 24-h time frame. For the empirical investigation of this paper, the time until an individual starts the tour (at-home activity) and the duration of out-of-home activities are the topics of interest. To model the departure time of every tour and time expenditure for various out-of-home activities, we adopted the Kuhn-Tucker demand system model which can explicitly capture individuals travel behaviour through baseline preference and satiation effects. In terms of mode choice, we adopted a dynamic discrete choice modelling (DDCM) approach which is a combination of dynamic programming and random utility maximization (RUM) principle. The proposed DDCM explicitly captures the state dependence and future expectation at the end of every trip within the tour.

The modelling framework presented here is developed as a module of an operational dynamic activity-based modelling framework named CUSTOM (Habib et al. 2017; Habib 2018). CUSTOM tackles the mode choice component exogenously. Therefore, this study is a very first step to endogenously model tour-based mode choice with other elements of the CUSTOM. To do so, we are experimenting with various joint discrete–continuous choices (e.g., tour-based mode choice, departure time choice and time-expenditure choice). One possible future work would be adding activity type choice and location choice within the proposed modelling framework of this study. This next step will make CUSTOM robust, and in this way all essential components of an activity-based model will be added to CUSTOM. In the literature, there is evidence of joint discrete–continuous models in terms of trip-based or four-step modelling (FSM) paradigm. There is a series of studies which developed joint discrete–continuous models to analyze three components (mode choice, departure time choice and activity duration) from trip-based modelling aspect (Habib 2012, 2013; Shabanpour et al. 2017). So, we believe that applying the same concept in the activity-based modelling paradigm contributes to the existing literature.

The next section presents an extensive review of time-expenditure choice and mode choice models. This section is followed by sections explaining econometric model formulations, data for empirical modelling, discussion about the model results, model validations and policy scenario analysis. The last section presents the research summary and some ideas for future research.

## Literature review

A unified econometric modelling framework that captures the tour departure time, tour-based mode choice and time expenditure choice is rare in the literature. As such, given the nature of the study, this section is split into two main sections. First, we discussed how operational ABMs capture these interconnected elements. Then, we focused on examining various stand-alone models that tried to model mode choice in conjunction with departure time and time expenditure choice.

Conceptually, ABMs acknowledge the interrelationships between several interconnected elements such as activity type choice, time expenditure choice, location choice and mode choice at the disaggregate level. In CEMDAP, the scheduling model systems are constituted of pattern-level, tour-level and stop-level model system. Tour-level model system takes care of the tour-mode and tour duration, and the trip-level model system takes care of the trip-level mode and duration (Bhat et al. 2004). TASHA simulates activity frequencies, start time, and durations based on random draws from observed joint probability distribution functions (Miller et al. 2005). These predicted activity schedules are used as an exogenous input to the tour-based mode choice models. In the CT-RAMP, an ABM platform, departure time and activity duration (including travel time) are discretized to represent time as a discrete entity (Davidson et al. 2010). In the DaySim modelling structure, main tour mode and tour time-of-day (TOD) are modelled in the tour-level model and trip-based mode and departure time, conditional upon the primary destination of the tour, are modelled in the trip-level model (Bradley et al. 2010). Similar to CT-RAMP, tour time-of-day is represented as a discrete value. CUSTOM is a unified econometric modelling framework which jointly models activity type choice, location choice and activity duration (Habib 2018). Currently, the mode choice component is exogenous to the CUSTOM framework. Mode-specific parameters are incorporated to capture the modal influences in this dynamic ABM.

Mode and departure time choices are particularly crucial in terms of commuting trips. Therefore, joint mode and departure time choice models received considerable attention in the literature.

Bhat proposed a multinomial logit (MNL) model for mode choice and ordered generalized extreme value (OGEV) for the departure time choice in the context of urban shopping trips (Bhat 1998). This study finds that MNL-OGEV provides flexible correlation structure among choices and outperforms the MNL and nested logit (NL) models. Ding et al. (2014) presented a series of generalized extreme value (GEV) models for modelling mode choice and departure time choice jointly. Their proposed cross-nested logit (CNL) model allows non-proportional substitution patterns between a pair of alternatives. Besides, two NL models are presented. In the first NL model, the upper tier is the mode choice, and lower tier is the departure time choice. In the second NL model, the upper tier is the departure time choice, and lower tier is the mode choice. The work of Yang et al. (2013) highlights the similar approach (CNL and two different NL) for modelling a joint choice of residential location, travel mode, and departure time.

Multiple discrete–continuous extreme value (MDCEV) model is a robust modelling framework to model multiple discreteness and continuous choices (Bhat 2005). MDCEV uses Random Utility Maximization (RUM) principle to model discrete and continuous choices. The MDCEV model adopts classical Kuhn–Tucker demand modelling system to model the continuous choice (e.g., time expenditure choice). The model assumes that an individual tries to maximize the total utility in allocating time-use for a specific activity. The Kuhn–Tucker demand modelling system explicitly considers 24-h time budget constraint within the modelling framework. Bhat and Sen (2006) jointly model vehicle types and miles of usage of each vehicle type using MDCEV model. MDCEV is adopted in numerous studies to account for activity duration and activity type choice. In a seminal paper, Bhat et al. (2006) developed a joint modelling framework for activity type choice and time-expenditure choice. Spissu et al. (2009) employed MDCEV for modelling activity duration and activity-participation. Bhat et al. (2013) applied MDCEV model that jointly models household members activity participation and their activity duration. Due to the complex nature, MDCEV modelling framework is challenging while forecasting the model for policy scenarios. Though, there have been a few efforts to find efficient forecasting procedure for MDCEV such as Pinjari and Bhat (2010).

Habib (2013) argues in favour of adopting a joint discrete–continuous model that follows random utility maximization (RUM) principle for both discrete and continuous choice. In this modelling framework, mode choice is considered as a discrete choice and departure time choice is considered as a continuous choice under a 24-h daily time budget constraint. Similar to Habib (2013) and Shabanpour et al. (2017) treated departure time as a continuous variable but modelled by log-linear regression, without explicit consideration of time-budget constraints though. They used a Copula approach to capture the dependency between the mode choice and departure time choice. The significance of modelling activity duration in conjunction with mode and departure time choice model is well established in the literature. Habib (2012) jointly modelled activity duration with other decision processes (trip-based mode choice and departure time) considering that activity duration is not just an exogenous factor, but an endogenous factor to the modelling framework.

In terms of tour formation, the bottom-up approach is one of the most commonly adopted approaches where tours and their associated attributes (i.e. mode, number of stops, and their locations) are determined in a dynamic fashion (Bowman and Ben-Akiva 2001). In the bottom-up approach, lower level decisions are conditioned upon higher-level decisions and higher-level decisions get feedback from lower-level ones through logsum measures (accessibility measures). Bowman et al. (1999) presented an operational activity-based model where the bottom-up approach has been adopted. Expected maximum utilities from the stop location choice model are fed into the mode and destination choice model. Then, expected tour mode and destination utilities are fed into the time-of-the-day choice model. Eventually, time-of-the-day utilities are plugged into the activity pattern model. Both the Portland and San Francisco models follow a bottom-up approach (Ruiter and Ben-Akiva 1978; Bowman et al. 1999). In CT-RAMP, simplified tour-level logsum (accessibility measures) is integrated into the upper-level models (Davidson et al. 2010). These accessibility measures facilitate capturing the sensitivity of the model to level-of-service and land-use attributes. SACSIM also implements a similar bottom-up approach. However, to avoid computational burden SACSIM only includes the most important accessibility measures. More details can be found in Bradley et al. (2010). TASHA also uses bottom up approach where activities are generated at the beginning from random-draws and scheduling is performed by applying various rule-based approaches (Miller et al. 2005). Table 1 shows a summary of the relevant studies discussed above.

From the discussion above, it is evident that none of these studies mainly focused on developing a unified tour departure time, tour-based mode choice and time expenditure model. To address this research gap, this paper presents a dynamic discrete–continuous modelling approach to capture individuals' tour departure time choice, tour-based mode choice and continuous time expenditure choice tradeoffs in a 24-h time frame. The proposed RUM based model structure explicitly complies with dynamic time–space constraints and endogenously captures various choice dimensions in the context of ABM.

## Econometric model

The proposed modelling framework has two components: 1. Discrete tour-based mode choice and 2. Continuous time expenditure choice. In the case of the tour-based mode choice, we make use of an innovative modelling structure which harnesses the power of dynamic programming and discrete choice. Regarding time expenditure choice we employed the Kuhn-Tucker demand system model which can explicitly capture individuals time expenditure choices through baseline preference and satiation effects. Figure 1 shows a home-work-home tour which is a two-trip tour. Figure 2 shows a home-work-gym-home tour which is a three-trip tour. In this study, tour-based mode choice model is used to model all tour combinations. Figure 3 shows how dynamic time constraint (24-h time budget) is applied in the proposed modelling framework. Figure 4 reveals graphical illustration of the modeling components and behavioral assumptions underlying the framework. One prerequisite of the proposed modelling framework is the number of trips in a tour, the activity schedule (sequence of activities) and the location choice information is required to know before the model estimation.

**Table 1** Summary of the relevant studies

| Studies | Behavioural facets modelled | Dynamics of activity-travel scheduling | Dependent variable(s) | Independent variables | Taxonomy of the dynamics included |
|---|---|---|---|---|---|
| *Stand-alone models* | | | | | |
| Bhat (1998) | Mode and departure time choice | Trip-based mode choice, so dynamics of activity travel scheduling is absent | Joint mode and departure time choice | Employment status, age, gender, ethnicity (Non-Caucasian), destination locations | *Tour formation:* Only a single shopping trip is included. Mode choice is handled at the trip level, not the tour-level<br>*Temporal budgets:* 24-h time is divided into five discrete departure time choices |
| Ding et al. (2014) | Mode and departure time choice | Trip-based mode choice, so dynamics of activity travel scheduling is absent | Joint mode and departure time choice | Travel cost and time, household size, income, car and bicycle ownership, age, gender, ethnicity, occupation, job, and office-based policies | *Tour formation:* Only commuting trips are included in the model<br>*Temporal budgets:* Two departure time choices (peak and off-peak) are considered in this model |
| Yang et al. (2013) | Residential location choice and commuting pattern | Trip-based mode choice, so dynamics of activity travel scheduling is absent | Joint residential location choice, mode choice and departure time choice | Housing price, travel cost and time, age, income, car ownership | *Tour formation:* The mode choice component only deals with commuting mode choice. Four residential locations, three mode choices, and three departure time choices are considered as alternatives<br>*Temporal budgets:* The model system divides the entire day into three time segments which are used as the basic unites of temporal resolution |

**Table 1** (continued)

| Studies | Behavioural facets modelled | Dynamics of activity-travel scheduling | Dependent variable(s) | Independent variables | Taxonomy of the dynamics included |
|---|---|---|---|---|---|
| Habib (2013) | Continuous departure time choice and discrete mode choice | Home-work tour is considered as the core of the modelling structure. Simultaneous modelling framework is adopted | Joint discrete–continuous choice of mode and departure time choice | Travel time, cost, distance, employment status, number of vehicles, age, gender, income, home and work zone density, work duration | *Tour formation:* Total number of stops within the home-work tour is considered as an explanatory variable in the model. Five different mode choices are considered in this study. The modelling paradigm is trip-based<br>*Temporal budgets:* The Kuhn–Tucker optimality condition is used to capture the 24-h time budget. The continuous time budget eliminates the issue with arbitrary time discretization |
| Shabanpour et al. (2017) | Continuous departure time choice and discrete mode choice | Trip-based mode choice, so dynamics of activity travel scheduling is absent | Joint discrete–continuous choice of mode and departure time choice | Travel time, accessibility, age, income, number of bikes, activity duration, employment status, road density, Weekend trips | *Tour formation:* Only trip-based mode choice is handled in this model<br>*Temporal budgets:* A log-linear regression model is adopted to model departure time choice. Consequently, it is difficult to impose 24-h time budget constraints |

**Table 1** (continued)

| Studies | Behavioural facets modelled | Dynamics of activity-travel scheduling | Dependent variable(s) | Independent variables | Taxonomy of the dynamics included |
|---|---|---|---|---|---|
| Habib (2012) | Mode choice, work start time, and work duration | All modelling components are tackled simultaneously | Mode choice, work start time, and work duration | Employment status, travel time, cost and distance, vehicle ownership, work duration, dwelling type, household size, age, gender, work and home zone density | *Tour formation:* A tour-based mode choice model is estimated. The sequence of activities is home-work-home. Only two-trip tours are considered<br>*Temporal budgets:* Hazard models are used for the trip start time and work duration models. Hazard model deals with the time until the termination of the current episode |
| Bhat et al. (2013) | Multiple Discrete–Continuous Extreme Value (MDCEV) model for household activity generation | All components are modelled jointly. | Activity purpose and activity duration | Various activity purposes interacted with 1. The number of school going and non-school going kids, 2. The senior adults, 3. High income, 4. The number of vehicles, 5. Work end time, 6. Work duration, 7. Adults who need to drop-off or pick-up from school. Various accessibility measures: 1. Retail and service employment accessibility, 2: Population accessibility | *Tour formation:* This is an activity-based model. Therefore, each activity is modelled using the MDCEV modelling framework. All tour combinations are considered in this model<br>*Temporal budgets:* Each household member's activity duration is modelled in this study. The MDCEV modelling framework tackles the 24-h time budget constraint within the modelling system |

**Table 1** (continued)

| Studies | Behavioural facets modelled | Dynamics of activity-travel scheduling | Dependent variable(s) | Independent variables | Taxonomy of the dynamics included |
|---|---|---|---|---|---|
| Spissu et al. (2009) | Daily time expenditure and activity pattern generation: Mixed Multiple Discrete–Continuous Extreme Value model (MMDCEV) | All components are modelled jointly | Daily time expenditure and activity pattern | Age, marital status, education, employment status, income, flexible work time, dog ownership, home location characteristics | *Tour formation:* All activities are modelled using the MMDCEV modelling framework. All tour combinations are considered in this model<br>*Temporal budgets:* 24-h time budget constraint is considered within the modelling framework |
| *Activity-based models* | | | | | |
| *Notes:* Each activity-based model has multiple components. In this discussion, we only discussed elements that pertain to mode choice, departure time choice, and time expenditure choice | | | | | |
| CEMDAP (Bhat et al. 2004) | Pattern-level, tour-level and stop-level | Work/school activities are tackled first. Then rest of the activities are considered | For pattern- and tour-level: mode and number of stops, duration. For stop-level: activity type, duration and location of stop | Due to space constraint, independent variables are not reported here. For more detail, please see Bhat et al. (2004) | *Tour formation:* In CEMDAP, work activities are considered as temporally fixed elements and other activities are scheduled around work activity. This is a comprehensive modelling framework. Models are tackled at the tour, pattern and stop levels. Each level has a series of components<br>*Temporal budgets:* Linear regression model is used for activity duration and tour duration. Linear regression is not ideal for capturing 24-h time budget constraint |

**Table 1** (continued)

| Studies | Behavioural facets modelled | Dynamics of activity-travel scheduling | Dependent variable(s) | Independent variables | Taxonomy of the dynamics included |
|---|---|---|---|---|---|
| TASHA (Miller et al. 2005) | Activity generation, location choice, rule-based activity scheduling, tour-based mode choice, and traffic assignment | TASHA uses bottom-up approach: activities are first generated, and scheduling is performed by rule-based methods | Location choice and tour-based mode choice | Travel time, cost, trip purpose dummy, intrazonal dummy and adjacent zonal dummy | *Tour formation:* First, TASHA randomly draw from work activities and then randomly draw from other activities. The tour-based mode choice model in TASHA tackles both tour mode and trip mode. TASHA models all feasible tour-mode combinations<br>*Temporal budgets:* After activity generation, rule-based scheduling is used to make sure that all activities fit within 24-h time budget |
| CT-RAMP (Davidson et al. 2010) | Activity participation, tour formation and time allocation, tour-level destination choice, mode choice, stop frequency and location | Bottom-up approach is used to integrate lower-level and higher-level components | Activity participation, tour formation and time allocation, tour-level destination choice, mode choice, stop frequency and location | Age, gender, employment status, occupation, income classification, education level, level of service-related attributes and many other variables. | *Tour formation:* CT-RAMP uses bottom-up approach. Tour level destination choice, mode choice, stop frequency and stop location. A main tour mode choice model is estimated. Then, a trip-level mode choice model is estimated conditioned on main tour mode and destination location<br>*Temporal budgets:* Discrete-time choice is used to model activity duration and tour departure time. A total of the 42-time intervals are considered in the modelling system |

**Table 1** (continued)

| Studies | Behavioural facets modelled | Dynamics of activity-travel scheduling | Dependent variable(s) | Independent variables | Taxonomy of the dynamics included |
|---|---|---|---|---|---|
| DaySim (Bradley et al. 2010) | Four components: 1. longer term person and household choices, 2. activity pattern choices, 3. tour-level choices, 4. and trip-level choices | Bottom-up approach is adopted to connect lower-level and higher-level components | Work and school location, auto-ownership, activity pattern choice, destination choice, main mode choice, primary activity scheduling | Household characteristics, person characteristics, parcel-level land use and accessibility variables. Zone-level accessibility variables, endogenous activity-pattern, location, mode and transit-oriented development variables | *Tour formation:* Daysim adopts bottom-up approach. Main tour mode and tour time-of-day (TOD) are modelled at the tour-level model and trip-based mode and departure time, conditional upon the primary destination of the tour, are modelled in the trip-level model<br>*Temporal budgets:* 24-h is divided into 48 discrete choices (each interval is 30 min) |

**Table 1** (continued)

| Studies | Behavioural facets modelled | Dynamics of activity-travel scheduling | Dependent variable(s) | Independent variables | Taxonomy of the dynamics included |
|---|---|---|---|---|---|
| CUSTOM (Habib 2018) | Activity type choice, location choice, and activity-duration | Time-of-the-day specific attributes are used to tackle the dynamics | Activity type choice, location choice, and activity-duration. | *First out of activity:* Various activity purpose interacted with the full-time worker, male, and age. Travel time. *Subsequent activity:* travel time interacted with mode. *Location choice:* Various activity purposes interacted with travel time, population density, employment density, school density, restaurant density, shop density, art and entertainment center density. *Time expenditure choice:* time of the day of activity start time interacted with various activity types | *Tour formation:* CUSTOM jointly models all components using simultaneous modelling approach (i.e., activity type, location choice and activity duration). Work schedules begin with the choice to participate in an out-of-home activity choice or stay at home for the entire day. After that location and activity duration choices are generated *Temporal budgets:* 24-h time budget constraint is captured by a Kuhn–Tucker optimality condition |

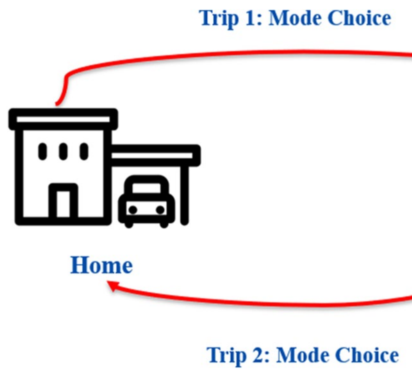


**Fig. 1** Home-work-home tour (two-trip tour)

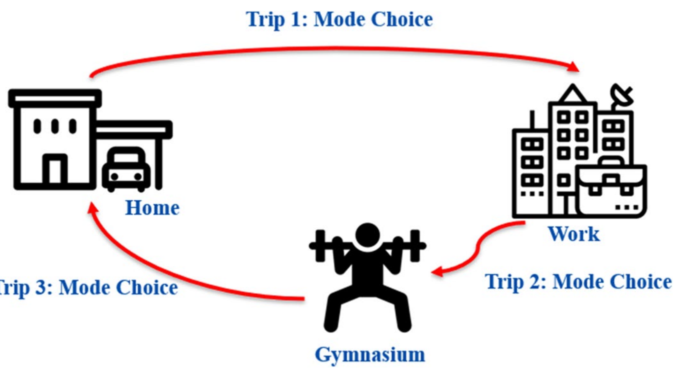


**Fig. 2** Home-work-gym-home tour (three-trip tour)

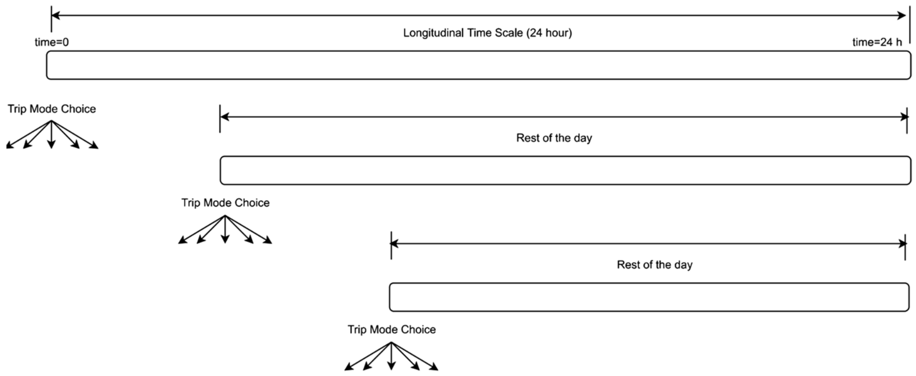


**Fig. 3** Dynamic discrete–continuous approach to model tour departure time, tour-based mode choice and time-expenditure choice

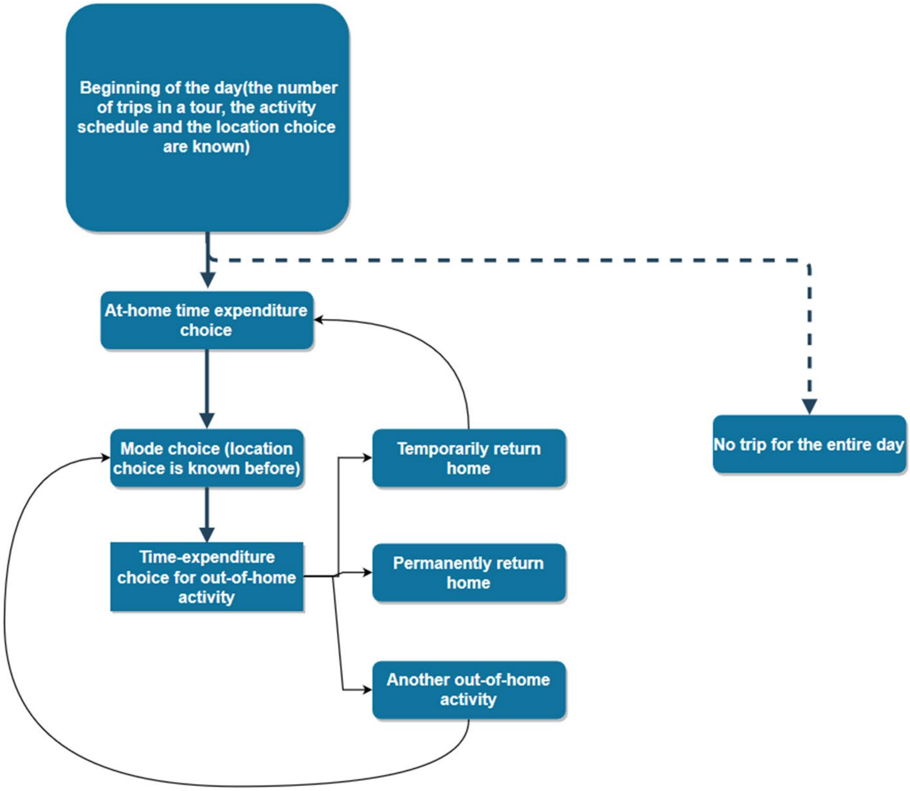


**Fig. 4** Graphical illustration of the modeling components and behavioral assumptions underlying the framework

The time expenditure choices are modelled as a continuous variable where balances between the time expenditure to a particular activity and the rest of the activities (composite activity) are explicitly taken into consideration. Time expenditure choices are modelled based on RUM-based direct utility function of time expenditure which is proposed by Habib et al. (2017) and Habib (2011). Let's assume that $T_j$ is the time expenditure to the scheduling activity, and $T_c$ is the time expenditure to composite activity. $\alpha_j$ is the satiation parameter for time expenditure to the scheduling activity and $\alpha_c$ is the satiation parameter for time expenditure to the composite activity. Also, $\Omega$ is the parameter vector, and $x$ is an attribute vector, and $\varepsilon$ is the random utility component of the baseline utility of time expenditure choice. Now, the total utility ($U_j$) of the time expenditure ($T_j$) to a scheduling activity ($j$) under time budget $T$ ($T = T_j + T_c$) can be written as:

$$U_j = \left(\frac{1}{\alpha_j}\right)\left(e^{\Omega_j x_j + \varepsilon_j}\right)\left(T_j^{\alpha_j} - 1\right) + \left(\frac{1}{\alpha_c}\right)\left(e^{\Omega_c x_c + \varepsilon_c}\right)\left(T_c^{\alpha_c} - 1\right) \tag{1}$$

Now, if we adopt Kuhn–Tucker optimality condition assuming Type I Generalized Extreme Value (GEV) distribution for the random utility component, the probability of spending time ($t_j$) to the scheduling activity can be written as follows:

$$P_{T_j} = \left(\frac{1-\alpha_j}{T_j} + \frac{1-\alpha_c}{T_c}\right)\mu_{t_j} \cdot \left(\frac{e^{\left(-\mu_{t_j}\left(V_{T_c}-V_{T_j}\right)\right)}}{\left(1+e^{\left(-\mu_{t_j}\left(V_{T_c}-V_{T_j}\right)\right)}\right)^2}\right) \tag{2}$$

In Eq. (2) utility of the scheduling activity $\left(V_{T_c}\right)$ and utility of the composite activity $\left(V_{T_j}\right)$ can be defined as follows:

$$V_{T_c} = \left(\alpha_c - 1\right)\ln\left(T - T_j\right) \tag{3}$$

$$V_{T_j} = \Omega_j x_j + \left(\alpha_j - 1\right)\ln\left(T_j\right) \tag{4}$$

In the case of tour-based mode choice, the dynamic discrete choice method (DDCM) is adopted (Aguirregabiria and Mira 2002, 2007; Rust 1987). The DDCM approach assumes that individual maximize their expected future utility during their current choice. To formulate the tour-based mode choice, we assume a finite time horizon. In this study, we adopted the DDCM approach for tour-based mode choice proposed by Hasnine and Habib (2018). The value function for expected discounted future utility can be written:

$$V\left(x_t\right) = \int \underset{d\varepsilon C\left(x_t\right)}{Max}\left\{m\left(x_t, c_t\right) + \varepsilon_t\left(c_t\right) + \beta \sum_{x_{t+1}\varepsilon X} \int V\left(x_{t+1}, \varepsilon_{t+1}\right) \cdot p\left(x_{t+1} | x_t, c_t\right)\right\} p\left(d\varepsilon_{t+1} | x_{t+1}\right) \tag{5}$$

Here, $m$ = mode choice utility which depends on two vectors of state variables $m(x_t, \varepsilon_t)$ which follow controlled Markov process, $x_t$ is the attribute vector for a certain trip at time t, $\varepsilon_t$ is a random error component with variance $\sigma^2$, $c_t$ is a decision variable which indicated the transition from one trip $\left(x_t\right)$ to another trip $\left(x_{t+1}\right)$ using Markov transition probability $p(x_{t+1}, \varepsilon_{t+1} | x_t, \varepsilon_t, c_t)$, $\beta$ is a discount factor which should be in between zero to one.

In Eq. (5), if we assume that $p(d\varepsilon|x)$ is given by a multivariate extreme value distribution, this assumption simplifies Eq. (5) as follows:

$$V\left(x_t\right) = ln\left[\sum_{c\varepsilon C\left(x_t\right)} e^{\left\{m\left(x_t, c_t\right) + \beta EV\left(x_t, c_t\right)\right\}}\right] \tag{6}$$

Now the conditional probability $p(c|x, \eta)$ can be written as an MNL formulation:

$$p(c|x, \eta) = \frac{e^{\left\{m\left(x_t, c_t\right) + \beta EV\left(x_t, c_t\right)\right\}}}{\sum_{j\varepsilon C\left(x_t\right)} e^{\left\{m\left(x_j, c_j\right) + \beta EV\left(x_j, c_j\right)\right\}}} \tag{7}$$

Here, $\eta$ is the set of parameters which we need estimate and EV is the expected value function. Tour-based mode choice is a finite-horizon problem since we know the full day activity schedule beforehand. To handle this non-stationary problem, we adopted the log-sum enumeration approach. Now, the likelihood of any tour-based mode choice in conjunction with the time expenditure choice to the scheduling activity can be written as $L_{mT} = p(c|x, \eta) \cdot P_{T_j}$. Maximum likelihood estimation technique is adopted to estimate the parameters ($\eta$) of this joint likelihood equation. This joint discrete–continuous model is estimated by a program written in the GAUSS matrix programing language (Aptech 2018).

## Data description

The data came from a household level travel survey, which represents 5% of the households within the Greater Toronto and Hamilton Area (GTHA). This survey is well known as Transportation Tomorrow Survey (TTS) 2016. A total 162,700 numbers of households are surveyed in this survey which consists of 395,885 individuals and around 798,000 trip records. TTS 2016 collected a wide range of household and personal attributes. In addition, this survey collected a single-day travel diary for all household members which includes origin, destination, start time, activity purpose of each trip. For the empirical investigation, we retrieved two subsets where individuals performed two-trip and three-trip tours. Despite the proposed dynamic discrete–continuous modelling structure can model any number of trips, due to space constraints we only presented the models for tours with two trips and three trips.

The TTS 2016 survey sample, which is used for empirical modelling, is compared to the Census 2016 sample for the Toronto census metropolitan area (CMA). For the external validity of our finding, it is essential to compare the TTS 2016 and the Census 2016. Table 2 shows a comparison between the vital descriptive statistics for the TTS 2016 sample and the Census 2016. Table 2 shows that the average individual age in the Census 2016 is 40.6, whereas the average respondents' age in the TTS 2016 is 49.713 (two-trip tour) and 51.61 (three-trip tour). The TTS 2016 only collects travel diaries from individuals aged more than 12. This is the reason behind this skewed age distribution in the TTS 2016. In terms of gender distribution, male and female have equal representation (nearly 50%) in the TTS 2016 and Census 2016. The average household size is 2.4 in Census and 2.7 in the TTS, which is very close. In terms of dwelling type, Census and TTS do not have similar classification. In the TTS, more people are living in the apartment (65.211%), and in the Census, only 44.323% of people are living in the apartment. Since the Census only includes a building that has five or more storeys as an apartment, this may be the cause behind the low percentage of apartments in Census. In terms of mode choice, Census only collects commuting mode choice information whereas TTS collects detail travel diaries of individuals for all purposes. Therefore, it is not straightforward to compare mode choice between the TTS and the Census. However, the underlying trends in mode choice for both the Census and the TTS are close. Since the overall descriptive statistics are close, it can be reasonably concluded that the TTS sample is a good representation of the population.

It is found that individuals who performed tours with two trips stayed at home on an average 15.45 h (after midnight) before the first out-of-home activity while the individuals who performed three-trip tours stayed 15.68 h (after midnight) before the first out-of-home activity. This means an individual who makes two or three-trip tours tend to leave home around 9 am in the morning. In the case of tours with two trips, it is found that the average activity duration for the out-of-home activity is 6.43 h. In the case of three-trip tours, it is found that the average activity duration for the first out-of-home activity is 3.93 h and average activity duration for the last out-of-home activity is 2.57 h. For the three-trip tours, working activities are spread in between the first and second out-of-home activity. Hence, the average activity duration is less than the two-trip tours. In terms of mode choice, 26 different tour mode combinations are observed in the two-trip tours, and 34 different tour mode

**Table 2** Comparison between Census 2016 data and TTS 2016 data (two-trip tour and three trip tour)

| Attribute | TTS 2016 (two-trip tour) | | TTS 2016 (three-trip tour) | | Census 2016 | |
|---|---|---|---|---|---|---|
| Gender (%) | Female: 48.638<br>Male: 51.362 | | Female: 54.819<br>Male: 45.181 | | Female: 51.911<br>Male: 48.089 | |
| Average age | 49.713 | | 51.61 | | 40.6 | |
| Average household size | 2.723 | | 2.677 | | 2.4 | |
| Dwelling type (%) | Apartment | 65.211 | Apartment | 66.362 | Apartment in a building that has five or more storeys: | 44.323 |
| | Townhouse | 24.869 | Townhouse | 23.977 | Single-detached house | 24.231 |
| | House | 9.920 | House | 9.661 | Other | 31.446 |
| Mode choice (%) (Note: For census only commuting mode choice) | AP-AP | 64.487 | AD-AD-AD | 69.6989 | AD | 45.982 |
| | AP-LT | 8.244 | PR-LT-Reverse PR | 0.6452 | AP | 4.570 |
| | AP-W | 0.786 | PR-W-LT | 0.1046 | LT | 37.009 |
| | AP-Taxi | 0.491 | AP-AP-AP | 12.8575 | W | 8.606 |
| | LT-AP | 0.037 | AP-AP-LT | 0.4011 | B | 2.746 |
| | LT-LT | 0.473 | AP-AP-W | 0.3139 | Other modes | 1.087 |
| | LT-KR | 13.714 | AP-LT-LT | 0.3662 | | |
| | LT-W | 0.035 | AP-LT-AP | 0.2674 | | |
| | LT-Uber | 0.348 | AP-KR-LT | 0.1918 | | |
| | LT-Taxi | 0.037 | AP-W-W | 0.1104 | | |
| | PR-PR | 0.108 | AP-W-AP | 0.4824 | | |
| | KR-AP | 2.319 | LT-AP-AP | 0.4243 | | |
| | KR-LT | 0.050 | LT-LT-AP | 0.6161 | | |
| | BR-BR | 1.121 | LT-LT-LT | 5.5627 | | |
| | W-AP | 0.027 | LT-LT-W | 1.1393 | | |
| | W-LT | 0.136 | LT-LT-Uber | 0.0698 | | |
| | W-W | 0.170 | LT-LT-taxi | 0.1337 | | |
| | B-B | 4.631 | LT-W-LT | 1.5113 | | |
| | Uber-LT | 1.310 | LT-W-W | 0.1744 | | |
| | Uber-Uber | 0.030 | KR-LT-AP | 0.2093 | | |
| | mc-mc | 0.119 | KR-LT-LT | 0.1511 | | |
| | Sbus-Sbus | 0.116 | B-B-B | 0.9416 | | |
| | Taxi-AP | 0.783 | W-AP-AP | 0.3023 | | |
| | Taxi-LT | 0.034 | W-LT-AP | 0.1104 | | |
| | Taxi-Taxi | 0.055 | W-LT-LT | 0.7847 | | |
| | | 0.339 | W-LT-W | 0.1104 | | |
| | | | W-W-AP | 0.1337 | | |
| | | | W-W-LT | 0.1221 | | |
| | | | W-W-W | 1.5462 | | |
| | | | Taxi-Taxi-Taxi | 0.1221 | | |
| | | | MC-MC-MC | 0.1279 | | |
| | | | Sbus-AP-AP | 0.1569 | | |
| | | | Sbus-W-AP | 0.0407 | | |
| | | | Sbus-Sbus-AP | 0.0698 | | |

*AD* auto drive, *AP* auto passenger, *LT* local transit with walk access, *PR* park and ride, *KR* kiss and ride, *BR* bike and ride, *W* walk, *B* bike, Uber, Taxi, *MC* motorcycle, *Sbus* School Bus

combinations are observed in the three-trip tours. In terms of the two-trip tour, the most dominant tour mode is auto-drive (64.49%) and the second dominant tour mode is transit-walk access (13.72%). In terms of the three-trip tour, the most dominant tour mode is also auto-drive (69.70%) and the second dominant tour mode is transit-walk access (5.56%).

To generate level-of-service information, a Google application programming interface (API) based tool was developed (Hasnine et al. 2017). Using origin, destination and departure time as inputs, this API based tool can accurately predict travel time and distance for various modes including public transit, auto-drive, walk and bike. The common practice in travel demand modelling is to develop various traffic assignment models and generate level-of-service matrices based on these models. In the four-stage modelling (FSM) paradigm, these traffic assignment models are aggregated at the traffic analysis zone (TAZ) level. Due to this spatial aggregation, it is hard to calculate the exact travel time and distance between two points. Such traffic assignment models also suffer from temporal aggregation. Typically, we divide the entire day into multiple discrete time periods (e.g., AM peak, midday, PM peak, evening, night). Such an approach could not differentiate between a trip starting at 8 am versus at 9 am because both are considered as AM peak. To get rid of this spatial and temporal aggregation, Google application programming interface (API) based framework, namely Tool for Incorporating Level of Service attributes (TILOS), is adopted in this study (Hasnine et al. 2017). TILOS can generate level-of-service information from the exact origin (longitude and latitude), destination (longitude and latitude) and departure time (date and time). TILOS collects auto-drive data from a mix of historical travel data and real-time travel information. Therefore, it provides a very close match to traffic assignment model results but naturally, TILOS is more precise and accurate. The transit level-of-service information is mainly retrieved from The General Transit Feed Specification (GTFS) data. Thus, transit level-of-service is sensitive to daily changes of transit service provision that might affect the mode choices of the individuals. In TTS 2016, individuals reported their origin, destination and departure time for each trip. These inputs are feed into the TILOS, and level-of-service matrices are generated. To generate cost by motorized mode and transit fare we employed a list of available cost matrices which are widely used for transportation planning by various government and public agencies in this region (Natural Resources Canada 2018). For ride-hailing services such as Uber and Taxi, a distance-based fare matrix is used for estimating the fare.

Regarding trip-mode, twelve types of trip-modes are observed in both datasets. Auto drive and motorcycle modes are available for an individual if the respondent has a driving license and the household has an automobile. The auto passenger is available if the household owns an automobile. Transit-walk access and bike and ride are available if the Google API tool shows transit availability. Park and ride is available if Google API shows transit availability, if park and ride designated stations are available based on the origin and access distance to park and ride station, and if the auto drive mode is available for the individual. Kiss and ride is available if Google API shows transit availability and if auto passenger mode is available for the individual. Bike and walk mode availability depend on the threshold commuting distance of 10 km and 5 km respectively. Uber and Taxi are available for everyone. The school bus mode is available if the school bus is available in the home location zone of a student. The dynamic discrete–continuous model presented in this paper tracks the status of the automobile, transit and other modes availability and generate the feasible choice set at the beginning of every trip within a tour. For instance, if an individual does not choose the auto-drive on the first trip, then auto-drive is not available for the rest of the tour. The following section presents the empirical results.

## Empirical model

The summary of the empirical models is presented in Tables 3, 4, 5, and 6. The model results for each type of tour is split into two tables: 1. tour departure time and time expenditure choice model, 2. tour-based mode choice model. In the case of model estimation, we employed a subset of randomly selected 80% of the total sample, and the remaining 20% are treated as a holdout sample for model validation. In the case of the two-trip tour model, we estimated a total of 99 parameters while in the case of the three-trip tour model we estimated a total of 92 parameters. A majority of the parameters presented in this study are statistically significant with a 95% confidence interval. Various types of level-of-service, trip-level, household-and person-level of variables are incorporated in the systematic utility equation of the final models. A list of these variables are mentioned as follows:

Level-of-service attributes: Travel time, cost and distance for all modes
Trip-level attributes: Trip purpose, activity duration
Household-level attributes: Number of vehicles in the household, transit pass information
Person-level attributes: Gender, age

The goodness-of-fit of the joint model is estimated using adjusted Rho-squared values against the null model. For the joint model of the two-trip tours, the adjusted Rho-squared value against the null model is 0.15 while for the joint model of three-trip tours the adjusted Rho-squared value against the null model is 0.143. Since this is a multi-component joint discrete–continuous model, the goodness-of-fit is reasonable considering the complex modelling structure.

## Tour departure time choice for the first tour of the day: time expenditure choice for at-home activities before the first out-of-home activity

Tables 3 and 4 present the estimated parameters for the tour departure time choices for two-trip tour and three-trip tour. For both types of tour, departure time is treated as a continuous choice at home before the first out-of-home activity. The time-expenditure choice model has two components such as a baseline utility of time expenditure and satiation parameter. The baseline utility component reveals the baseline preference of spending time at-home before leaving home in comparison to the rest of the activities (composite activities). In the case of satiation parameter, the positive value of satiation parameters indicates that individuals tend to spend a longer duration for a specific activity and vice versa. According to the econometric specification, the satiation parameter should be less than one. To ensure such restriction, we adopted the following specifications of satiation parameter, $\alpha = 1 - \exp(-\theta y)$. In this equation, y is a vector of attributes and θ is a parameter vector.

The baseline utility component of an individual's time expenditure is defined as an exponential function which is parameterized as a function of employment status, individual's age, activity type and vehicle ownership. A high constant value is found for both tour types which essentially suggest that there are some unobserved determinants which are not captured by this dataset and these unobserved determinants influence the marginal utility of the departure time choice for the first tour of the day. It is found that full-time employees tend to leave home earlier than the part-time employees. The model results reveal that older people are more likely to leave home later than younger people. These findings echo the finding of another research where the study area was another Canadian region, the Ottawa–Gatineau metropolitan region (Habib 2018). It is challenging to find attributes which capture the satiation function for at-home activities. We incorporated only dwelling type and a constant as explanatory variables in the satiation function for both two-trip and three-trip tours. It is found that apartment owners tend to spend more time at home before

**Table 3** Departure time choice of the two-trip tour and time expenditure choice for out-of-home activity

| | | | |
|---|---|---|---|
| Number of observations | | 70,476 | |
| Number of estimated parameters | | 99 | |
| Adjusted Rho squared against a null model | | 0.15 | |
| | | Estimates | t-stat |
| *Baseline utility function: Tour departure time choice for the first tour of the day: Time expenditure choice for at-home activities before the first out-of-home activity* | | | |
| | Constant | 32.507 | 164.393 |
| | Activity type: at-home | 0.165 | 2.601 |
| | Logarithm of age | 0.786 | 43.74 |
| Employment status | Full-time | −2.318 | −121.309 |
| | Part-time | −0.849 | −34.753 |
| | Number of vehicle in the household | −0.073 | −12.073 |
| *The exponential function of satiation parameter: at-home activities before first out-of-home activity* | | | |
| | Constant | −1.875 | −457.574 |
| Type of dwelling unit | House | −0.003 | −4.567 |
| | Apartment | 0.004 | 5.69 |
| *Baseline utility function: Time expenditure choice of the first out-of-home activity in a two-trip tour* | | | |
| Constant: activity type | First school trip of the day | 35.333 | 21.257 |
| | First work trip of the day | 46.609 | 101.957 |
| | Shopping | 2.389 | 7.412 |
| | Facilitate passenger | −3.637 | −11.588 |
| Time-of-day (as a fraction of 24 h) interaction with activity type | First school trip of the day | −11.906 | −5.137 |
| | First work trip of the day | −3.634 | −5.266 |
| | Shopping | −1.454 | −2.669 |
| | Facilitate passenger | −0.099 | −0.167 |

**Table 3** (continued)

| | | | |
|---|---|---|---|
| *The exponential function of satiation parameter: The first out-of-home activity in a two-trip tour* | | | |
| Constant: activity type | First school trip of the day | − 2.311 | − 42.614 |
| | First work trip of the day | − 2.364 | − 234.323 |
| | Shopping | − 1.307 | − 30.067 |
| | Facilitate passenger | − 1.487 | − 15.236 |
| Time-of-day (as a fraction of 24 h) interaction with the activity type | First school trip of the day | 0.896 | 11.495 |
| | First work trip of the day | 0.404 | 26.685 |
| | Shopping | 1.149 | 15.356 |
| | Facilitate passenger | 3.032 | 14.873 |

**Table 4** Departure time choice of the three-trip tour and time expenditure choice for out-of-home activities

| | | | |
|---|---|---|---|
| Number of observations | | 17,204 | |
| Number of estimated parameters | | 92 | |
| Rho squared against a null model | | 0.143 | |
| | | Estimates | t-stat |
| *Tour departure time choice for the first tour of the day: Time expenditure choice for at-home activities before first out-of-home activity* | | | |
| | Constant | 39.176 | 96.131 |
| | Activity type: at-home | −0.57 | −6.465 |
| | Logarithm of age | 0.897 | 24.848 |
| Employment Status | Full-time | −2.217 | −58.117 |
| | Part-time | −0.946 | −18.884 |
| | Number of vehicle in the household | −0.049 | −3.159 |
| The exponential function of satiation parameter: at-home activities before first out-of-home activity | | | |
| | Constant | −2.024 | −269.105 |
| Type of dwelling unit | Apartment | 0.004 | 5.743 |
| *Baseline utility function: Time expenditure choice of the first out-of-home activity in a two-trip tour* | | | |
| Constant: activity type | First school trip of the day | 13.502 | 27.615 |
| | First work trip of the day | 16.432 | 32.251 |
| | Shopping | 0.433 | 3.959 |
| | Facilitate passenger | −3.312 | −40.197 |
| Time-of-day (as a fraction of 24 h) interaction with the activity type | First work trip of the day | 5.463 | 5.324 |
| *The exponential function of satiation parameter: the first out-of-home activity in a two-trip tour* | | | |
| Constant: activity type | First school trip of the day | −1.635 | −39.165 |
| | First work trip of the day | −1.854 | −81.439 |
| | Shopping | −1.207 | −42.794 |
| | Facilitate passenger | −1.333 | −26.546 |

**Table 4** (continued)

| | | | |
|---|---|---|---|
| Time-of-day (as a fraction of 24 h) interaction with the activity type | First school trip of the day | 0.671 | 14.207 |
| | First work trip of the day | 0.585 | 13.365 |
| | Shopping | 1.166 | 26.079 |
| | Facilitate passenger | 2.380 | 20.256 |
| *Baseline utility function: Time expenditure choice of the last out-of-home activity in a two-trip tour* | | | |
| Constant: activity type | First school trip of the day | 6.991 | 8.603 |
| | First work trip of the day | 21.526 | 52.635 |
| | Shopping | 0.460 | 6.259 |
| | Facilitate passenger | −2.565 | −20.988 |
| *The exponential function of satiation parameter: the last out-of-home activity in a two-trip tour* | | | |
| Constant: activity type | First school trip of the day | −0.798 | −12.105 |
| | First work trip of the day | −1.728 | −84.321 |
| | Shopping | −1.181 | −58.667 |
| | Facilitate passenger | −1.395 | −21.09 |
| Time-of-day (as a fraction of 24 h) interaction with the activity type | First work trip of the day | 0.323 | 19.598 |
| | Shopping | 0.948 | 34.306 |
| | Facilitate passenger | 1.763 | 17.84 |

**Table 5** Dynamic mode choice model (tours with two trips)

| | | | |
|---|---|---|---|
| Number of observations | | 70,476 | |
| Number of estimated parameters | | 99 | |
| Adjusted Rho squared against a null model | | 0.15 | |
| Parameters | Mode | Estimates | t-stat |
| First trip: Alternative Specific Constant (ASC) | Auto drive | 4.012 | 19.944 |
| | Auto passenger | 1.754 | 8.777 |
| | Transit-walk access | 0.000 | – |
| | Park and Ride | − 1.927 | − 2.846 |
| | Kiss and Ride | − 2.975 | − 11.608 |
| | Bike and Ride | − 2.827 | − 8.796 |
| | Walk | 0.501 | 2.059 |
| | Bike | 1.974 | 9.165 |
| | Uber | − 2.824 | − 9.840 |
| | Motorcycle | − 2.307 | − 7.695 |
| | School bus | 3.139 | 10.827 |
| | Taxi | − 1.174 | − 4.870 |
| ASC of the second trip when the first trip is made by auto passenger | Auto passenger | 0.000 | – |
| | Transit-walk access | − 1.288 | − 15.102 |
| | Walk | − 1.376 | − 12.999 |
| | Taxi | − 4.657 | − 20.842 |
| ASC of the second trip when the first trip is made by Transit-walk access | Auto passenger | 0.000 | – |
| | Transit-walk access | 3.711 | 43.345 |
| | Kiss and Ride | − 2.181 | − 10.123 |
| | Walk | 1.255 | 10.153 |
| | Uber | − 2.209 | − 9.941 |
| | Taxi | − 0.845 | − 5.356 |
| ASC of the second trip when the first trip is made by Kiss and Ride | Auto passenger | 0.000 | – |
| | Transit-walk access | 4.661 | 23.595 |
| ASC of the second trip when the first trip is made by Walk | Auto passenger | 0.000 | – |
| | Transit-walk access | 1.427 | 7.907 |
| | Walk | 3.447 | 26.213 |
| ASC of the second trip when the first trip is made by Uber | Transit-walk access | 0.000 | – |
| | Uber | 1.667 | 6.418 |
| ASC of the second trip when the first trip is made by Taxi | Auto passenger | 0.000 | – |
| | Transit-walk access | 1.137 | 4.368 |
| | Taxi | 3.100 | 12.684 |
| Cost: First trip | Auto Drive, Auto Passenger, Transit-walk access, Park and Ride, Kiss and Ride, Bike and Ride | − 0.238 | − 23.763 |
| | Uber and Taxi | − 0.039 | − 9.765 |
| Cost: Second trip | Auto Passenger, Transit-walk access, Park and Ride, Kiss and Ride, Bike and Ride | − 0.039 | − 9.765 |
| | Uber and Taxi | − 0.027 | − 5.704 |
| Travel Time: First and second trip | All motorized mode | − 0.057 | − 48.619 |
| | All motorized mode | − 0.005 | − 5.703 |

**Table 5** (continued)

| | | | |
|---|---|---|---|
| Distance: Trip one | Walk and Bike | −0.625 | −26.986 |
| Distance: Trip two | Walk and Bike | −0.077 | −3.12 |
| Local transit pass ownership: First trip | Park and Ride | 3.909 | 63.914 |
| | Kiss and Ride | 3.124 | 20.747 |
| | Bike and Ride | 3.584 | 26.857 |
| Regional transit pass ownership: First trip | Park and Ride | 1.367 | 35.697 |
| | Kiss and Ride | 3.349 | 39.959 |
| | Bike and Ride | 2.552 | 27.452 |
| Number of vehicles: First trip | Auto drive | 0.438 | 44.102 |
| Number of vehicles: Second trip | Transit-walk access | −0.306 | −11.053 |
| | Auto passenger | 0.914 | 24.084 |
| Dummy variable for female: First trip | Transit-walk access | 0.312 | 9.453 |
| | Kiss and Ride | 0.989 | 12.345 |
| | Bike | −0.998 | −13.583 |
| | Motorcycle | −1.448 | −4.782 |
| Age less than or equal to 25 years: First trip | Auto passenger | 2.056 | 29.388 |
| | Transit-walk access | 0.877 | 12.785 |
| | Kiss and Ride | 0.775 | 4.973 |
| | Walk | 0.992 | 9.307 |
| Age less than or equal to 25 years: Second trip | Auto passenger | −0.975 | −14.783 |
| Age greater than 25 years and less than or equal to 30 years: First trip | Walk | 0.945 | 10.827 |
| | Bike | 0.586 | 5.138 |
| Age greater than 25 years and less than or equal to 30 years: Second trip | Transit-walk access | 0.249 | 3.311 |
| | Auto drive | −1.411 | −6.312 |
| First trip purpose: school trip | Auto passenger | −0.630 | −2.838 |
| | Transit-walk access | 0.519 | 2.315 |
| | Park and Ride | 0.712 | 2.438 |
| | Kiss and Ride | 1.346 | 4.642 |
| | Walk | 1.304 | 5.388 |
| | Bike | 1.494 | 6.12 |
| | Auto drive | 0.440 | 2.908 |
| | Auto passenger | −0.515 | −3.377 |
| | Transit-walk access | 1.176 | 7.771 |
| First trip purpose: work trip | Park and Ride | 2.148 | 10.472 |
| | Kiss and Ride | 1.884 | 9.087 |
| | Walk | 2.473 | 15.679 |
| | Bike | 2.715 | 15.922 |
| | Uber | 1.507 | 5.857 |
| | Motorcycle | 1.139 | 3.874 |
| Second trip purpose: returning home | Park and Ride | 1.344 | 2.087 |

**Table 5** (continued)

| | | | |
|---|---|---|---|
| Coefficient of the function of forward-looking term: Number of Car per number of household members | Auto passenger, Transit-walk access, Kiss and Ride, Walk, Uber, and Taxi | 1.226 | 14.376 |
| Coefficient of the function of forward-looking term: Constants | Transit-walk access | – 1.319 | – 4.697 |
| | Walk | – 1.263 | – 4.942 |

the first tour of the day. In Toronto, the majority of the apartments and work locations are situated in the downtown core. Thus, the majority of the apartment owners live near to their work location, and they require less travel time to reach work. Since the majority of the houses are situated outside of the downtown core, it requires higher travel time for homeowners to reach to the work location (if the work location is in downtown). Therefore, homeowners tend to leave home earlier than the apartment owners.

## Time expenditure choices for out-of-home activities

Tables 3 and 4 present the estimated parameters for the time expenditure choices for out-of-home activities for two-trip tour and three-trip tour, which are defined by a baseline utility function and a satiation parameter function. The baseline utility function indicates the constant marginal utility of spending time for a specific activity. A positive value for baseline utility means that individuals tend to spend more time in current activity than the other activities scheduled later part of the day. Various activity types are incorporated in the baseline utility function.

In terms of out-of-home activities, empirical model reveals that individuals tend to spend more time at work than at the school, which is intuitive. Besides, individuals comparatively spend much less time in facilitating a passenger. In the time expenditure choice model, departure time-of-day (as a fraction of 24 h) for a specific trip is interacted with different activity types and these variables depict significant influences on the baseline utility function. Individuals are likely to spend a longer duration at work or school if they start at home early in the morning. On the other hand, individuals likely to schedule other activities such as shopping and facilitating a passenger at later parts of the day.

The positive value of satiation parameters reveals that individuals tend to spend a longer duration for a specific activity and vice versa. The empirical model shows that work and school activities have the lowest constant satiation parameters which mean individuals do not enjoy spending long hours on such activities and they have little flexibility on such activity durations. Model results indicate that individuals enjoy spending more time in shopping activities. Departure time-of-day (as a fraction of 24 h) for a specific trip is interacted with various activity types and these variables have significant influences on the satiation parameter. The model reveals that individuals like to enjoy shopping and facilitating passenger if they can schedule these activities in the later part of the day and vice versa.

## Mode choice

Tables 5 and 6 present the estimated parameters for the tour-based mode choices for two-trip tour and three-trip tour. The majority of the alternative specific constants (ASC) are highly

**Table 6** Dynamic mode choice model (tours with three trips)

| | | | |
|---|---|---|---|
| Number of observations | | 17,204 | |
| Number of estimated parameter | | 92 | |
| Rho squared against a null model | | 0.143 | |
| Parameters | Mode | Estimates | t-stat |
| First trip: Alternative Specific Constant (ASC) | Auto drive | 4.233 | 26.256 |
| | Auto passenger | 1.604 | 9.142 |
| | Transit-walk access | 0.000 | – |
| | Kiss and ride | −1.410 | −2.837 |
| | Walk | 2.363 | 14.623 |
| | Park and ride | 0.420 | 2.416 |
| | School bus | 0.379 | 1.318 |
| | Bike | 1.970 | 9.23 |
| | Taxi | −2.314 | −7.788 |
| | Motorcycle | −2.365 | −9.03 |
| ASC of the second trip: the first trip is auto passenger | Auto passenger | 2.560 | 5.035 |
| | Transit-walk access | 0.000 | – |
| | Kiss and ride | 0.009 | 0.018 |
| | Walk | 2.945 | 6.698 |
| ASC of the second trip: the first trip is transit-walk access | Auto passenger | −0.822 | −1.359 |
| | Transit-walk access | 0.000 | – |
| | Walk | 3.384 | 5.977 |
| ASC of the second trip: the first trip is walk | Auto passenger | 0.502 | 0.96 |
| | Trans it- walk access | 0.000 | – |
| | Walk | 4.335 | 8.339 |
| ASC of the second trip: the first trip is park and ride | Transit-walk access | 0.000 | – |
| | Walk | 3.117 | 5.286 |
| ASC of the second trip: the first trip is school bus | Auto passenger | 0.000 | – |
| | Walk | 2.821 | 5.057 |
| | School bus | 0.063 | 0.136 |
| ASC of trip three: when the first and second trips are auto passenger | Auto passenger | 3.012 | 22.834 |
| | Transit-walk access | 0.000 | – |
| | Walk | 2.562 | 12.116 |
| ASC of trip three: when the first trip is auto passenger and the second trip is transit-walk access | Transit-walk access | 0.000 | – |
| | Auto passenger | −0.376 | −1.841 |
| ASC of trip three: when the first trip is auto passenger and the second trip is walk | Walk | 0.000 | – |
| | Auto passenger | −1.732 | −5.163 |
| ASC of trip three: when the first and second trips are transit-walk access | Auto passenger | 0.000 | – |
| | Transit-walk access | 1.048 | 8.367 |
| | walk | 3.483 | 19.178 |
| | Uber | −2.191 | −4.979 |
| | Taxi | −1.213 | −2.853 |
| ASC of trip three: when the first trip is transit-walk access and the second trip is walk | Transit-walk access | 0.000 | – |
| | Walk | 2.245 | 7.474 |
| ASC of trip three: when the first trip is kiss and ride and the second trip is transit-walk access | Auto passenger | 0.556 | 1.937 |
| | Transit-walk access | 0.000 | – |

**Table 6** (continued)

| | | | |
|---|---|---|---|
| ASC of trip three: when the first trip is walk and the second trip is auto passenger | Auto passenger | 0.000 | – |
| ASC of trip three: when the first trip is walk and the second trip is transit-walk access | Auto passenger | −1.180 | −4.28 |
| | Transit-walk access | 0.000 | – |
| | Walk | 2.288 | 6.579 |
| ASC of trip three: when the first and second trips are walk | Auto passenger | 0.556 | 1.654 |
| | Transit-walk access | 0.000 | – |
| | Walk | 4.866 | 16.727 |
| Travel cost: all trip | All motorized mode except Uber and taxi | −0.026 | −3.052 |
| Travel cost: first trip | Taxi | −0.025 | −3.052 |
| Travel cost: second trip | Uber and taxi | −0.066 | −2.509 |
| Travel time: all trip | All motorized mode | −0.014 | −7.492 |
| | Walk and bike: first trip | −0.543 | −17.339 |
| Travel distance | Walk and bike: second and third trip | −1.184 | −24.647 |
| Regional transit pass ownership: first trip | Transit-walk access | 1.132 | 11.563 |
| Local transit pass ownership: first trip | Transit-walk access | 3.708 | 32.187 |
| Regional transit pass ownership: second and third trip | Transit-walk access | 0.465 | 4.774 |
| Local transit pass ownership: second and third trip | Transit-walk access | 1.153 | 10.768 |
| Number of vehicles | Auto drive | 0.198 | 5.91 |
| Dummy variable for female: first trip | Auto drive | −0.542 | −7.521 |
| | Auto passenger | 0.620 | 7.633 |
| | School bus | 0.497 | 1.515 |
| | Bike | −0.893 | −5.31 |
| Age less than or equal to 25 years: first trip | Auto passenger | 1.749 | 14.389 |
| | Transit-walk access | 1.103 | 10.085 |
| Age greater than 25 years and less than or equal to 30 years: first trip | Auto passenger | −0.080 | −0.526 |
| | Transit-walk access | 0.441 | 3.05 |
| Trip purpose: first school trip of the day: first trip | Transit-walk access | −1.442 | −10.466 |
| Trip purpose: first work trip of the day: first trip | Transit-walk access | −1.789 | −21.258 |
| Coefficient of function of forward-looking term in the first trip: Number of car per number of household members | First trip mode: auto passenger, transit-walk access, walk, park and ride, school bus | 3.182 | 8.28 |
| Constant | First trip mode: auto passenger | −1.070 | −5.003 |
| Constant | First trip mode: transit-walk access | −1.974 | −4.831 |
| Coefficient of function of forward-looking term in the second trip | | | |
| Constant | Second trip mode is transit-walk access | −0.935 | −0.699 |
| Constant | Second trip mode is walk | 0.463 | 0.463 |
| Constant | Second trip mode is auto passenger | −0.696 | −0.565 |

statistically significant. All level-of-service (LOS) parameters are showing proper signs, and they are statistically significant. Based on the paired *t* test value, tour-specific parameters are estimated for few LOS variables while trip-specific parameters are estimated for the rest of the LOS variables. The tour-based mode choice model reveals that values of travel time savings (VOTS) are higher for first trips than those of the second and third trips. In terms of two-trip tours, VOTS for auto-drive, auto-passenger and all transit mode is $14.244 per hour for the first trip, while the VOTS for the same modes for the second trip is $8.265 per hour. In addition, VOTS is much higher for Uber and Taxi passengers. In terms of mode selection, Uber passengers typically don't choose Taxi and Taxi passengers typically don't switch their mode to Uber. The model results reveal that possessing local and regional transit passes increases the likelihood of choosing local or regional transit mode. The model results show that individuals with a higher number of automobiles in the household tend to drive more.

For both models, we tested the effect of different age cohort and genders on tour-based mode choice. The empirical model shows that millennials are inclined to choose auto passenger, transit-walk access, kiss and ride and walk. A majority of the individuals who are aged less than 25 years old don't own a car. As such, they are dependent on another household member to drop them off, or they use public transit or walk. Students are inclined to choose to walk, bike or public transit as a commuting mode on their first trip which echoes other studies on students' mode choice in this region (Hasnine et al. 2018). An interesting trend is found for individuals aged more than 25 years where individuals are less likely to choose auto-passenger or kiss and ride mode. Both models reveal that when the activity type is work, individuals tend to choose Uber, auto-drive, various transit modes, walk, and bike.

According to the random utility maximization (RUM) theory, the parameter of the future expectation of mode choice ($\beta$) must be in between zero to one (Swait et al. 2004). To ensure such a constraint, we employed the following specifications: $\beta = 1/(1 + \exp(\text{constant} + \mu x))$. In this equation, x is a vector of attributes and $\mu$ is a parameter vector. The forward-looking agent of mode choice is parameterized as a function of the number of the cars per number of households and a constant. The results show that household auto ownership is statistically significant which means the number of cars in the household has a significant influence on the future mode choice. In terms of two-trip tours, if the first trip mode is auto-passenger, kiss and ride, transit-walk access, walk, Uber, or Taxi, there is a high correlation exists between the feasible future trip modes. For instance regarding two-trip tours, if the first trip mode is walking, the possible future modes are a walk, auto-passenger, transit-walk access, kiss and ride, Uber and Taxi. According to the empirical model, these possible future modes are highly correlated. The future expectation has 61.63% weight factor for local transit and 60.37% weight factor for walk mode. This result indicates that the forward-looking agent represents a substantial portion of the systematic utility in the current mode choice. In terms of three trip tour, auto ownership is not included in the systematic utility of the future expectation function for the second trip. The parameter was not significant, and this is intuitive since, after the first trip, auto availability is deterministic. If auto-drive is not chosen in the first trip, the auto-drive mode will not available for the entire tour.

## Model validation and policy scenario analysis

For model validation, a holdout sample is used (20% of the total sample). Figures 5, 6, and 7 show the validation results of the time-expenditure and mode choice component of the two-trip and three-trip tours. Figure 5a, b shows the validation result of the departure

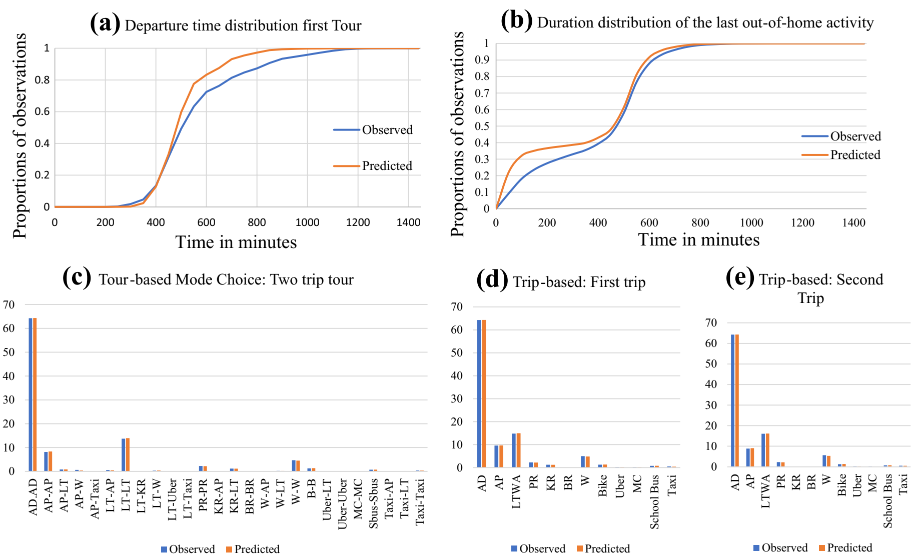


**Fig. 5** Validation Results of time expenditure choice and mode choice two-trip tour (n = 17650). AD: auto drive, AP: auto passenger, LT: local transit with walk access, PR: park and ride, KR: kiss and ride, BR: bike and ride, W: walk, B; bike, Uber, Taxi, MC: Motorcycle, Sbus: School Bus

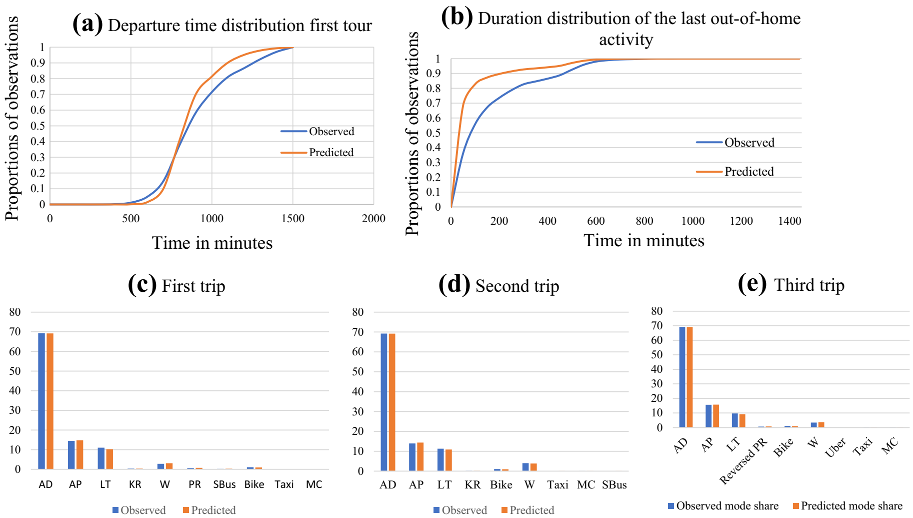


**Fig. 6** Validation Results of time expenditure choice and mode choice three-trip tour (n = 4411). AD: auto drive, AP: auto passenger, LT: local transit with walk access, PR: park and ride, KR: kiss and ride, BR: bike and ride, W: walk, B; bike, Uber, Taxi, MC: Motorcycle, Sbus: School Bus

time distribution of the first tour and the validation result of the duration distribution of the last out-of-home activity. The validation result clearly shows that the proposed dynamic discrete–continuous modelling structure can accurately predict the time expenditure choice for at-home and out-of-home activities. A similar result has been found for the three-trip

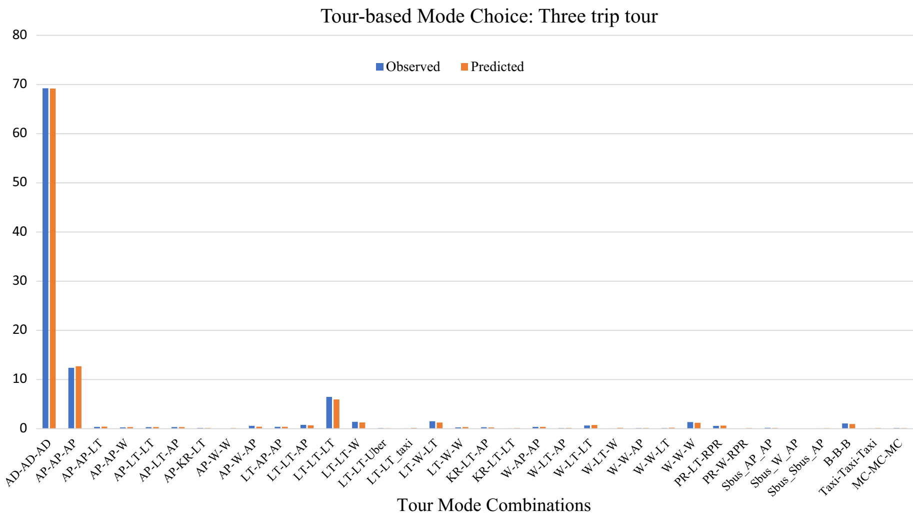


**Fig. 7** Validation results of tour mode choice (n = 4411). AD: auto drive, AP: auto passenger, LT: local transit with walk access, PR: park and ride, KR: kiss and ride, BR: bike and ride, W: walk, B; bike, Uber, Taxi, MC: Motorcycle, Sbus: School Bus

tours. The tour-based mode choice model provides the probability of the tour-mode. The trip-based mode choice probability is estimated using the conditional probability. Figure 5c–e show that the estimated model is capable of accurately predicting both tour-based mode choice and trip-based mode choice. Similar validation results are found for the three-trip tours (Figs. 6c–e, and 7).

The presented models are tested to predict the effect of various transportation policies on tour-mode choice. A difference between predicted demand and base case demand is showed in Fig. 8. Figure 8a shows the effect of providing transit pass incentive on two-trip tour modes. Figure 8a shows that reducing transit fares by 10% will increase transit tours by 0.17% and decrease auto-drive tours by 0.13%. Interestingly, decreasing transit fare reduces the utilization of tour patterns where an individual used transit for the first trip but used a taxi or Uber for the second trip. Figure 8b shows the effect of providing a reduced transit fare (10%) on three-trip tours. Similar to two-trip tours, transit tours are increased by 11% and auto-drive tours are decreased by 0.10%. Figure 8c shows the effect of increasing auto-drive cost by 200% and providing free transit services to individuals. Figure 8c shows that increasing auto-drive cost by 200% and providing free transit services will decrease auto-drive tour by 5.86%. Figure 8c also shows that increasing auto-drive cost by 200% and providing free transit services will increase transit tour by 1.36%. This policy scenario is particularly tested to see whether we can “stretch” the estimated model to extreme situations and test the model’s ability to simulate scenarios that are outside the range of the observed inputs. A wide range of policies can easily be tested using the models presented in this study.

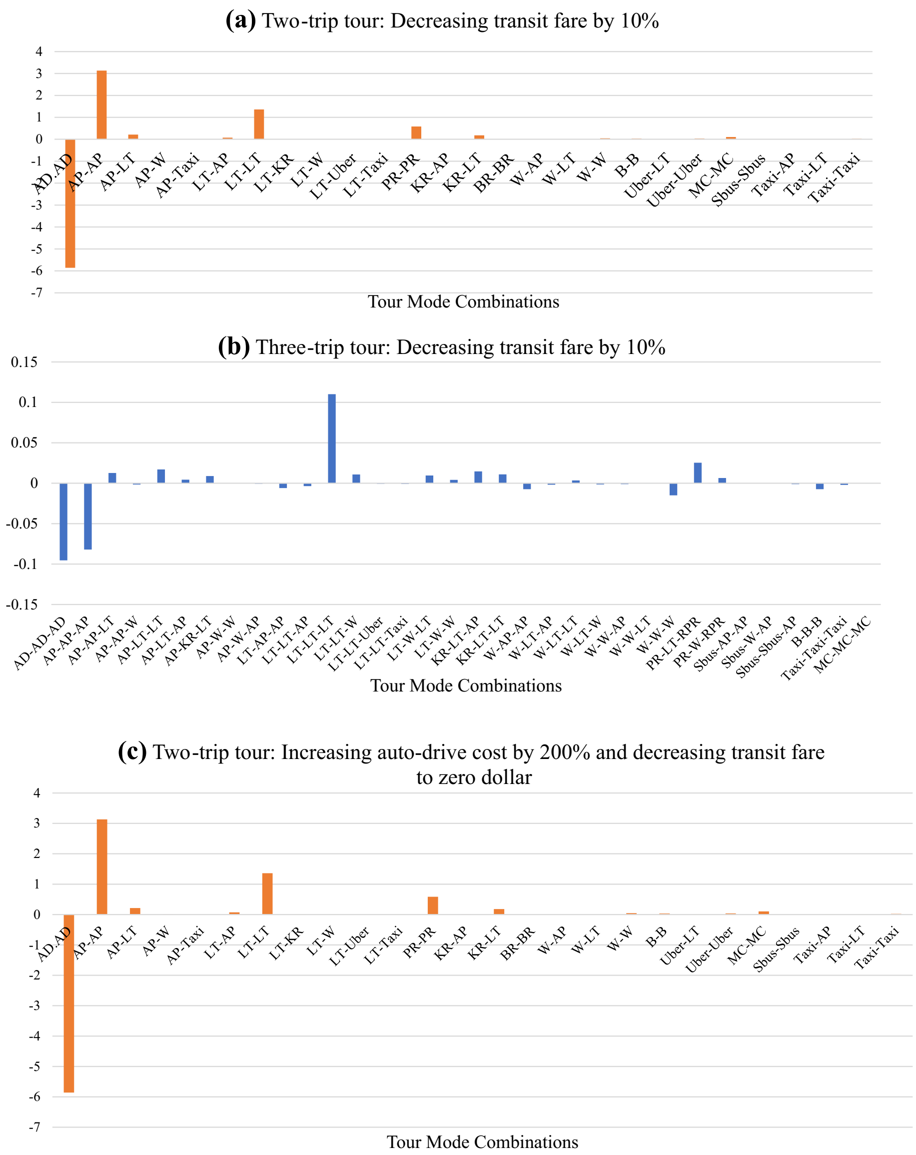


**Fig. 8** Policy scenario test. AD: auto drive, AP: auto passenger, LT: local transit with walk access, PR: park and ride, KR: kiss and ride, BR: bike and ride, W: walk, B; bike, Uber, Taxi, MC: Motorcycle, Sbus: School Bus

## Conclusions and recommendations of future research

The dynamic RUM based model presented in this paper endogenously captures the interactions of sequential discrete–continuous choices and is a significant step towards better understanding the tangible benefit of jointly modelling tour-based mode choice, tour departure time and time expenditure behaviour. In the case of the tour-based mode choice model, we used a combination of dynamic programming and discrete choice which explicitly captures the forward-looking behaviour of trip modes and state dependency.

The tour departure time and time expenditure to the scheduling activities are modelled adopting Kuhn-Tucker optimality condition, which captures the time expenditure behaviour through baseline utility function and satiation parameter. The proposed closed form joint dynamic discrete–continuous modelling structure has far broader applicability than to activity-based model only. The model validation and policy scenario test results are promising which states that the proposed modelling framework is compatible with existing operational activity-based modelling framework.

In terms of tour departure time, it is found that full-time employees and younger individuals tend to leave home earlier than the part-time employees and older individuals. This finding echoes the other studies which were conducted in different study areas in Canada and Switzerland (Spissu et al. 2009; Habib et al. 2017; Habib 2018). It is found that individuals likely to spend long hours at work or school if they leave home early. Individuals are likely to schedule non-mandatory activities such as shopping activity at later parts of the day. It is found that individuals do not enjoy spending long hours on work or school activities, but they enjoy spending long hours in shopping activities. These results are consistent with Habib (2018) time-expenditure choice model results.

The tour-based mode choice model can handle all types of tour combinations and reveals various behavioural insights. The VOTS of ride-hailing services is much higher than auto-drive and transit modes. Interestingly, investigating the tour pattern, it is found that Uber users typically don't change their mode to Taxi and vice versa. The policy scenario test reveals that subsidized public transit will encourage individuals to choose transit. It is also found that if the mode for the first trip is auto-passenger, Uber, or Taxi, transit-walk access, kiss and ride, walk, there is a high correlation exist between the available future modes. A majority of the cases, it is found that forward-looking component represents a substantial portion of the systematic utility of current mode choice. The validation result shows that the models presented in this paper are capable of accurately capturing both time expenditure choice and tour-based mode choice.

One caveat of the model is we need to know the number of trips, the activity schedule, and location choice before the model estimation. Since we modelled the tour departure time and time expenditure choices, the time-constraints is explicitly tackled by the Kuhn–Tucker optimality condition. Since one assumption made in this study is, we know the activity schedule and locations beforehand, the spatial constraint is also inherently considered within the modelling framework. Besides, the modelling formulation presented in this paper is 'tightly coupled' model, since a single function is used to model discrete–continuous choices. Possible future work would be developing 'loosely coupled' modelling framework which will explicitly capture the correlation between all three components such as departure time, mode choice and time expenditure choice. If we use multi-day travel diaries, there are possibilities that idiosyncratic errors are spatially dependent and serially correlated (Pesaran and Tosetti 2011). In this study, we had access to a single-day travel diary only. Besides, we did not estimate the location choice model in this study. Therefore, spatial dependence and spatial correlation are not considered in this study. We added this limitation in conclusion.

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**Authors' contribution** Md Sami Hasnine: Dataset preparation, econometric model estimation, validation and policy scenario testing. Mr. Hasnine contributed to the manuscript. Prof. Khandker Nurul Habib: Prof. Khandker Nurul Habib contributed to the manuscript and supervised the project.

## Compliance with ethical standards

**Conflict of interest** On behalf of all authors, the corresponding author states that there is no conflict of interest.

## References

Aptech Systems: Gauss User's Manual. Maple Valley, CA (2018). http://www.aptech.com Accessed June 2018

Aguirregabiria, V., Mira, P.: Swapping the nested fixed point algorithm: a class of estimators for discrete Markov decision models. Econometrica **70**(4), 1519–1543 (2002)

Aguirregabiria, V., Mira, P.: Sequential estimation of dynamic discrete games. Econometrica **75**(1), 1–53 (2007)

Bowman, J.L., Ben-Akiva, M.E.: Activity-based disaggregate travel demand model system with activity schedules. Transp. Res. Part A: Policy Pract. **35**(1), 1–28 (2001)

Bowman, J., Bradley, M., Shiftan, Y., Lawton, T., Ben-Akiva, M.: Demonstration of an activity-based model for Portland. In: World Transport Research: Selected Proceedings of the 8th World Conference on Transport Research 1998, vol. 3. (pp. 171–184.) Oxford: Elsevier (1999)

Bhat, C.R., Goulias, K.G., Pendyala, R.M., Paleti, R., Sidharthan, R., Schmitt, L., Hu, H.H.: A household-level activity pattern generation model with an application for Southern California. Transportation **40**(5), 1063–1086 (2013)

Bhat, C.R., Srinivasan, S., Sen, S.: A joint model for the perfect and imperfect substitute goods case: application to activity time-use decisions. Transp. Res. Part B: Methodol. **40**(10), 827–850 (2006)

Bhat, C.R., Sen, S.: Household vehicle type holdings and usage: an application of the multiple discrete-continuous extreme value (MDCEV) model. Transp. Res. Part B: Methodol. **40**(1), 35–53 (2006)

Bhat, C.R.: A multiple discrete–continuous extreme value model: formulation and application to discretionary time-use decisions. Transp. Res. Part B: Methodol. **39**(8), 679–707 (2005)

Bhat, C., Guo, J., Srinivasan, S., Sivakumar, A.: Comprehensive econometric microsimulator for daily activity-travel patterns. Transp. Res. Rec.: J. Transp. Res. Board **1894**, 57–66 (2004)

Bhat, C.R.: Analysis of travel mode and departure time choice for urban shopping trips. Transp. Res. Part B: Methodol. **32**(6), 361–371 (1998)

Bradley, M., Bowman, J.L., Griesenbeck, B.: SACSIM: an applied activity-based model system with fine-level spatial and temporal resolution. J. Choice Model. **3**(1), 5–31 (2010)

Davidson, W., Vovsha, P., Freedman, J., Donnelly, R.: CT-RAMP family of activity-based models. In: Proceedings of the 33rd Australasian Transport Research Forum (ATRF) Canberra, Australia, 29, 29 Sept–1 Oct (2010)

Ding, C., Mishra, S., Lin, Y., Xie, B.: Cross-nested joint model of travel mode and departure time choice for urban commuting trips: case study in Maryland-Washington, DC Region. J. Urban Plan. Dev. **141**(4), 04014036 (2014)

Habib, K.M.N.: A comprehensive utility-based system of travel options modelling (CUSTOM) considering dynamic time-budget constrained Potential Path Area (PPA) in activity scheduling process: application in modelling worker's daily activity-travel schedules. Transportmetr. Part A: Transp. Sci. **14**(4), 292–315 (2018)

Habib, K.N., El-Assi, W., Hasnine, M.S., Lamers, J.: Daily activity-travel scheduling behaviour of non-workers in the National Capital Region (NCR) of Canada. Transp. Res. Part A: Policy Pract. **97**, 1–16 (2017)

Habib, K.M.N.: A joint discrete-continuous model considering budget constraint for the continuous part: application in joint mode and departure time choice modelling. Transportmetr. A: Transp. Sci. **9**(2), 149–177 (2013)

Habib, K.M.N.: Modeling commuting mode choice jointly with work start time and work duration. Transp. Res. Part A: Policy Pract. **46**(1), 33–47 (2012)

Habib, K.M.N.: A random utility maximization (RUM) based dynamic activity scheduling model: application in weekend activity scheduling. Transportation **38**(1), 123–151 (2011)

Hasnine, M.S., Lin, T., Weiss, A., Habib, K.N.: Determinants of travel mode choices of post-secondary students in a large metropolitan area: the case of the city of Toronto. J. Transp. Geogr. **70**, 161–171 (2018)

Hasnine, M.S., Habib, K.N.: What about the dynamics in daily travel mode choices? A dynamic discrete choice approach for tour-based mode choice modelling. Transp. Policy **71**, 70–80 (2018)

Hasnine, M.S., Kamel, I., & Habib, K.N.: Using Google Map to impute transportation level-of-service attributes: application in mode and departure time choice modelling. In: 11th International Conference on Transport Survey Methods, Esterel, Quebec, Canada, Sept 24–29 (2017)

Jara-Díaz, S.R.: On the goods-activities technical relations in the time allocation theory. Transportation **30**(3), 245–260 (2003)

Miller, E.J., Roorda, M.J., Carrasco, J.A.: A tour-based model of travel mode choice. Transportation **32**(4), 399–422 (2005)

Munizaga, M.A., Correia, R., Jara-Díaz, S.R.De, Dios Ortúzar, J.: Valuing time with a joint mode choice-activity model. Int. J. Transp. Econ. **33**, 1000–1018 (2006)

Natural Resources Canada. Fuel Consumption Guide (2018) http://www.nrcan.gc.ca/sites/www.nrcan.gc.ca/files/oee/pdf/transportation/tools/fuelratings/2018%20Fuel%20Consumption%20Guide.pdf. Accessed Feb 2018

Pesaran, M.H., Tosetti, E.: Large panels with common factors and spatial correlation. J. Econom. **161**(2), 182–202 (2011)

Pinjari, A.R., & Bhat, C.: An efficient forecasting procedure for Kuhn–Tucker consumer demand model systems. Technical paper. Department of Civil and Environmental Engineering, University of South Florida (2010)

Ruiter, E.R., Ben-Akiva, M.: Disaggregate travel demand models for the San Francisco Bay area. Transp. Res. Rec. **673**, 121–128 (1978)

Rust, J.: Optimal replacement of GMC bus engines: an empirical model of Harold Zurcher. Econom. J. Econom. Soc. **55**(5), 999 (1987)

Shabanpour, R., Golshani, N., Derrible, S., Mohammadian, A., Miralinaghi, M.: Joint discrete-continuous model of travel mode and departure time choices. Transp. Res. Rec.: J. Transp. Res. Board **2669**, 41–51 (2017)

Spissu, E., Pinjari, A.R., Bhat, C.R., Pendyala, R.M., Axhausen, K.W.: An analysis of weekly out-of-home discretionary activity participation and time-use behavior. Transportation **36**(5), 483–510 (2009)

Swait, J., Adamowicz, W., Van Bueren, M.: Choice and temporal welfare impacts: incorporating history into discrete choice models. J. Environ. Econ. Manag. **47**(1), 94–116 (2004)

Vovsha, P., Bradley, M.: Hybrid discrete choice departure-time and duration model for scheduling travel tours. Transp. Res. Rec.: J. Transp. Res. Board **1894**, 46–56 (2004)

Yang, L., Zheng, G., Zhu, X.: Cross-nested logit model for the joint choice of residential location, travel mode, and departure time. Habitat Int. **38**, 157–166 (2013)



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