Transportation Research Part A 46 (2012) 1386–1403

Contents lists available at SciVerse ScienceDirect

Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

Activity planning processes in the Agent-based Dynamic Activity Planning and Travel Scheduling (ADAPTS) model

Joshua Auld *, Abolfazl(Kouros) Mohammadian

Dept. of Civil & Materials Engineering, University of Illinois at Chicago, 842 West Taylor Street, Chicago, IL 60607-7023, USA

ARTICLE INFO

Article history:
Received 11 June 2010
Received in revised form 7 April 2012
Accepted 16 May 2012

Keywords:
Activity based modeling
Activity planning
Behavioral models
Activity scheduling behavior

ABSTRACT

This paper describes the representation of the activity planning process utilized in a new activity-based microsimulation model called the ADAPTS (Agent-based Dynamic Activity Planning and Travel Scheduling) model, which dynamically simulates activity and travel planning and scheduling. The model utilizes a dynamic activity planning framework within the larger overall microsimulation system, which is a computational process model that attempts to replicate the decisions which comprise time-dependent activity scheduling. The model presents a step forward in which the usual concepts of activity generation and activity scheduling are significantly enhanced by adding an additional component referred to as activity planning in which the various attributes which describe the activity are determined. The model framework, therefore, separates activity planning from activity generation and treats all three components, generation, planning and scheduling, as separate discrete but dynamic events within the overall microsimulation. The development of the planning order model, which determines when and in what order each activity planning decision is made is the specific focus of this paper. The models comprising the planning order framework are developed using recent survey data from a GPS-based prompted recall survey. The model development, estimation, validation, and its use within the overall ADAPTS system are discussed. A significant finding of the study is the verification of the apparent transferability of the activity planning order model.

1. Introduction

In response to demands for more realistic travel demand models which are capable of analyzing a wider range of transportation policies, the activity-based modeling (ABM) framework was originally developed. These models generally are better able to evaluate travel demand and transportation supply management strategies, such as road pricing intelligent transportation systems, and behavior modification programs (flexible scheduling, ride-sharing), better than the previous generation of aggregate flow models which generally focus on evaluating network capacity improvement. These models specify the full daily pattern of activity and travel at a disaggregate level for modeled regions, and generally have a more behavioral basis than aggregate travel demand models. However, many ABMs are better at replicating observed outcomes than at describing how those outcomes were arrived at. This potentially could make the models insensitive to changes in the activity scheduling process; a potential deficiency that has often been noted (Pas, 1985; Roorda et al., 2005a). A suggestion to correct for some of these deficiencies is the use of a rule-based or computational process model (Garling et al., 1994). Computational process models (CPMs) tend to use heuristics (Roorda et al., 2005b) or some other rule-based structure to represent the process of activity scheduling decision making, rather than simply modeling the outcomes of the process.

* Corresponding author. Tel.: +1 312 996 9840; fax: +1 312 996 2426.
E-mail addresses: auld@uic.edu, kouros@uic.edu (J. Auld).

0965-8564/$ - see front matter © 2012 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.tra.2012.05.017

The computational process models framework originated in work by Newell and Simon (1972) on modeling cognitive processes.

Several models using rule-based frameworks have been developed including models by Hayes-Roth and Hayes-Roth (1979), SCHEDULER (Golledge et al., 1994), ALBATROSS (Arentze and Timmemans, 2000) and TASHA (Roorda et al., 2005b) among others. These models all attempt to represent the process of activity scheduling, and are therefore potentially more behaviorally realistic as well as potentially more policy sensitive. However, to date scheduling process models have rarely captured short-term scheduling dynamics, as discussed in several conceptual models (Litwin and Miller, 2004; Miller, 2005). Empirical observations of some of the dynamic aspects of activity scheduling, however, have been conducted (Lee and McNally, 2006; Joh et al., 2005; Roorda et al., 2005b, 2005a; Clark and Doherty, 2008; Ruiz and Roorda, 2008). Also recently, models of certain aspects of dynamic activity scheduling such as planning horizons and conflict resolution (Mohammadian and Doherty, 2005; Lee and McNally, 2006; Ruiz and Timmermans, 2006; Auld et al., 2008, 2009a) and activity attribute flexibilities (Lee-Gosselin et al., 2006) have been modeled. Some newer modeling frameworks have even begun to account for short-term adjustment and rescheduling processes, such as the AURORA model (Joh et al., 2002; Joh, 2004) and the related FEATHERS model (Arentze et al., 2006). These developments have been enabled through the collection and use of new sources of scheduling process data such as CHASE (Doherty et al., 2004), REACT (Lee and McNally, 2001), UTRACS (Frignani et al., 2010) and others (Ruiz and Timmermans, 2006; Zhou and Golledge, 2007; Clark and Doherty, 2008).

Operational process models necessarily make simplifying assumptions about the scheduling process such as using a fixed sequence for making activity attribute decisions as in ALBATROSS (Arentze and Timmemans, 2000) among many others. To the best of the authors' knowledge, all activity-based modeling systems assume some fixed planning order for specifying the activity attributes. Recent data sources such as UTRACS (Frignani et al., 2010) have shown that planning order assumptions are unrealistic. Analysis of planning time horizons from scheduling process data shows that many activities are opportunistically planned (Mohammadian and Doherty, 2005), during execution of a tour which could not be handled by scheduling models, where the activities are selected first, then formed into tours. Therefore to fully capture the process underlying activity scheduling a dynamic planning and scheduling model is needed, where choice regarding activity generation, attribute planning, etc. is dependent on the choices regarding the activity scheduling context that have previously been made.

This difference can best be exemplified with a planning/scheduling example, as shown in Fig. 1. Consider in Situation A, a person is planning to meet two friends for lunch. She realizes she has some shopping to do, and decides to go shopping at nearby store beforehand. In this case, the previously planned activity of eating lunch constrains the choices regarding the planning of the shopping activity. Alternatively, in Situation B, a person is planning to do some shopping in a retail area and impulsively decides to call some friends to meet for lunch nearby after her completion of the shopping trip. Here the already planned shopping trip constrains the eating out activity.

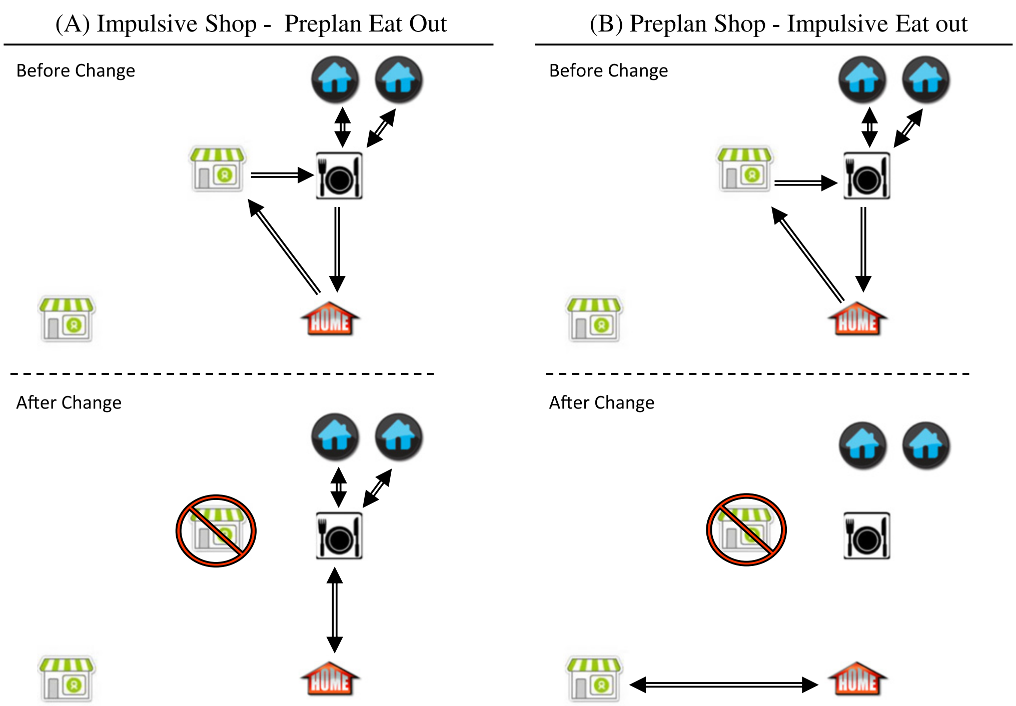

Fig. 1. Example of a choice situation depending on planning order.

In both examples shown, the existing activity-travel pattern looks identical. However, the process by which the schedule was arrived was very different, meaning the responses to changes are potentially not identical. To relate this to potential travel demand management policies, imagine a policy was put in place which makes the original store unavailable. In this case in Situation A the person merely skips the impulsive shopping stop and continues onto lunch with friends, resulting in one less trip than before. Meanwhile in Situation B since the shopping is preplanned the individual would react to the new policy by shopping at another available store and forgoing the lunch with friends, resulting in only one trip to the store and back. So a simple policy change can result in very different travel patterns depending on when each activity, and each activity attribute, was planned. It is critical to note that any model that does not explicitly take into account planning order cannot represent the distinction between Situations A and B, as the only difference lies in the order and degree of impulsiveness with which the activities are planned. Many policies of interest are likely to have differing effectiveness and impacts depending on the planning process for the individual, especially in the area of travel demand management. It would be difficult, for example, to divert individuals to alternative modes for commuting who have preplanned engagements during the commuting tour as transit, carpooling, etc. generally preclude sub-tours during commuting. Therefore to determine the effectiveness of these types of strategies it will be important to understand and model how the existing tours are formed.

For these reasons, an activity-based modeling framework, the Agent-based Dynamic Activity Planning and Travel Scheduling (ADAPTS) model has been developed that simulates the underlying activity and travel planning and scheduling processes (Auld and Mohammadian, 2009). The model can represent a wide range of travel demand management policies, especially policies which are expected to impact the planning process of individuals. In contrast with previous activity scheduling models, by considering activity planning and scheduling steps as discrete events within the overall activity-travel simulation, and furthermore considering each attribute decision as a separate event, a more complete picture of the dynamics of activity planning and scheduling will be developed. The model of activity planning and scheduling is truly dynamic since each event is simulated at specific times and the outcome of each decision depends on previous decisions. Incorporating planning and scheduling dynamics into the activity-based model will allow for a more realistic set of scenarios to be evaluated in the model.

The focus of the current work is on developing the framework for the activity planning model, which allows the activity attributes to be planned in any order. Therefore there is no pre-determined planning order assumed in the model. Rather the order in which the activity attributes are planned is determined at the time the activity is generated using an attribute planning order model based on personal characteristics, existing schedule characteristics, activity type, space–time constraints, etc.

The fundamental concept implemented in the planning order model is the extension of the planning horizon concept (Doherty, 2005) from activity planning to activity attribute planning such that each component attribute of each activity has its own planning horizon. Some initial work along these lines has been conducted by Lee-Gosselin et al. (2006) looking into habitual versus planned activity start times and locations using the OPFAST survey data (Lee-Gosselin, 2005). This is expanded for the current work to cover five activity attributes and separates the concept of flexibility from the plan time for the attributes. The planning order is then set by evaluating a plan horizon for each attribute which defines an event at some later time in the simulation for that attribute to be planned. Therefore, an activity can be generated at a given time and each attribute of the newly generated activity would be chosen at some set of future times. Each attribute decision would then depend on the current state of the individual and schedule at the future time when it is made as well as all previous planned attributes of the activity. Together, this creates a fully dynamic time-dependent planning model incorporating dynamic scheduling constraints and even potential random events or changes to the schedule.

The incorporation of dynamics into activity planning and scheduling and removing the fixed planning order assumption for activity planning should allow for a more realistic and policy sensitive microsimulation model. The various stages of the model that are implemented in an overall simulation framework to achieve this are discussed. In addition, data results from a GPS-based prompted recall survey used to capture the underlying activity attribute planning process are presented and discussed in the context of the overall model framework and used to validate the use of an activity attribute planning order model in place of an assumed fixed sequential planning order. The rest of the paper is structured as follows. First the overall ADAPTS simulation methodology and the planning framework are discussed. Next the planning order model within the overall planning framework is developed, and the modeling methodology is introduced. The data source to develop the model is then discussed, followed by the actual modeling results and validation exercises. The paper concludes with a discussion of the planning order model, the results obtained and its overall use within the ADAPTS framework.

2. Adapts model framework

The ADAPTS model is an Activity-Based Computational Process Model, which simulates activity planning, scheduling and execution for household and individual agents. The underlying theory of the development of the ADAPTS model is that activity planning and scheduling is a time-dependent process and should be modeled as such. The planning and scheduling of activities is a process much as the actual execution of the activity-travel patterns, and is inextricably linked to the activity-travel outcomes. For this reason ADAPTS attempts to also simulate the planning and scheduling of activities in addition to their execution. The ADAPTS model simulates activity planning and scheduling over a specified timeframe, and integrates directly with a traffic simulator by outputting a list of trips to assign to the network at each time step. As such, the ADAPTS model is dynamic, with planning and scheduling occurring in a time-dependent manner and impacted by the results of the time-dependent traffic network. In addition, the ADAPTS model is a learning based model, i.e. agents store the results of their actions in a long-term memory and these results are used to make future decisions. An overview of the ADAPTS simulation framework is shown in Fig. 1. The simulation process includes three primary stages: initialization of the simulation environment, household and individual planning at each time step, and trip vector generation and traffic assignment at each time step.

The ADAPTS model planning and scheduling framework is called at each timestep for both household and individual agents to update/plan their activity schedules, as shown in Fig. 2 as "Household Planning" and "Individual Planning". The planning and scheduling model simulates the dynamic process of schedule formation and attempts to account for the varying interdependencies and potential differences in planning times, between the various attributes of the activity. This forms the core of the ADAPTS model. For example, an activity can be added and a location chosen at the same time, but the timing for the activity may be left open. If the timing is decided later, it will therefore depend on the location choice. However, the timing may not depend on the location choice at all, i.e. it could be planned first or even at the same time. It is felt that there could be fundamental differences between, for example, location choice decision processes when timing is known, versus when timing is unknown. This framework attempts to capture those effects.

Fundamentally, the model splits the activity scheduling process into three distinct phases. The first phase is activity generation which refers only to the decision of whether or not to plan on adding an activity of a certain type to the schedule. Certain high-level aspects of the activity which are assumed to be fundamental are specified at this point, including general flexibility values for the various attributes, the overall plan horizon of the activity, and individual plan horizons for each activity attribute, determining the order that the attribute decisions are made. This "Planning Order Model", forms the core of the ADAPTS model. The second phase of the model framework is activity planning. In this phase, the actual values of the various activity attributes are specified as in any other activity-based model, except that the order the decisions are made in and the constraints this implies are determined from the activity plan order model. So attributes can be determined in any order, with attributes planned later dependent on the already planned attributes leading to a system of conditional dependencies between the various attribute choice models. Finally, the last phase of the framework would be the actual activity scheduling, where the activities would be added to the planned schedule and conflicts would be resolved. Further detail about the activity scheduling system used in the ADAPTS model can be found in Auld et al. (2009b). An overview of the activity planning and scheduling framework for the ADAPTS model is presented in Fig. 3. This figure shows the process that an individual agent within the ADAPTS model would follow at each timestep, in building up and executing the activity-travel pattern. It presents activity scheduling as a dynamic process, completed over time with the final executed schedule resulting from a series of decisions. The high level decisions represented in the framework include: whether to add a new activity, whether to update (or initialize) attribute values for an existing activity, whether to resolve conflicts between planned activities (either when one of the activities is attempted to be executed or beforehand), and finally, whether a planned activity can

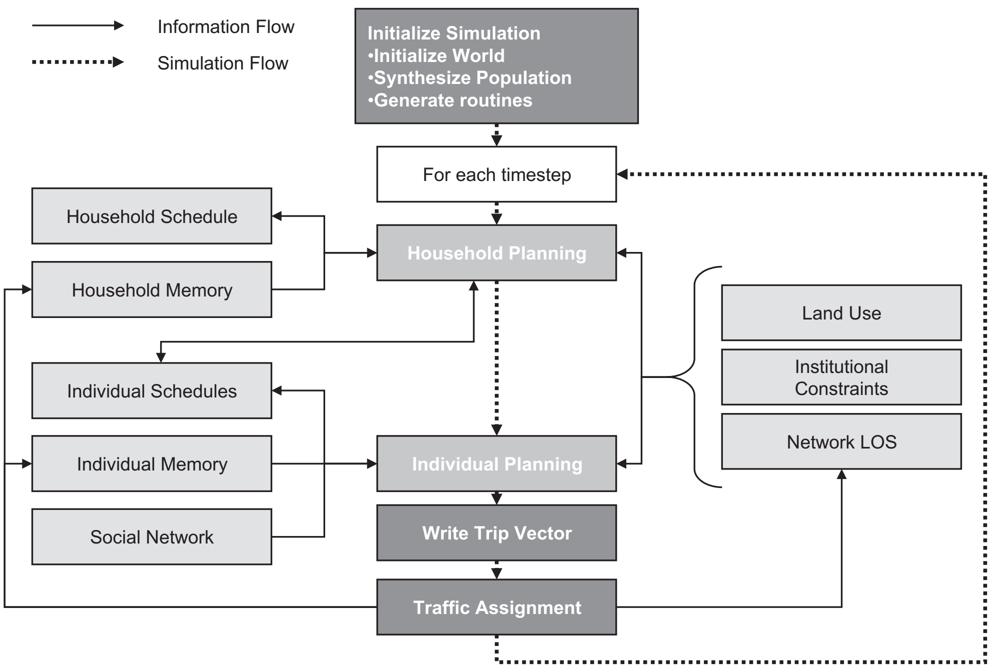

Fig. 2. ADAPTS simulation framework.

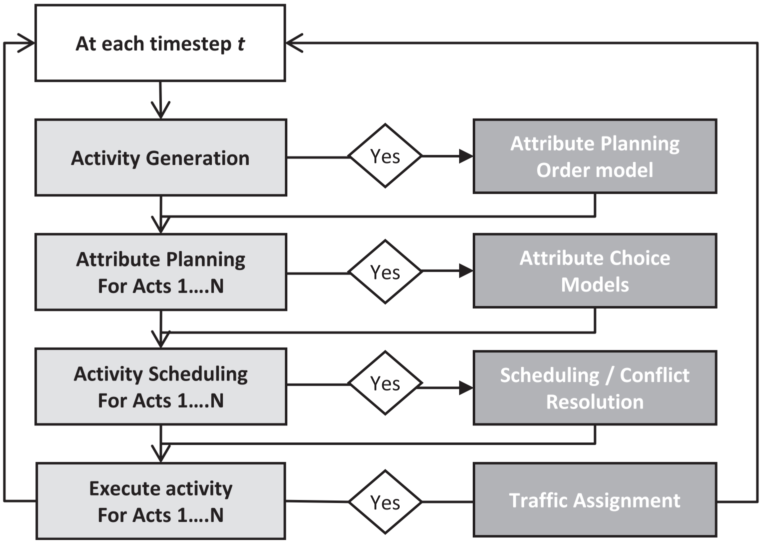

Fig. 3. ADAPTS activity planning framework.

be executed. As shown in the figure, each high-level decision can occur for any activity that has previously or currently been generated, so at each timestep, each activity is checked to see whether any additional planning occurs, whether it needs to be added to the schedule, whether it is to be executed, etc. The focus for the rest of the paper is on the Activity Planning Order model, more detail about the overall ADAPTS framework, including details about activity generation, scheduling processes, etc. can be found in Auld and Mohammadian (2009).

3. Framework for activity attribute planning order model

The activity planning order model forms the core of the ADAPTS model system by representing planning and scheduling dynamics within the activity-based travel demand model. The fundamental concept of the planning order model is that activity planning is a dynamic process which can be influence by current needs, outside constraints and the past experiences of the individual. As discussed in the previous section, the activity planning order model is implemented immediately following the generation of any new activity within the overall ADAPTS planning framework shown in Fig. 3. This is due to the fact that the planning order model sets what are considered in the ADAPTS framework to be intrinsic attributes of the activity such as the location, who-with, start time, etc. flexibilities, the activity planning horizon, and the attribute plan horizons, which are acted on in later stages, and usually at later timesteps, in the planning and scheduling framework. The current paper does not focus on the methodology behind the actual generation of a new instance of an activity, but rather on how these intrinsic characteristics beyond the activity type are set for the newly generated activity to enable later planning. There has been some consideration of the idea that such models may even be able to eventually replace the traditional generation of specific activity types, i.e. instead of generating a "work" activity a "long-average duration, fixed-location, fixed-time, routine" activity could be generated (Doherty, 2005), although this approach has not been entirely adopted in the ADAPTS framework as activities of a specific type are still generated.

A more detailed diagram of the general "Activity Planning Order model" or "Plan Order" step of the ADAPTS framework is shown in Fig. 4. The "Generate New Activity" step is shown in the diagram for clarity although it is in actuality a preceding step to the Plan Order model within the overall framework. This stage of the framework is referred to as the "Activity Planning Order model" because it defines the order and timing within the simulation when the various attribute decisions are made, in addition to other important activity attributes such as the overall activity planning horizon "Plan Activity" and the various flexibility measures. The final output of this stage is the attribute plan horizons, i.e. "plan person", "plan location", etc. which are used to set the attribute planning times, which controls when attribute planning occurs as shown in Fig. 3. The attribute fixities are also determined, which are used to constrain subsequent decisions.

Fig. 4 shows that several models are needed in order to complete the "Plan Order" step. These include a model for the activity attribute flexibilities, a model of the overall activity planning horizon and a model for the individual attribute planning horizons. The outputs estimated for each model are expected to be used as lag variables for the models which follow, so that the flexibility results are determined solely based on activity type and personal characteristics, while the results of this model feed into the activity plan horizon model which follows. The flexibility and plan horizon results are then both used within the attribute plan horizon model, which determines the final planning order for the attributes. Due to the expected high correlations between responses for individual attributes, both the flexibility and attribute plan horizon models are

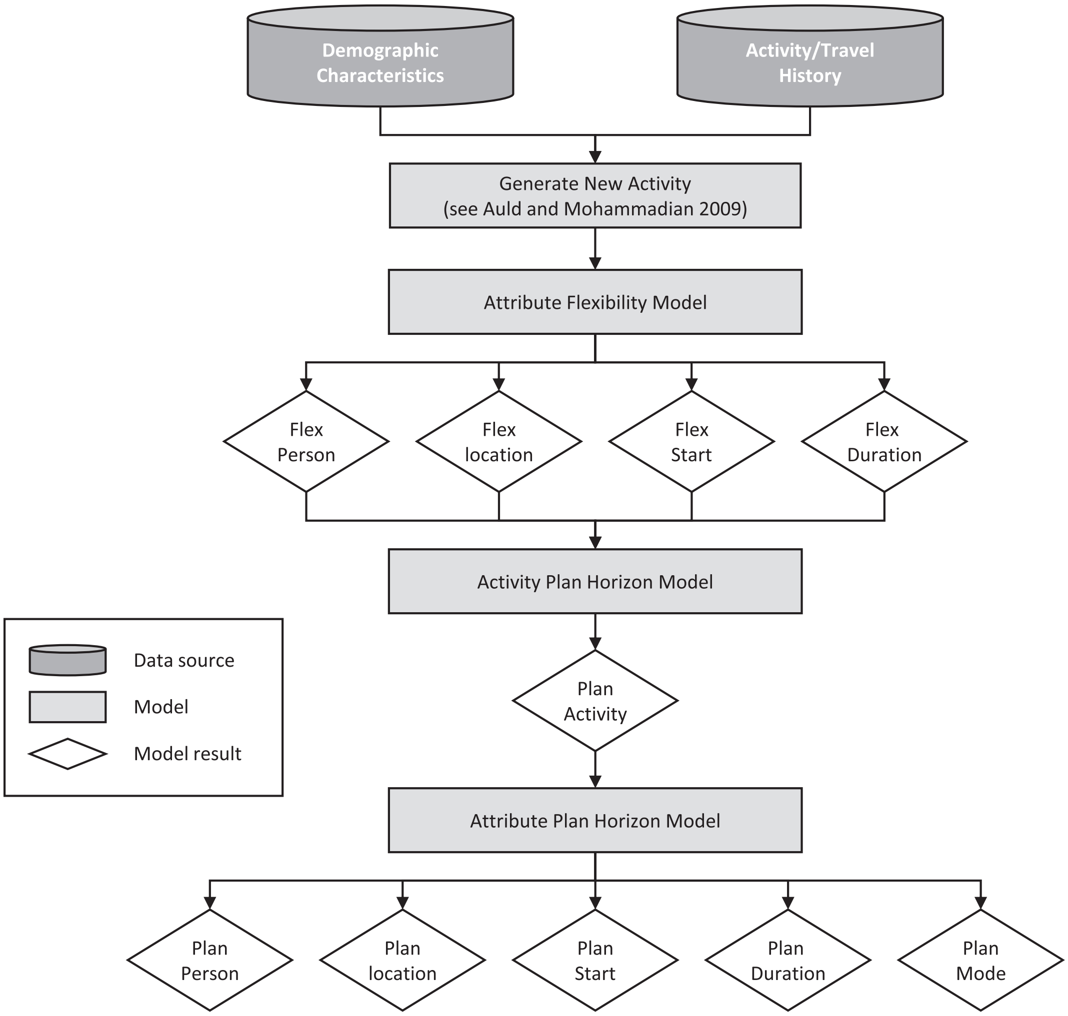

Fig. 4. Activity attribute planning order model system.

estimated as multivariate probit models, discussed in the following section, while the overall activity plan horizon model is formulated as a standard univariate ordered probit model.

The current layout of the activity planning order model represents the core hypothesis that planning context at the time of the conception of the activity impacts the timing of the activity planning. This is represented by including the attribute flexibility as the top level of the model, representing that flexibility is the most fundamental defining property of an activity, and that these flexibilities then determine how much lead time is needed for making a final decision. This relates the activity planning to the required planning and scheduling effort to make a decision, with more highly constrained planning situations likely to require more effort in planning and scheduling.

4. Univariate and multivariate ordinal probit modelling

The dependent variables in the models to be estimated are binary and ordinal measures of the degree of flexibility and preplanning for the various activity attributes, as well as an ordinal measure of the overall activity plan horizon. The response values range from “impulsively planned” to “planned over a week ago” to “routine” for the plan horizon responses and “inflexible” or “flexible” for the flexibility responses, indicating the use of an ordinal response model for the plan horizons and a binary response model for the flexibilities. In addition, the flexibility and attribute plan horizon models account for multiple responses – for mode, party composition, location, start time and duration choices – made on the same unit of analysis, which is a single activity observation. This is the common situation – multiple responses obtained from the same observation unit – in which correlated responses arise, potentially indicating the use of a multivariate model. The likelihood is high that unobserved factors on each observation about how a mode, location, etc. choices are made are related to the unobserved impacts on the other choices for the same activity observation, potentially giving rise to the cross-response correlations. Multivariate Probit models are a type of model capable of representing these correlations.

The Ordered Probit model is an extension of the basic probit model for binary responses extended to ordinal responses (McKelvey and Zavoina, 1975). In the univariate Ordered Probit model, discrete values of the ordinal response Y_i having values $1, 2, \ldots, K$ are for each individual i are observed. It is assumed then that there is an underlying random latent variable $y^*_i = x_i\beta + \varepsilon$, where ε is the random error term, which, along with a set of threshold-values α_k for ($k = 1, 2, \ldots, K - 1$), determine the discrete value by:

$$Y_i = k,\ \text{if}\ \alpha_{k-1} < y_i^* \leq \alpha_k, \text{where}\ (\alpha_0 = -\infty\ \text{and}\ \alpha_K = \infty) \tag{1}$$

When the error term on the latent variable ε, is assumed to be distributed with the standard normal distribution, this produces the Ordered Probit model as follows, where ϕ and Φ are the standard normal density and cumulative distribution functions, respectively:

$$\begin{aligned}
P(Y_i = k) &= P(y_i^* \leqslant \alpha_k) - P(y_i^* \leqslant \alpha_{k-1}) \\
P(Y_i = k) &= P(x_i\beta + \varepsilon_i \leqslant \alpha_k) - P(x_i\beta + \varepsilon_i \leqslant \alpha_{k-1}) \\
P(Y_i = k) &= P(\varepsilon_i \leqslant \alpha_k - x_i\beta) - P(\varepsilon_i \leqslant \alpha_{k-1} - x_i\beta) \\
P(Y_i = k) &= \int_{-\infty}^{\alpha_k - x_i\beta} \phi(x)dx - \int_{-\infty}^{\alpha_{k-1} - x_i\beta} \phi(x)dx \\
P(Y_i = k) &= \Phi(\alpha_k - x_i\beta) - \Phi(\alpha_{k-1} - x_i\beta)
\end{aligned} \tag{2}$$

In the extension of the Ordered Probit model to the multivariate case, first described for binary responses by Ashford and Sowden (1970), there are multiple observed ordinal response observations Y_{ij} for responses $j = 0, 1, \ldots, J$, with K_j discrete outcomes for each response, and the error terms in the latent variables for each response are distributed multivariate normal, $\varepsilon_j \sim N(0, \Sigma)$. The error terms in the latent variables thus have a standard multivariate normal distribution, where Σ is the variance–covariance matrix for the error terms. The Multivariate Ordered Probit (MVOP) model can then be written as:

$$Y_{ij} = k,\ \text{if}\ \alpha_{j,k-1} < x_{ij}\beta_j + e_{ij} \leq \alpha_{j,k},\ \text{where}\ (\alpha_{j,0} = -\infty\ \text{and}\ \alpha_{j,kJ} = \infty) \tag{3}$$

In the bivariate case, for example, manipulations similar to that shown in Eq. (2) leads to the joint probability of the first response having categorical value m and the second response have the categorical value n (dropping the individual subscript i):

$$P(Y_1 = m, Y_2 = n) = \int_{\alpha_{1,m-1} - x_1\beta_1}^{\alpha_{1,m} - x_1\beta_1} \int_{\alpha_{2,n-1} - x_2\beta_2}^{\alpha_{2,n} - x_2\beta_2} \phi(x_1, x_2)dx_2dx_1 \tag{4}$$

The probability defined above can be used to define the likelihood function for the observed data and the parameters estimated through approximate solution methods (Fu et al., 2000; Li and Schafer, 2008). The use of this formulation for developing the model of the activity attribute planning horizons increases the efficiency of the parameter estimates by accounting for the correlation between the responses as compared to developing individual ordinal models for each response, much in the way that a seemingly unrelated regression model (Zellner, 1962) does for a linear system. Multivariate probit models are used to model both the flexibility and attribute plan horizon responses, while a univariate ordered probit model is used to model the overall activity plan horizon. Models of this type have been used to estimate various transportation related topics, for example Choo and Mokhtarian (2008), and have even been applied to look at various aspects of activity planning/scheduling as in Miranda-Moreno and Lee-Gosselin (2008) and Ruiz and Roorda (2008). The coefficients for the various probit models were all estimated using the QLIM procedure in the SAS statistical analysis program. The data used to estimate the planning order models is discussed in the next section.

5. Activity planning survey data

The data used in the development of the planning order models was obtained from the Urban Travel Route and Activity Choice Survey (UTRACS), which was a GPS-based prompted recall activity-travel survey that collected data regarding respondents activity planning and activity attribute flexibilities (Auld et al., 2009c). The UTRACS survey was conducted on 100 households from four counties in the Chicago region, Cook, Lake, DuPage and Will. Data collection was begun in April 2009 and ran through October 2009. Every individual completed an upfront interview collecting basic demographic data and routine activity patterns, and then carried a GPS data logger and completed the prompted recall survey for up to fourteen days. The prompted recall included self-reports of activity plan horizons and perceived attribute flexibilities, which were compared against prospective preplanning estimates and observed flexibilities over the survey period. The dataset that was used in this study comprises more than 4100 activities and 3700 trips. The data was validated against reference data from the 2007 ACS and a recent household travel survey conducted in Chicago. A full description of the current data collection effort, including sample validation, bias estimation, recruitment, etc., can be found in Frignani et al. (2010). Note that for modeling purposes the overall sample was filtered for non-routine out-of-home activities and split into “training” and “test” datasets for later validation purposes.

Table 1
Model variable descriptions.

	Dependent variable distributions				
	Inflex (%)	Flex (%)			
Mode Flexibility	52	48			
Personal Flexibility	42	58			
Location Flexibility	45	55			
Start Time Flexibility	17	83			
Duration Flexibility	43	57			
	Impulsive (%)	Same day (%)	Same week (%)	Preplan (%)	Routine (%)
Activity Plan Horizon	30	32	28	10	–
Mode Plan Horizon	21	25	23	9	22
Who-with Plan Horizon	31	30	25	10	5
Location Plan Horizon	30	26	23	10	11
Start Time Plan Horizon	43	29	16	7	4
Duration Plan Horizon	70	11	8	3	8
	Independent variable descriptive statistics				
		Average	Stdev	Min	Max
Avg Gen. Travel Cost ($)[a,b]		3.19	3.15	0.00	67.97
Avg Duration (in days)[a]		0.06	0.10	0.00	1.12
Avg Frequency (per day)[a]		0.72	0.79	0.05	4.18
Student		0.09	0.28	0	1
Employed		0.82	0.38	0	1
Teleworker		0.19	0.39	0	1
ICT User		0.72	0.45	0	1
ACT1 (work/school)[c]		0.11	0.31	0	1
ACT2 (personal/services)[c]		0.12	0.33	0	1
ACT3 (HH needs)[c]		0.10	0.30	0	1
ACT4 (discretionary)[c]		0.28	0.45	0	1
ACT5 (shopping)[c]		0.32	0.46	0	1
ACT6 (other)[c]		0.07	0.26	0	1

[a] Calculated over all activities of specific activity type (20 types) for each person.
[b] Cost calculated as sum of travel time cost, travel distance cost, transfer costs and fare/parking/toll charges.
[c] Specific activity types are grouped into 6 general activity categories.

The distributions of the three dependent variable categories, i.e. attribute flexibilities, activity plan horizon, attribute plan horizons, obtained from the survey are shown in Table 1 below, with missing values omitted for the attribute plan horizons. The dependent variable descriptions show the distributions for each response in each variable category, while sample descriptive statistics for all independent variables are shown for the training data set. Note that the average frequency and duration variables are averaged over all observations of a specific activity type (from a total of 20 types – see Frignani et al., 2010 for full description), such as "Primary Work", "Grocery Shop", and "Eat meal", for each individual. These averages are then assigned to all observations of that type for each individual. The activity type indicators shown in the table and used in the model are aggregations of the 20 specific activity types into common categories, such as "Work", "Shop", and "Discretionary", as shown in the table. The distributions show that most of the observations are evenly split between inflexible and flexible attributes except for start time which tends to be much more flexible than the rest of the attributes. The activity and attribute plan horizon distributions display results which are realistic and compare favorably to observations from other plan horizon observations such as CHASE (Doherty et al., 2004). The attribute plan horizon distributions show that the mode and location choices tend to be the most routine, with the start time and especially the duration decisions tending to be quite impulsive.

6. Results for attribute flexibility model

The first model estimated under the activity planning framework shown in Fig. 3 is the Activity Attribute Flexibility model. This model determines the perceived flexibilities for the five primary activity attributes: mode, who with, location, start time and duration. As this is the first model estimated immediately after the activity is generated, it depends solely on the general activity type, the characteristics of the individual, and some simple history characteristics, such as the expected duration and the expected weekly frequency. In other words the variables utilized in the activity flexibility model are limited to the data that is expected to be available at this point in the simulation. More accurate models of attribute flexibility could be generated, where the flexibilities depend on other attributes of the activity, such as the duration, mode selected, etc., but these characteristics are not known at the point the flexibility model is utilized. This is due to the assumption of the flexibilities being fundamental, intrinsic aspects of a generated activity, rather than planned attributes, which in turn act as constraints on further planning. The model determines whether each of the five attributes is perceived as flexible or inflexible by the individual. The results of this model estimation are shown in Table 2.

Overall, the model displays an acceptable fit to the multivariate flexibility responses. The results of the model estimation show that the use of a multivariate model in this case is warranted with significant, moderate correlations between the unobserved error terms of the who-with and start time latent variables and significant but minor correlations between the remaining attributes, with only the mode-location, person-location and duration-location correlations being insignificant. All coefficients of the model are significant at the 0.1 level and most are significant at the 0.05 level. The table shows the estimated coefficients for each response grouped into three categories. First there are direct and interaction effects of the individual characteristics. Second are the general characteristics of the activity. Finally, activity-type specific effects are shown, where some of the individual and general activity characteristics are interacted with activity type indicators with the "other" activity type as the reference category.

The signs and magnitudes for the model mostly conform to expectations of variable impacts on the underlying latent variable. As an example, consider the mode flexibility model as shown. The coefficients show that in general individuals who are employed or are students have increased flexibility in mode choice, possibly due to the higher priority activities these individuals are presumably engaging in. In other words they may have first choice of transport within their respective households. Males and seniors are generally less flexible (although male-seniors are in fact more flexible as compared to the base case of non-senior-females) as is often seen in mode choice studies. The frequency with which the activity is performed

Table 2
Activity attribute flexibility multivariate probit model results.

	Mode flexibility		Interpersonal flexibility		Location flexibility		Start time flexibility		Duration flexibility	
	β	*t*-Stat	β	*t*-Stat	β	*t*-Stat	β	*t*-Stat	β	*t*-Stat
Constant	−0.386	−4.0	−0.509	−2.4	−0.226	−2.6	1.215	11.8	−1.239	−8.8
Individual										
Employed	0.368	3.7	–	–	–	–	–	–	1.294	9.2
Student	0.435	3.3	0.378	2.7	–	–	–	–	1.461	12.2
Male	−0.235	−2.0	−0.577	−4.2	−1.166	−9.2	−0.427	−2.9	–	–
Senior	−0.272	−3.3	0.267	2.8	−0.186	−1.7	−0.240	−2.5	−0.246	−2.8
Male × Senior	0.709	4.5	0.517	2.9	1.333	7.1	0.528	2.9	−0.374	−3.7
ICT user	–	–	0.568	5.2	−0.403	−3.3	−0.296	−3.2	–	–
Teleworker	–	–	1.570	5.1	1.022	3.1	0.185	1.8	–	–
ICT × Teleworker	–	–	−1.759	−5.6	−0.776	−2.5	–	–	−0.235	−2.4
Act										
Avg. Gen. Cost	–	–	0.043	3.0	−0.049	−3.1	0.045	3.6	–	–
Avg. Frequency	0.232	4.1	–	–	–	–	–	–	–	–
Avg. Duration	–	–	–	–	–	–	–	–	1.300	2.2
Activity type										
ACT1 (Work)	–	–	−1.208	−7.3	–	–	–	–	0.621	1.8
× *ICT user*	0.437	3.3	–	–	–	–	–	–	0.995	2.9
× *Teleworker*	–	–	1.456	5.5	1.046	2.5	–	–	−1.124	−3.5
× *Avg Gen. Cost*	0.045	1.3	–	–	–	–	−0.050	−2.0	–	–
× *Avg Frequency*	−1.104	−5.9	–	–	2.374	6.9	–	–	−0.562	−3.5
× *Avg Duration*	–	–	–	–	–	–	–	–	−2.071	−2.7
ACT2 (Personal)	–	–	−0.576	−3.6	–	–	–	–	–	–
× *Avg Duration*	–	–	11.048	4.3	−8.898	−4.0	3.426	1.7	–	–
ACT3 (HH Needs)	–	–	−0.609	−3.0	–	–	−0.437	−1.7	–	–
× *Avg Frequency*	–	–	1.723	3.0	−0.982	−1.9	1.351	1.7	–	–
ACT4 (Discr.)	–	–	–	–	0.933	5.7	–	–	–	–
× *Avg Frequency*	–	–	0.415	2.2	0.662	2.8	–	–	0.770	4.8
× *Avg Duration*	–	–	6.647	6.1	−8.096	−7.3	–	–	–	–
ACT5 (Shopping)	–	–	−0.583	−4.8	2.377	17.7	−0.602	−5.6	–	–
× *Avg Frequency*	–	–	0.343	4.3	–	–	0.206	2.5	0.488	7.5

Error−term correlation coefficients (Σ_{ij})

	ρ	*t*-Stat	ρ	*t*-Stat	ρ	*t*-Stat	ρ	*t*-Stat	ρ	*t*-Stat
Mode	1	–								
Person	0.10	2.4	1	–						
Location	−0.05	−1.1	−0.02	−0.6	1	–				
Time	0.10	2.1	0.30	7.3	−0.09	−2.1	1	–		
Duration	0.13	3.0	0.16	3.9	0.03	0.5	−0.10	−2.1	1	–
Likelihood ratio:	0.183									

also impacts the mode flexibility, with flexibility generally increasing with increasing frequency, although this is not the case for work activities, where the flexibility is greatly decreased with frequency. This shows the difference between mode choices for traveling to the frequent work activity, where the choice may be locked into a routine pattern, versus the mode flexibility for frequent non-work activities. The final parameter in the mode choice flexibility model is if the individual is a frequent Information and Communications Technology (ICT) user, as determined by cell phone and internet usage. For frequent ICT users the mode choice decision for work activities is more flexible, perhaps reflecting the greater opportunities for coordination and planning for different mode types, such as carpooling, transit, etc. which are enabled by these technologies.

Similar analyses can be performed for the remaining four flexibility responses; however several interesting results can be highlighted. One focus of the survey was on the use of teleworking and ICT by the survey respondents and the impacts these may have on the planning process. In general, being an ICT user increases the flexibility for the mode, who-with and durations of activities, where this is limited to work activities only for the mode and who-with decisions, and it decreases the flexibility of the location and start time decisions. The impact of ICT use on mode flexibility for work activities was discussed above, while the use of ICT may increase the duration flexibility of work activities through a type of substitution effect, whereby employees who are not truly teleworkers may still be able to finish work at home or elsewhere through the use of ICT resulting in more flexible work durations. Note that this is effect is not seen for true teleworkers who actually show less duration flexibility than traditional workers, further supporting this partial substitution possibility. In contrast, and somewhat unexpectedly, the individuals who use ICT show less flexibility in location and start time. Finally, the expected generalized travel cost also impacts the perceived flexibilities, with higher travel costs related to more flexible work mode selection, more flexible interpersonal planning and more flexible starting times, but less flexibility in location choice. These are all natural and expected results of longer trips, with individuals building in more timing cushion and considering more alternatives the more the expected cost, but alternatively focusing more on one location the longer the trip – i.e. if there were many available locations to participate in an activity there would not be a need to travel as far.

Overall the model fits well and should be able to give acceptable estimates of attribute flexibility for later use in activity planning simulation. The model includes several important policy variables of interest, including ICT use and teleworking, and several state variables, the average frequency and duration of the activity type and the expected generalized travel cost, which can be updated during simulation to represent dynamic effects. In addition to serving as important inputs to the subsequent plan order models, the flexibilities can also serve as constraints on later attribute planning models. For example, for a location decision perceived as inflexible a limited choice set can be developed, possibly from a list of acceptable past locations, while in contrast a flexible location choice could have a more extensive choice set.

7. Results for activity plan horizon model

The results of the overall activity plan horizon ordered probit model are shown in Table 3. The model specifies the activity plan horizon in one of four levels; the activity can be impulsive, planned the same day, planned the same week, or preplanned. Note again that this modeling framework specifically excludes "routine" activities, which are modeled separately and in a different fashion within the simulation. The model coefficients shown are all significant at the 0.05 level except for several of the activity type interact terms which were retained for conceptual reasons. The model is similar to others that have been developed from different activity planning data sources, for example Mohammadian and Doherty (2006), except that again the model does not depend on any specific characteristics of the activity. Only general characteristics of the activity type (type, average duration, and average frequency) and the flexibilities of the specific instance of the activity, in addition to the individual characteristics are utilized in the model, as specified by the framework shown in Fig. 2.

The model coefficient estimates had effects as expected. Employed individuals tended to have a greater degree of preplanning for "personal" and "discretionary" activities. This was expected as these types of activities tend to require a greater planning/scheduling effort which is more difficult to fit around a work schedule, as they usually tend to involve others. Users of ICT tended to exhibit more preplanning in "work", "maintenance" and "other" activities and less preplanning in "personal" and "shopping" activities, possibly due to the greater ease with which personal and shopping activities can be planned through the use of ICT. Teleworkers exhibited less preplanning for all activity types, probably due to greater scheduling freedom from working at home.

The average frequency and duration of the activity type also impacted the plan horizon, with longer, more frequent activities generally being more preplanned, since the longer an activity is and the more the activity is conducted, the more scheduling effort seems to be required. Finally, the flexibilities of the various activity attributes also impacted the overall activity plan horizon. For example, an activity with an inflexible location decision tended toward being more preplanned, except for the "work" activities. In contrast, inflexible start times and durations tended to either have no impact or to make the activity less preplanned, except for inflexible duration "work" activities which tended to be more preplanned.

The location results are intuitive as travel to a specific location is probably more difficult to plan and therefore more preplanned (impulsive activities tend to have more flexible locations as they are usually planned opportunistically). Meanwhile, the inflexible start time results may reflect that generally preplanned start times are viewed as changeable. Work activities with inflexible durations are more preplanned as would be expected when scheduling a large portion of the day for an inflexible amount of time, while maintenance activities with inflexible durations are less preplanned as maintenance activities tend to be short activities ("pick-up/drop-off", etc.), where the inflexible duration probably represents more of a minimum time in which the activity can be completed, rather than a true scheduling inflexibility. Finally, higher generalized travel

Table 3
Activity planning horizon ordered probit model.

Variable	β	t-Stat	Variable	β	t-Stat
Constant	0.088	0.62			
Person			*Activity*		
Employed	0.717	4.23	Inflexible Location	0.617	4.93
Frequent ICT usage	0.549	2.4	Inflexible Start Time	−0.663	−5.47
Teleworker	−0.612	−4.38	Inflexible Duration	−1.416	−5.34
Activity type			*Activity type*		
ACT1 (Work/School)	1.061	2.47	ACT4 (Discretionary)		
× *Employed*	−1.223	−2.09	× *Student*	0.833	2.74
× *Student*	1.809	2.25	× *Senior*	0.717	3.63
× *Inflexible Location*	−0.805	−1.92	× *Male*	−0.787	−3.99
× *Inflexible Duration*	2.081	5.03	× *ICT User*	−0.425	−1.67
× *Average Gen. Cost*	0.101	2.08	× *Inflexible Duration*	1.317	4.22
× *Average Frequency*	−0.459	−2.48	× *Average Frequency*	0.563	2.59
			× *Average Duration*	2.409	1.95
ACT2 (Personal)					
× *ICT User*	−0.897	−2.09	ACT5 (Shopping)		
× *Inflexible Duration*	1.459	4.11	× *Employed*	−0.653	−2.55
× *Average Gen. Cost*	0.133	2.7	× *Senior*	0.456	2.22
× *Average Duration*	13.816	4.73	× *ICT User*	−0.809	−2.89
ACT3 (Maintenance)			× *Inflexible Duration*	1.0009	3.55
× *Employed*	−0.659	−2.52	× *Average Gen. Cost*	0.051	2.11
× *Student*	−1.103	−2.21	× *Average Frequency*	0.293	3.49
× *Senior*	1.045	3.42			
× *Male*	−0.59	−1.92			
× *Inflexible Duration*	0.554	1.69			
× *Average Frequency*	1.586	2.59			
Limits					
α_2	1.66	27.23			
α_3	3.53	36.52			
Likelihood ratio:	0.099				

costs result in increased preplanning of work, personal and shopping activities as expected, but had no impact on maintenance/discretionary activities perhaps because these are often conducted over short distances (for errands and pick up/drop off) or are scheduled with others (for many discretionary acts like socializing, eating out, etc.).

8. Activity attribute plan horizon modelling results

The final model within the "Activity Planning Order" model framework is the individual attribute planning order model. This model uses the previous two models as input, along with the individual and activity type attributes, to estimate general plan times for each of five activity attributes (mode, who-with, location, start time, duration), within the overall simulation. The determination of each correlated attribute plan time through the use of the multivariate ordered probit model creates the overall order in which the attributes are planned. The results for each response can be either "impulsive", "same day", "same week" or "preplanned". These then give a general time frame within the overall simulation at which each decision is made. The actual coefficient estimates, threshold values, and correlation parameters for each response, as well as the overall model fit are shown in Table 4. The model shows reasonable fit and the correlation coefficient results also show some interesting results. The mode plan horizon and who-with plan horizon are weakly positively correlated with the planning of all of the other attributes. The location plan horizon has a small to moderate positive correlation with the start time and duration plan horizon response. And finally, the start time and duration have a strong correlation as expected. All correlation parameters are significant at the 0.01 level, except the "who with"–"location" parameter which is significant at the 0.05 level.

The table shows all of the parameter estimates for the five attribute plan horizon responses. The coefficients are almost all significant at the 0.10 level with most significant at the 0.05 level. Some marginally significant parameter estimates were retained for their policy relevance, such as the average duration of the work activity under the mode planning response. Overall, the model displays effects for each response that were generally in line with expectations. All attribute plan horizons are greatly impacted by the overall activity plan horizon with more impulsive activities logically having more impulsive attribute plan horizons, to a greater or lesser degree, for each response. Interestingly, the generalized travel cost does not have much direct impact on any of the activity attribute planning horizons, although it does have an indirect impact through its effects on the flexibility and overall activity plan horizon which do affect the attribute horizons. The impacts of the other variables are discussed below for each individual attribute response.

Table 4
Activity Attribute Planning Horizon Multivariate Ordered Probit Model.

Variable	Mode		Who-with		Location		Start		Duration	
	β	*t*-Stat	β	*t*-Stat	β	*t*-Stat	β	*t*-Stat	β	*t*-Stat
Constant	0.618	3.09	4.096	22.37	2.017	8.96	1.612	9.24	−1.268	−6.85
Individual										
Employed	0.634	5.83	–	–	0.268	2.56	0.359	3.52	0.745	5.31
Student	1.044	9.24	–	–	0.391	3.25	–	–	–	–
Senior	−0.115	−1.61	–	–	–	–	–	–	0.159	1.82
Male	–	–	–	–	–	–	–	–	0.126	1.56
Frequent ICT usage	0.130	1.60	–	–	0.388	3.83	−0.146	−1.58	–	–
Activity										
Actplan-impulsive	−1.527	−8.64	−5.533	−28.62	−3.258	−17.67	−3.178	−20.47	−1.462	−9.70
Actplan-same day	−0.492	−3.36	−2.912	−16.85	−1.465	−7.48	−1.570	−10.21	−0.518	−3.74
Actplan-same week	−0.272	−1.74	−1.231	−7.13	−0.613	−3.03	−0.933	−6.50	−0.357	−2.54
Inflexible start time	–	–	–	–	–	–	–	–	0.295	2.59
Inflexible duration	0.106	1.55	–	–	–	–	0.163	2.32	0.839	8.89
Avg duration (days)	–	–	–	–	2.191	9.36	–	–	–	–
Avg daily frequency	–	–	–	–	–	–	–	–	0.266	3.67
Activity type										
Act1 (work/school)	–	–	–	–	–	–	–	–	–	–
× *Teleworker*	0.456	1.75	–	–	–	–	0.756	2.86	0.877	2.57
× *Inflexible Location*	–	–	–	–	0.748	5.85	–	–	–	–
× *Avg Gen. Cost*	–	–	–	–	0.228	14.81	–	–	–	–
× *Avg Duration*	0.786	1.52	–	–	–	–	–	–	–	–
Act2 (personal)	0.262	2.12	–	–	–	–	–	–	0.321	2.26
× *Student*	–	–	0.825	3.86	–	–	–	–	–	–
× *ICT User*	–	–	–	–	−0.230	−1.70	–	–	–	–
× *Inflexible Duration*	–	–	–	–	–	–	–	–	−0.397	−2.01
Act3 (maintenance)	–	–	–	–	–	–	–	–	–	–
× *ICT User*	–	–	–	–			–	–	–	–
× *Inflexible Start*	–	–	–	–	–	–	0.616	3.53	–	–
× *Actplan − Sameweek*	0.354	1.59	–	–	–	–	–	–	–	–
Act4 (discretionary)	0.377	3.13	–	–	–	–	–	–	–	–
× *ICT User*	–	–	0.359	2.95	−0.543	−3.33	0.186	2.01	–	–
× *Inflexible Location*	–	–	–	–	0.285	1.81	–	–	–	–
× *Avg Duration*	−3.922	−3.88	−5.691	−6.93	–	–	–	–	–	–
Act5 (shopping)	0.196	2.19	–	–	–	–	0.206	1.57	–	–
× *ICT User*	–	–	–	–	−0.651	−5.81	−0.498	−3.09	–	–
× × *Inflexible Duration*	–	–	–	–	–	–	–	–	−0.277	−2.25
× *Inflexible Start*	–	–	–	–	–	–	–	–	−0.334	−1.98
Limits										
α_2	0.835	17.43	2.029	17.55	1.305	16.73	1.151	17.24	0.435	10.32
α_3	1.486	26.87	3.614	30.29	2.316	27.63	2.027	21.91	0.879	−2.01
α_4	1.794	30.76	4.402	44.22	2.796	34.88	2.643	33.04	1.096	2.58
Correlation coefficients										
	ρ	*t*-Stat	ρ	*t*-Stat	ρ	*t*-Stat	ρ	*t*-Stat	ρ	*t*-Stat
Mode	1	–								
Who-with	0.143	3.8	1	–						
Location	0.148	4.2	0.104	2.2	1	–				
Start time	0.159	4.1	0.181	3.4	0.352	11.4	1	–		
Duration	0.187	4.5	0.178	3.2	0.218	5.7	0.539	19.2	1	–
Likelihood ratio:	0.152									

The mode choice plan horizon is shifted toward preplanning for individuals who are employed and/or who are students, and to a lesser extent by ICT usage, while there is a slight shift toward impulsive mode planning for seniors. These parameter estimates all fall in line with expectations as employees/students tend to have more preplanned/routine mode choice due to the mandatory work/school activities, while seniors do not. As far as activity-type specific effects, individuals who are teleworkers and activities with long durations tend to have more preplanned mode choices for "work" activities. Mode choices also tend to be more preplanned in general for "personal", "discretionary" and "shopping" activities, although this is most likely due to many of these type of activities occurring during routine or preplanned tours in the case of "shopping" and "personal" activities, while discretionary trips (socializing, eating out, entertainment, etc.) tend be conducted more as stand-alone tours and often involve others, leading to more preplanning. One unusual result is that long average duration discretionary trips tend to be more impulsive in the mode choice. This counteracts the discretionary activity constant such that discretionary activities less than approximately 2 h long have a net increase in mode preplanning while longer activities have a decrease in preplanning.

The interpersonal plan horizon is determined almost entirely by the overall activity plan horizon. However, students tend to preplan the party composition more for "personal" activities, while discretionary activities show a small increase in preplanning for ICT users and a large decrease in preplanning for long average duration activities similar to the mode choice. The results for the discretionary activities are interesting, because as the results in Table 3 show, longer duration discretionary activities have an increased propensity toward preplanning for the overall activity while the results for the mode and who-with plan horizons show increased impulsiveness with increased average duration, showing that activities of this type are planned first while the details of who is involved and the mode chosen are filled in later.

The location plan horizon is influenced by several important attributes of the individual and the specific activity type. Similar to the mode plan horizon, employed individuals and students have more preplanned location choices in general, due to the more mandatory nature of their activity patterns. ICT users have more preplanned location choices for work/school activities, but more impulsive discretionary and shopping location choices, possibly due to the greater planning possibilities available through the use of communications technology. Especially for discretionary types of activities, ICT lets users more quickly and easily find suitable locations through internet searches, location-based services available on cell phones, etc., which probably reduces the need for preplanning. The average duration of the activity also is a factor in the location planning, with longer activities which possibly have higher priorities having a higher degree of preplanning. Finally, as would be expected, for work and discretionary activities with an inflexible location, the location choice is more preplanned.

The start time planning horizon also shows some interesting results. Much like with the other attributes, employed individuals and students exhibit a higher degree of preplanning for all activity start times, again due to the more mandatory nature of their schedules. One interesting result is that frequent ICT users show slightly more impulsive start time planning for all activities except for discretionary activities (which are often conducted with others and therefore prescheduled) and much more impulsive planning for shopping activities, as expected due to the greater information gathering and scheduling coordination possibilities provided by ICT. For one example of this, looking up operating hours for a store can allow for more impulsive start time planning as the user can save time by predetermining that the store will still be open rather than wasting time driving to a store to find that it is closed. For teleworkers the start time tends to be more preplanned for work activities to an even greater degree than other employed individuals, which shows that even teleworkers tend to organize their at-home working schedules around routine blocks of time. Finally, the flexibility of the activity durations and the start times for maintenance activities also impacts the start time planning, with less flexibility in these measures leading to greater preplanning as expected.

Finally, the duration plan horizon results are similar to those for the start time, with similar impacts from the employed, student and teleworkers indicators. Additionally, the flexibility measures of the start time and duration choices have a similar impact as seen in the start time planning, with less flexibility leading to more preplanning (although the impact is smaller on personal and shopping activities). The duration tends to be more preplanned for more frequent activities, probably due to the more frequent activities being part of a routine pattern. Finally, a greater degree of preplanning of the duration is seen for both seniors and males, although the effect is fairly small.

9. Model validation and accuracy estimation

After the various models of the activity planning order framework were estimated, an assessment of the accuracy and validity of the model was needed. This was evaluated in a number of ways. First, the accuracy of the overall simulation for each response from the input or "training" sample was evaluated against the expected "null model" response accuracies, which were obtained from applying the observed response distributions. This enables a determination of the effectiveness of the model system in predicting responses. Next, the same procedure was applied to a second data set, the "test" data set, obtained through the same UTRACS survey to test for potential overfitting in the model system. For both the training and test sets, in addition to the response accuracies, two additional accuracy measures were calculated. These measures evaluate how well the overall order of the activity attribute planning is estimated. Finally, the model was partially validated against other activity planning data sources, where available.

The first validation exercises performed were the comparisons between the simulated responses from the training and test datasets to the expected null model responses, with each data set as defined in Section 5. The results for this analysis are shown in Table 5. The accuracies show the average percentage for each response in the three components of the planning order framework which were estimated as observed in each dataset, averaged over 1000 simulation runs. So, for example, the table shows that 53% and 54% of mode flexibility measures were estimated correctly on average for the training and test datasets respectively. It should be noted here that the accuracies shown for the activity plan horizon and activity attribute plan horizon include the effects of the lag variables from the prior models. In other words, the errors from the previous model are propagated and accounted for in this analysis, i.e. the simulated flexibility values are used in the plan horizon models, etc.

The planning order accuracies represent an important validation, as the overall intent of the model framework is to specify the planning order. The accuracy of the planning order was calculated in two ways; for the exact and the approximate planning order. The exact order accuracy is the percentage of observations for which the attributes are simulated in the exact

Table 5
Model accuracy compared to null model.

	Simulated accuracy[a]		Null model accuracy[b]		% Improvement over null	
	Train (%)	Test (%)	Train (%)	Test (%)	Train (%)	Test (%)
Mode flexibility	53	54	50	50	5	7
Personal flexibility	59	54	51	50	16	9
Location flexibility	74	73	51	50	47	46
Start time flexibility	69	69	68	67	1	3
Duration flexibility	60	58	50	50	20	15
Activity plan horizon	32	32	28	28	16	13
Mode plan horizon	24	22	17	17	42	30
Who-with plan horizon	33	34	26	26	27	30
Location plan horizon	30	31	22	23	37	34
Start time plan horizon	37	34	30	28	21	19
Duration plan horizon	55	48	51	44	9	7
Order exact[c]	4	3	1	1	261	177
Order approximate[d]	53	50	34	34	54	45

Note: All differences between simulated average and null model accuracies are significant at the 0.01 level.
[a] Averaged over 1000 simulation runs.
[b] Null model estimated by applying response distributions from training dataset randomly to each dataset.
[c] Accuracy of predicting the exact order in which attributes are planned.
[d] Accuracy of predicting the approximate order in which attributes are planned (no attribute out of order by more than one place).

order in which they are observed. The order is determined based on the planning horizons, i.e. "routine" comes before "pre-planned" comes before "same week", etc. with the attributes then sorted into first, second, third, etc. planned attributes. Simulating all five attributes in the exact observed order when each attribute can have five response values is fairly difficult, however, with a null model expected accuracy of only 1%. Therefore an "approximate" plan order accuracy measure was also utilized. The approximate accuracy is defined as the number of simulated observations which have no attribute out of place by more than one spot from the observed orders, i.e. if the mode is planned first in the observed activity order, it can be planned no more than second for the order to still be approximately correct.

The response and order accuracies have been compared to null model expectations for both the training and test datasets, calculated from the observed response observations. The results in Table 5 show that the model gives marginal to moderate improvements in the accuracies (from a low of 5% for the mode and start time flexibilities to a high of 48% for the location flexibility) showing that the model gives some performance benefit. In addition, similar improvements over the null model are also seen in the test dataset, showing that overfitting is not likely to be an issue. In addition to the improvement in the individual response accuracies, both the training and test set simulations showed an improved ability to correctly estimate the proper planning orders as compared to the average of a null model simulation (no closed form expected values can be determined for null model order accuracy so it was determined through simulation). So overall the modeling framework for estimating the activity attribute planning order shows good improvement over the null models, demonstrating that the framework is useful as it relates the planning order to various policy sensitive variables and measures endogenous to the simulation such as the frequency and average duration.

A second validation exercise was performed to determine how well the estimated models can replicate activity flexibility and planning horizon responses from other surveys, from different spatial and temporal contexts. No single data source available includes all of the flexibility and plan horizon responses estimated by the model, but several different data sources do contain observations on several of the responses separately. These include the CHASE dataset (Doherty et al., 2004), which includes observations on four of the five flexibility measures as well as the overall activity plan horizon measure, and the OPFAST dataset (Lee-Gosselin, 2005). The OPFAST dataset includes measures of spatial and temporal flexibility that approximate a combination of both the flexibility and attribute plan horizons as defined in the current work. The flexibilities in the OPFAST dataset are given in terms of whether each decision is habitual/routine (Fixed), Planned, or Impulsive, which correspond to an aggregated version of the attribute planning horizons collected in UTRACS (with same-day, same-week and pre-planned responses in UTRACS corresponding to the "Planned" category in OPFAST). The OPFAST data further refines the timing plan horizon by defining various plan horizons within the "Planned" category that correspond to those used in this work. Therefore the "flexibilities" in OPFAST are compared to the plan horizons in UTRACS, rather than to the UTRACS flexibility measures, although this can only be done for the start time and location horizons. The combination of the CHASE and OPFAST comparisons allows most of the responses estimated by the plan order models to be validated against data collected in different contexts in order to demonstrate the transferability of the framework. The same accuracy comparisons as performed for the training/test datasets were performed for the CHASE and OPFAST data for all available responses.

The results in Table 6 show the results of these various validation exercises. The accuracies and improvement over the null models are shown for all available responses found in each dataset. These include four of the five flexibility measures (excluding mode flexibility) and the activity plan horizon found in CHASE, and the location and start time plan horizons found in OPFAST. The input data sets for each test were derived from each data source using similar methods as for the UTRACS data, with conversions being made as necessary so all dependent and independent variables conform to the required input. This primarily means that all at-home activities and all routine activities were excluded from each dataset, while input

Table 6
Validation with CHASE and OPFAST data.

	Simulated accuracy[a]		Null Model accuracy[b]		% Improvement over null	
	CHASE (%)	OPFAST (%)	CHASE (%)	OPFAST (%)	CHASE (%)	OPFAST (%)
Personal flexibility	63	–	55	–	15	–
Location flexibility	53	–	50	–	6	–
Start time flexibility	52	–	51	–	2	–
Duration flexibility	52	–	51	–	1	–
Activity plan horizon	29	–	26	–	13	–
Location plan horizon	–	38	–	36	–	6
Start time plan horizon	–	30	–	26	–	17

Note: All differences between simulated average and null model accuracies are significant at the 0.01 level.
[a] Averaged over 1000 simulation runs.
[b] Null model estimated using observed response distributions from each dataset.

variables such as the ICT usage were imputed from existing variables in each case and activity types were transformed to match those used in UTRACS. All of the null model accuracies were calculated using the response distributions from each individual data set.

The results show that the model outperformed the null model assumptions for both the flexibilities and the plan horizon for the CHASE test. Although the performance is only moderately greater in some cases, such as the start time and duration flexibilities, it is important to remember that these comparisons are against the null model as calculated using the actual CHASE data. Therefore, these improvements show that the model is transferable to some degree to other contexts, i.e. it is not overfit to the UTRACS dataset or Chicago region. Similar results are shown for the OPFAST test, where the location and start time attribute plan horizons do show significant and more than marginal improvement over the null model. The improvement seen over the null model results for these tests are encouraging. Overall, the model framework shows potential for having good transferability properties although clearly more test, preferably with data containing all of the modeled responses together, are needed to further evaluate this potential.

10. Adapts policy sensitivity

The policy sensitivity of the full ADAPTS activity-based model has been investigated in order to verify that the planning order framework is having the appropriate impact on the simulated travel patterns. To evaluate the policy sensitivity of the model, the planning order framework has been implemented within the ADAPTS activity-based model, as outlined in Auld and Mohammadian (2009) and documented in Auld (2011). The ADAPTS activity-based model includes the components described in Section 2 above, along with a simulated dynamic traffic assignment module which assigned the simulated travel episodes to the transportation network and feeds back experienced travel times to the activity-planner every 15-min.

The initial policy sensitivity test involves running two ADAPTS scenarios, one of which is a baseline 2009 model and the other which is the same as the baseline model except that 15% of workers are reassigned as teleworkers. This scenario, then, could be used to test the effectiveness of a regional policy of encouraging teleworking through the use of incentives or some other mechanism. Each case was run through a simulated week, which provides 7-days worth of simulated outcomes to compare., the equivalent of running seven iterations for each model. Past experience has shown that the simulation variance is low enough that seven iterations is sufficient to evaluate the significance of observed differences in aggregate travel patterns (although this is clearly not the case on an individual level). Therefore, in the sensitivity tests, differences in aggregate outcomes are analyzed.

Overall, the teleworking scenario increases the number of trips that individuals engage in, from 3.9 per day to 4.0 per day, and the number of tours from 1.54 to 1.59, while the number of trips per tour remains the same, with differences significant at the 0.05 level. The number of activities increases from 2.48 to 2.52 per day, with significance of 0.10. This shows that individuals have more time to engage in activities due to the reduced commuting burden, and rather than chaining the new activities, they engage in extra activity tours as the tours are closer to home.

The impact of the tested policy can best be seen in the travel time distributions for various activities, as shown in Fig. 5. The results show that as specified, there is an 11% increase in trips to work less than 5 min, which represents the new teleworkers staying at home rather than traveling to the office. This change is expected as it is inherent in the policy set up. However, this change leads to changes in other activity patterns. The shopping activity is now more likely to occur within 10 miles of home, as they are no longer planned opportunistically along the home-work route, as also occurs for errands. The social activity type similarly exhibits a greater propensity to be conducted within 15 min of home. These results demonstrate the impact of the planning horizon model, and the effect that the planning time for one activity (here the work activity) can have on other activities.

11. Discussion and conclusions

This paper has presented an overview of the ADAPTS planning framework that was developed to simulate planning, scheduling and execution of activity patterns in an integrated, dynamic framework. The development of the series of models

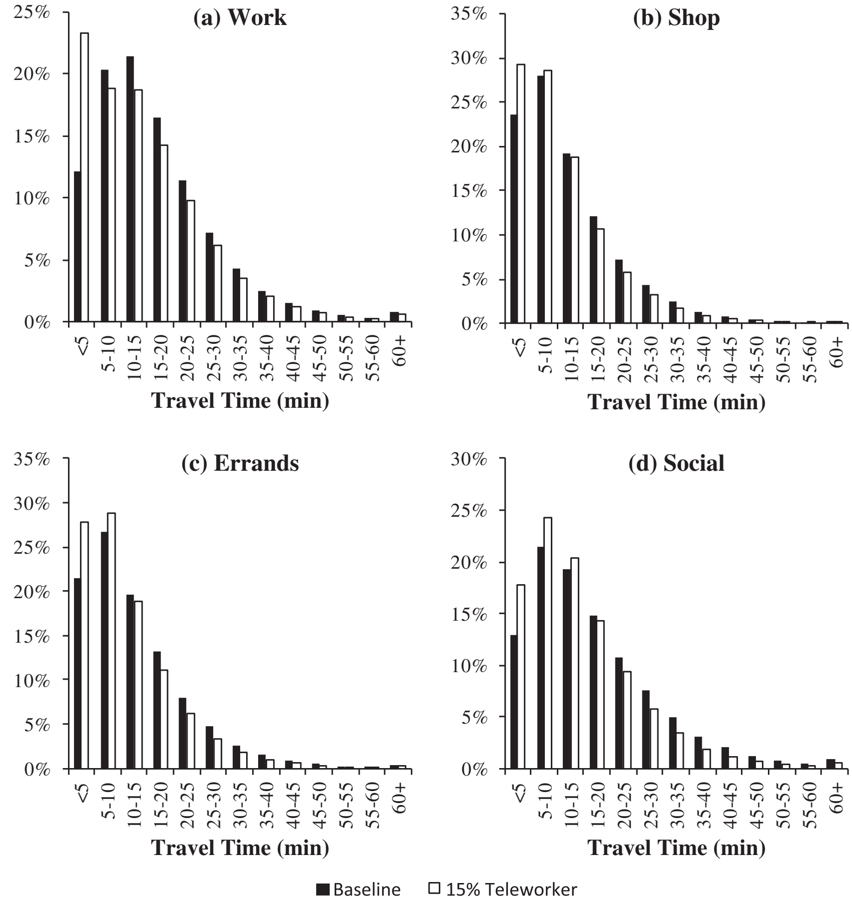

Fig. 5. Impact of teleworking on trip travel time distribution for various activity types.

which comprise the activity planning order framework was documented. This system of models forms the core of the ADAPTS planning framework which allows the simulation of activity planning in a non-sequential fashion, where the individual attribute choice decisions, i.e. destination choice, start time, party composition, mode and duration, can be made at any time before the activity is executed and in any order. This helps relax some of the assumptions regarding activity planning and allows the simulation to more closely approximate the actual underlying process of activity scheduling.

The activity planning order framework was developed using data collected from a GPS-based prompted recall activity and travel survey, the UTRACS survey. This survey collected data on activity-travel patterns, attribute plan horizons and spatial, temporal and interpersonal fixities over a period of two weeks. The survey shows similar results on some of the fundamental activity planning measures (activity plan horizon, attribute horizons, flexibilities) to observations seen in other survey.

The activity planning measures from the survey, along with other socio-demographic and activity related variables, were used as input to a series of probit models (multivariate, ordered and multivariate ordered probit) which model the flexibilities, activity plan horizon, and attribute plan horizons, in that order, where the results from the previous model are used as lag variables in the subsequent models. Two of the models, the flexibility and plan horizon models, were multivariate in nature with responses for each primary attribute of an activity modeled simultaneously. This enabled an estimate of the correlations between the random errors for each model, in addition to the other model parameters. The models all show moderate goodness-of-fit, with parameter estimates which were reasonable and conformed to prior expectations about their impacts on each dependent variable (or variables for the multivariate models). More importantly after a full simulation is run using the input data, the model responses all show an improvement in accuracy over expected null model accuracies for both the data used to develop the model and a test data set. This shows that the full planning order model system is working, not propagating an excessive amount of simulation error between models, and is not overfit to the training data. In addition, similar results are even observed when using other datasets, namely the CHASE and OPFAST data from Toronto and Quebec City respectively, showing that the model is fairly transferable, which is a significant finding.

Although the goodness-of-fit measures and improvement over null model accuracies are marginal for some responses, the model does provide a transferable framework that outperforms null model expectations and relates the flexibility and planning horizons to important planning and policy variables. These variables include average frequency and duration of activities and trips, employment/student status, teleworking, ICT usage, and so on. The modelshows how changes in any of these variables can impact the underlying activity planning process. These changes can then have a direct impact on the activity-travel outcomes as demonstrated through the application of an increased teleworking scenario, where travel patterns for other activities such as shopping, socializing, etc.

Acknowledgements

The authors would like to acknowledge the financial support provided to this project from the National Science Foundation (NSF) Integrative Graduate Education and Research Traineeship (IGERT) program in Computational Transportation Science at UIC under Grant DGE-0549489. In addition, the authors are grateful to Professors Sean Doherty and Martin Lee-Gosselin for providing access to some of the data used for validation in this work.

References

Arentze, T., Timmemans, H., 2000. ALBATROSS – A Learning Based Transportation Oriented Simulation System. European Institute of Retailing and Services Studies (EIRASS), Technical University of Eindhoven.

Arentze, T., Timmermans, H., Janssens, D., Wets, G., 2006. Modeling short-term dynamics in activity-travel patterns: from aurora to feathers. In: Paper Presented at the Innovations in Travel Modeling Conference Austin, TX, May 2006.

Ashford, J.R., Sowden, R.R., 1970. Multi-variate probit analysis. Biometrics 26 (3), 535–546.

Auld, J.A., 2011. Agent-based Dynamic Activity Planning and Travel Scheduling Model: Data Collection and Model Development. Ph.D. Thesis, University of Illinois at Chicago, Department of Civil and Materials Engineering, UMI.

Auld, J.A., Mohammadian, A., Doherty, S.T., 2008. Analysis of activity conflict resolution strategies. Transportation Research Record: Journal of the Transportation Research Board 2054, 10–19.

Auld, J.A., Mohammadian, A., 2009. Framework for the development of the Agent-based Dynamic Activity Planning and Travel Scheduling (ADAPTS) model. Transportation Letters: The International Journal of Transportation Research 1 (3), 243–253.

Auld, J.A., Mohammadian, A., Doherty, S.T., 2009a. Modeling activity conflict resolution strategies using scheduling process data. Transportation Research Part A 43 (4), 386–400.

Auld, J.A., Mohammadian, A., Roorda, M., 2009b. Implementation of a scheduling conflict resolution model in an activity scheduling system. Transportation Research Record: Journal of the Transportation Research Board 2135, 96–105.

Auld, J.A., Williams, C., Mohammadian, A., Nelson, P., 2009c. An automated GPS-based prompted recall survey with learning algorithms. Transportation Letters: The International Journal of Transportation Research 1 (1), 59–80.

Choo, S., Mokhtarian, P.L., 2008. How do people respond to congestion mitigation policies? A multivariate probit model of the individual consideration of three travel-related strategy bundles. Transportation 35 (2), 145–163.

Clark, A.F., Doherty, S.T., 2008. Examining the nature and extent of the activity-travel preplanning decision process. In: Proceedings of the 87th Annual Meeting of the Transportation Research Board, January 2008.

Doherty, S.T., 2005. How far in advance are activities planned? Measurement challenges and analysis. Transportation Research Record: Journal of the Transportation Research Board 1926, 41–49.

Doherty, S.T., Nemeth, E., Roorda, M., Miller, E.J., 2004. Design and assessment of the toronto area computerized household activity scheduling survey. Transportation Research Record: Journal of the Transportation Research Board 1894, 140–149.

Frignani, M., Auld, J.A., Mohammadian, K., Williams, C., Nelson, P., 2010. Urban Travel Route and Activity Choice Survey (UTRACS): an internet-based prompted recall activity travel survey using GPS data. Transportation Research Record: Journal of the Transportation Research Board 2183, 19–28.

Fu, T.-T., Li, L.-A., Lin, Y.-M., Kan, K., 2000. A limited information estimator for the multivariate ordinal probit model. Applied Economics 32, 1841–1851.

Garling, T., Kwan, M.-P., Golledge, R.G., 1994. Computational-process modeling of household travel activity scheduling. Transportation Research B. 25, 355–364.

Golledge, R.G., Kwan, M.-P., Garling, T., 1994. Computational-process modelling of household travel decisions using a geographical information system. Working Paper, UCTC No. 218, The University of California Transportation Center, University of California at Berkeley.

Hayes-Roth, B., Hayes-Roth, F., 1979. A cognitive model of planning. Cognitive Science 3, 275–310.

Joh, C.-H., 2004. Measuring and Predicting Adaptation in Multidimensional Activity-Travel Patterns. Ph.D. Thesis, Technische Universiteit Eindhoven, Faculteit Bouwkunde, Capaciteitsgroep Stedebouw, Eindhoven University Press Facilities.

Joh, C.-H., Arentze, T., Timmermans, H.J.P., 2002. Modeling individuals' activity-travel rescheduling heuristics: theory and numerical experiments. Transportation Research Record: Journal of the Transportation Research Board 1807, 16–25.

Joh, C.-H., Doherty, S.T., Polak, J.W., 2005. Analysis of factors affecting the frequency and type of activity schedule modification. Transportation Research Record: Journal of the Transportation Research Board 1926, 19–25.

Lee, M.S., McNally, M.G., 2001. Experiments with a computerized self-administered activity survey. Transportation Research Record: Journal of the Transportation Research Board 1752, 91–99.

Lee, M., McNally, M.G., 2006. An empirical investigation on the dynamic processes of activity scheduling and trip chaining. Transportation: Planning, Policy, Research, Practice 33 (6), 553–565.

Lee-Gosselin, M.E.H., 2005. A data collection strategy for perceived and observed flexibility in the spatio-temporal organisation of household activities and associated travel. In: Timmermans, H. (Ed.), Progress in Activity-Based Analysis. Elsevier, The Netherlands.

Lee-Gosselin, M.E.H., Rondier, P., Miranda-Moreno, L., 2006. The evolution of perceived spatio-temporal flexibility in activity patterns. In: 11th International Conference on Travel Behaviour Research, Kyoto, Japan.

Li, Y., Schafer, D.W., 2008. Likelihood analysis of the multivariate ordinal probit regression model for repeated ordinal responses. Computational Statistics and Data Analysis 52, 3474–3492.

Litwin, M., Miller, E.J., 2004. Event-driven time-series based dynamic model of decision making processes: philosophical background and conceptual framework. In: Proceedings of the 83th Annual Meeting of the Transportation Research Board, January 2004.

McKelvey, R.D., Zavoina, W., 1975. A statistical model for the analysis of ordinal level dependent variables. Journal of Mathematical Sociology 4 (3), 103–120.

Miller, E.J., 2005. Propositions for modelling household decision-making. In: Lee-Gosselin, M., Doherty, S.T. (Eds.), Integrated Land-Use and Transportation Models: Behavioural Foundations. Elsevier, Oxford, pp. 21–60.

Miranda-Moreno, L.F., Lee-Gosselin, M., 2008. A week in the life of baby boomers: how do they see the spatial–temporal organization of their activities and travel? Transportation 35 (5), 629–653.

Mohammadian, A., Doherty, S.T., 2005. Mixed logit model of activity scheduling time horizon incorporating spatial–temporal flexibility variables. Transportation Research Record: Journal of the Transportation Research Board 1926, 33–40.

Mohammadian, A., Doherty, S.T., 2006. Modeling activity scheduling time horizon: duration of time between planning and execution of pre-planned activities. Transportation Research Part A 40 (6), 475–490.

Newell, A., Simon, H.A., 1972. Human Problem Solving. Prentice-Hall, Englewood Cliffs, NJ.
Pas, E., 1985. State of the art and research opportunities in travel demand: another perspective. Transportation Research Part A 19A (5/6), 460–464.
Roorda, M.J., Doherty, S.T., Miller, E.J., 2005b. Operationalising household activity scheduling models: addressing assumptions and the use of new sources of behavioral data. In: Lee-Gosselin, M., Doherty, S.T. (Eds.), Integrated Land-use and Transportation Models: Behavioural Foundations. Elsevier, Oxford, pp. 61–85.
Roorda, M.J., Lee-Gosselin, M., Doherty, S.T., Miller, E.J., Rondier, P., 2005a. Travel/activity panel surveys in the toronto and quebec city regions: comparison of methods and preliminary results. In: Proceedings of the PROCESSUS Second International Colloquium on the Behavioural Foundations of Integrated Land-Use and Transportation Models: Frameworks, Models and Applications, Toronto, June 12–15, 2005.
Ruiz, T., Timmermans, H., 2006. Changing the timing of activities in resolving scheduling conflicts. Transportation 33, 429–445.
Ruiz, T., Roorda, M.J., 2008. Analysis of planning decisions during the activity-scheduling process. Transportation Research Record: Journal of the Transportation Research Board 2054, 46–55.
Zellner, A., 1962. An efficient method of estimation seemingly unrelated regressions and tests for aggregation bias. Journal of the American Statistical Association 57, 348–368.
Zhou, J., Golledge, R., 2007. Real-time tracking of activity scheduling/schedule execution within a unified data collection framework. Transportation Research Part A 41, 444–463.