# An Empirical Investigation on the Dynamic Processes of Activity Sceduling and Trip Chaining

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Ming S. Lee[1]
and
Michael G. McNally[2]

[1]DKS Associates
1956 Webster Street, Suite 300; Oakland, CA 94612-2925, U.S.A.
msl@tjdksassociates.com

[2]Department of Civil and Environmental Engineering and
Institute of Transportation Studies
University of California, Irvine; Irvine, CA 92697-3600, U.S.A.
mmcnally@uci.edu

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Institute of Transportation Studies
University of California, Irvine
Irvine, CA 92697-3600, U.S.A.
http://www.its.uci.edu

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Ming Lee*
DKS Associates
1956 Webster Street, Suite 300
Oakland, CA 94612-2925
Tel: (510) 763-2854 x404
Email: msl@dksassociates.com
*Corresponding author

Michael G. McNally
Institute of Transportation Studies and
Department of Civil & Environmental Engineering
University of California, Irvine
Irvine, CA 92697-3600
Tel: (949) 824-8462
Email: mmcnally@uci.edu

## ABSTRACT

The dynamic process of how individuals organize their activities and travel is often termed activity scheduling. Investigation of the dynamic processes has been the interest of transportation researchers in the past decade, because of its relevance to the effectiveness of congestion management and intelligent transportation systems. To empirically examine this process, a computerized survey instrument was developed to collect household activity scheduling data. The instrument is unique in that it records the evolution of activity schedules from intentions to final outcomes for a weekly period. This paper summarizes the investigation on the dynamic processes of activity scheduling and trip chaining based on data collected from a pilot study of the instrument. With the data, ordered logit models are applied to identify factors that are related to the scheduling horizon of activities. Results of the empirical analyses show that activities of shorter duration were more likely to be opportunistically inserted in a schedule already anchored by their longer duration counterparts. Additionally, analysis of travel patterns reveals that many trip-chains were formed opportunistically. Travel time required to reach an activity was positively related to the scheduling horizon for the activity, with more distant stops being planned earlier than closer locations.

**KEYWORDS**: activity scheduling, trip chaining, dynamic processes, ordered logit

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## 1. INTRODUCTION

Investigation of the dynamics in travel behavior has been the interest of transportation researchers in the past decade, because of its relevance to the effectiveness of congestion management and intelligent transportation systems (Mahmassani, 1997). The success of policies such as tolling, congestion pricing, and travel demand management depends on how people would adjust their daily activity and travel patterns to the enforced changes in their everyday lives (Axhausen and Gärling, 1992). The dynamic process of how individuals organize their activities and travel is often termed activity scheduling, which can be defined as "the joint choice of the time, duration, location, mode, and route for a sequence of activities drawn from a given set of aware activity needs" (Axhausen, 1995). The out-of-home portion of an activity schedule is referred to as a trip chain or tour, which is also an important subject in transportation research as the dynamic evolution of collective trip chaining dictates the demand and performance of the transportation system.

Although various theoretical and analytical methods have been proposed to model activity scheduling behavior, "consensus" has yet to be reached due to the complex nature of the problem. Two general approaches have been applied to model activity scheduling. The first one follows the random utility maximization (RUM) framework rooted in the economic theory of consumer choice (McFadden, 2000). Models of trip chaining and activity scheduling (e.g., Adler and Ben-Akiva, 1979; Kitamura, 1984; Ben-Akiva and Bowman, 1995) constructed with the RUM theory produce "optimal" tours as results of individuals' internal utility maximization. The most often cited critique of the RUM-based models is their strong assumption on individuals' capability of making "rational" decisions that optimize their internal utility, represented by a function of expenditure for activity participation and travel. When applied to models of activity scheduling, the behavioral fallacy of the RUM approach is manifested. As Ben-Akiva *et al.* (1998) noted, the combinations of tour elements (e.g., the activities of the tour, the timing and locations of the sojourns, and the mode used for the tour) result in a very large choice set that is computationally burdensome. In reality, research in cognitive psychology has shown that the scheduling and execution of activities often involve a dynamic adjustment of unexpected opportunities and constraints and the final decisions may be merely satisfactory, rather than optimal (Hayes-Roth and Hayes-Roth, 1979).

The second approach to the modeling of activity schedules adopts rationales in the context of artificial intelligence (AI). Central to the AI approach is psychologists' assertion that decision-making is a process of problem solving driven by reasons and heuristic rules rather than utility maximization (Simon, 1990; Prelec, 1991). Due to limitation in cognitive capability, the choice outcomes are often merely satisfactory rather than optimal. Models in this category are often termed Computational Process Models

(CPM), which utilize search processes that explicitly account for the cognitive limitations by incorporating decision rules in the computational process (see Kurani and Kitamura, 1996 for reviews of the models). However, as noted by Kurani and Kitamura, the decision-making strategies adopted in these models are hypotheses that were not appropriately verified with data derived from naturalistic settings. Without such a validation, the fact that rules and strategies are used to relax the behavioral assumptions of "rational" decision-making does not itself attest that the results of the AI approach can approximate behavior.

The inefficiency of the current models is resulting from the conventional research approach adopted by travel behavior researchers. Traditionally, research in the field of travel demand modeling has followed in the footstep of its predecessor, economics, in adopting quantitative methods as the primary means of hypothesis testing and theory building. Individuals are randomly sampled in an "unbiased" manner and survey is conducted to query the outcomes of their executed activity schedules during the day. Consequently, most of the existing theories and models of activity scheduling behavior (see Kurani and Kitamura, 1996 for a review) describe revealed behavioral patterns rather than the scheduling processes. Data on attributes of executed activities rather than on the scheduling process were used in theory formation, but validation of the theories have never been achieved with direct observation on the dynamic processes.

In the past decade, there have been numerous advances in techniques of behavioral modeling. Random coefficient models (e.g., McFadden and Train, 1998) and latent class choice models (e.g., Ben-Akiva and Boccara, 1995) are two new techniques from the RUM school to address heterogeneity of preferences and the true number of alternatives faced by the decision makers. The concept and techniques of CPMs also spawn a set of powerful tools, intelligent agents and agent-based simulation, capable of mimicking how individuals behave in a complex system (O'Sullivan and Haklay, 2000). To capitalize on these advanced techniques and tools, research is needed to explore the dynamic processes needed for models of activity scheduling and trip chaining. As Simon (1990) suggested, to describe, explain, and predict the behavior of a system of "bounded" rationality, a theory of the system's processes needs to be constructed and the environments to which the system is adapting also need be accounted.

The focus of this paper is on an empirical investigation of the dynamic processes of activity scheduling and trip chaining. Recognizing that the difficulty to identify such behavioral processes is largely due to the lack of suitable data, an innovative data collection effort with a computerized survey instrument was recently conducted in Irvine, California (Lee and McNally, 2001). It broadened the dimensions of household activity/travel survey by questioning the entire decision process from pre-travel planning to post-travel schedules in a weekly period. With the data, questions such as when and how the decisions to participate in specific activities were made can be answered. By examining the scheduling horizons of the activities, the decision dynamics of activity scheduling can be identified. The investigation is performed with ordered logit models since the scheduling horizon is categorized into four levels of advance knowledge.

## 2. REVIEW OF BEHAVIORAL MODELS AND EMPIRICAL EVIDENCES

The RUM theory has been the mainstream behavioral model of travel demand analysis since the early 1970s. The original formulation of RUM as a decision theory was based on economic theory of consumer behavior, with features of a preference structure that were heterogeneous across individuals, and unobserved aspects of experience and knowledge on the choice alternatives, interpreted as random factors. By parameterizing preferences and the distribution of the random factors, a tractable model for the probabilities of choice, expressed as functions of observed attributes of travel and individual characteristics, can be derived. Discrete choice among different alternatives is hypothesized as the result of each individual maximizing the utility function over a finite set of alternatives distinguished by their attributes.

Behavioral scientists have long questioned the validity of RUM theory. Experimental evidences in cognitive psychology support the view that heuristic rules, rather than utility maximization, drive human decision-making. Simon (1990) argued that mainstream economists' acceptance of the utility maximization assumption enables them to predict certain behavior (correctly or incorrectly) without making empirical studies of human actors. Simon noted that human rational behavior is shaped by two major factors, the structure of the task environment and the computational capabilities of the actor. There exists a fundamental limitation in human memory and computational ability that make utility maximization infeasible. Human behavioral rationality, under cognitive psychologists' viewpoints, is bounded by such a limited capability, as opposed to the economists' assumption of omnipotent actors. Several behavioral theories of human problem solving developed in the field of cognitive psychology have the potentials to be the conceptual framework for bounded-rational models of trip chaining and activity scheduling. The cognitive model of planning by Hayes-Roth and Hayes-Roth (1979) is the most often cited behavioral model of the AI approach and served as the launching point for most of the CPMs of activity scheduling. They hypothesized that planning (of activity participation) is an opportunistic process, within which the planner's current decisions and observations suggest various opportunities for plan development. Initial plans are rarely fully formulated or integrated at the highest level of abstraction. Rather, interim decisions can lead to subsequent decisions at arbitrary points in the planning process. Hayes-Roth and Hayes-Roth collected from five different subjects the "thinking-aloud" protocols (i.e., the monologues of subjects' thought processes) of planning errands and illustrated that the opportunistic model is capable of producing similar protocols. They concluded that the model has the flexibility to handle the complexity and variability of human planning behavior.

Rebok (1989) noted that the cognitive model of planning by Hayes-Roth and Hayes-Roth and other similar models developed by AI researchers were intended for the fabrication of "intelligent" machines that can perform planning tasks efficiently. Meyer and Rebok

(1985) further cited that, as a behavioral model of human problem solving, the opportunistic planning model focuses almost exclusively on the first phase of problem solving, plan generation, and fails to consider how individuals monitor plan execution by using feedback from previously planned actions. Framed within the context of everyday problem solving, they formulated the transactional opportunistic model of planning, which is built on the opportunistic model and includes a transactional, thinking-in-action component. The three major tenets of the transactional opportunistic approach to planning and problem solving are: (1) plans are only partially elaborated prior to the execution, assuming they are elaborated at all, (2) problem solving is a process involving a dynamic transaction between plans and actions, and (3) subsequent plans are very much dependent on feedback from prior executions and reflections on the relative efficiency of those executions. Empirical supports of the major tenets were obtained from an experiment of grocery-shopping planning. Rebok (1989) further noted that individuals differ in knowledge structures, component cognitive processes, motivational levels, and problem solving styles.

## 3. DATA

Data used in this analysis were derived from the REACT! pilot study conducted in Irvine, California from April to June, 2000 (Lee and McNally, 2001). REACT! is a software application that automates many aspects of the activity survey process. For the pilot study, survey respondents executed a self-installation procedure on their own computers and were later guided by the program to complete the survey. Following the structure of another computerized instrument, CHASE (Doherty and Miller, 2000), the surveying process of REACT! comprises three self-completing data entry stages: initial interview, pre-travel planning, and post-travel updating. Fully computerized user interfaces were built for each stage. The initial interview was a series of questions designed to collect basic household and personal information. Tracing of the weekly scheduling process was accomplished in the pre-travel and post-travel stages. In the pre-travel stage, initiated on the Sunday evening when the survey week began, respondents were asked to enter activity plans that they had already known for the coming week. It is important to note that respondents were instructed to enter everything they had known, but not to intentionally plan more activities than those that they had thought about doing. In the post-travel stage at the end of each day in the week, respondents updated their executed schedules for the current day and entered new activity plans for the subsequent days. The process of post-travel reporting and plan updating continued until a respondent finishes reporting executed schedules for the last day of the survey week.

Voluntary participants (with compensation) were recruited from two apartment complexes near the campus of University of California, Irvine. Weekly diaries of 72 adults are included in the analysis. Among the participants, 45 were students, with 31 of them employed (i.e., part-time) and 14 of them unemployed. For the 27 respondents who were not students, 10 were employed and 17 unemployed. There were 12 single adult households (one with a child), 19 couples without children, and 11 couples with one to two children. The average age of the respondents was 29 years old (the oldest was 55 and the youngest 20). There were 34 male and 38 female respondents.

## 4. ANALYSIS OF ACTIVITY SCHEDULING PROCESSES

Based on the aforementioned transactional opportunistic model of planning behavior, it is hypothesized that the formation of one's daily schedule begins with certain activities pre-occupying the schedule. Other activities are later organized around these "pegs". It can be further hypothesized that events of shorter duration are more likely to be those with shorter planning horizons. The rationale behind this hypothesis is that, since the activity requires only a small amount of time to be completed, there usually would be several free time windows available for such activities. Individuals can wait for the opportunities when they are free from other engagements. Also, some activities may be naturally spontaneous in specific times and locations. It is reasonable to expect that short events are of this nature, because it is unlikely that someone would spontaneously do something for a few hours without being interrupted, unless there is a long, continuous period of free time available (e.g., in the evening or on a weekend). The above hypotheses can be tested by directly examining the relationship between characteristics of an activity and the time horizon when the decision of undertaking the activity was made.

*Scheduling Horizon Index*

An ordinal variable with four levels, indicating how far in advance the decision of participating in an activity was made, was derived from the REACT! data: (a) before week planning, (b) within week planning, (c) within day planning, and (d) spur of the moment (spontaneous).

Activity events labeled as "before week planning" are those planned (to some degree) and entered on the beginning Sunday. These activities had been recognized and scheduled prior to other events. Some of them were routines repeated every week. Events counted as "within week planning" were those known at least one day before they were performed, but not necessarily as early as the first Sunday. The "within day planning" level corresponds to decision timing of "earlier in the day", while the "spur of the moment" level contains activities scheduled in the nature of "right before the activity", "during previous activity", or "right after the previous activity". Although these two levels of planning were both performed within the same day, the difference is that "spur of the moment" could be relatively spontaneous and "within day" might have a minimal level of planning involved. The first two levels of planning correspond to the "structured" part of one's activity schedules while the latter two levels correspond to the "opportunistic" counterpart. It is important to note that the terms "planning horizon" and "scheduling horizon" used in this presentation do not necessarily suggest that people at all times consciously think about when to do each activity. The terms merely denote the advance horizon at which the occurrence of each activity was known and expected. Interpretation of each level should not be strictly based on the literal meanings of its label. Note that, to reduce the amount of data entry, respondents participating in the pilot study were instructed that they did not need to enter meal activities in their pre-travel plans. In the following analyses, meal activities were not included.

*Ordinal Regression Models*

The overall scheduling structure in terms of which activities anchored the schedule is examined by analyzing what types of activities have more advanced planning horizon, which is considered as an ordinal variable in the analysis (i.e., the four levels of advanced knowledge about the occurrence of activities). Although the planning horizon variable is discrete, multinomial probit or logit models would not be efficient for the analysis, because these models do not account for the extra information implicit in the ordinal nature of the dependent variable. Nor would ordinary linear regression models be appropriate. Ordinary regressions would erroneously treat the difference between planning level 4 and 3 the same as that between 3 and 2, whereas the coding of the planning horizon variable reflects a ranking (i.e., which activity is known earlier), not quantity or magnitude (Greene, 1997). McKelvey and Zavoina (1975) introduced ordinal regression models (ORM) for analyzing such ordinal responses. It is assumed that underlying the categorization of the ordinal dependent variable is a continuous latent variable. Defining $y^*$ as the underlying variable ranging from - ∞ to ∞, an ORM of $y^*$ can be represented as:

$$y^* = \beta' x + \varepsilon$$

$\beta$ is the vector of parameters to be estimated and $x$ is the matrix of observations on the independent variables. $\varepsilon$ is the vector of disturbances. In the model formulation, $y^*$ is an unobserved latent variable and measured by $J$ ordinal categories:

$$\begin{aligned}
&y = 0 \quad \text{if} \quad y^* \le 0, \\
&y = 1 \quad \text{if} \quad 0 < y^* \le \mu_1, \\
&y = 2 \quad \text{if} \quad \mu_1 < y^* \le \mu_2, \\
&\quad \vdots \\
&y = J \quad \text{if} \quad \mu_{J-1} \le y^*
\end{aligned}$$

The $\mu$'s are unknown parameters to be estimated with $\beta$. The probability of observing $y = m$ for given values of x is:

$$P(y = m \mid x) = P(\mu_{m-1} \le y^* \le \mu_m \mid x)$$

Substituting $\beta'x$ for $y^*$ leads to the standard formulation of the predicted probability of ordinal regression models:

$$P(y = m \mid x) = F(\mu_m - \beta' x) - F(\mu_{m-1} - \beta' x)$$

where $F$ is the cumulative density function for $\varepsilon$. Like multinomial models, ORM can also be estimated as probit or logit models. In ordinal probit, $F$ is normal with a mean 0 and a variance of 1; in ordinal logit, $F$ is logistic with a mean 0 and a variance of $\pi^2/3$.

Implicit in ORM is the assumption known as the parallel regression assumption, which determines if ORM is valid for the data under investigation. The parallel regression assumption can be demonstrated by deriving the probabilities of $y \quad m$ , which have the simple form:

$$P(y \leq m \mid x) = F(\mu_m - \beta' x) \quad \textit{for } m = 1 \quad \textit{to } J - 1$$

This equation shows that ORM is equivalent to *J - 1* binary regressions with the assumption that the slope coefficients are identical across each regression (i.e., the parallel regression). For example, with a dependent variable of four levels, the three binary regressions are:

$$\begin{aligned} P(y \leq 1 \mid x) &= F(\mu_1 - \beta' x) \\ P(y \leq 2 \mid x) &= F(\mu_2 - \beta' x) \\ P(y \leq 3 \mid x) &= F(\mu_3 - \beta' x) \end{aligned}$$

The parallel regression assumption can be tested by comparing the estimates from the *J-1* binary regressions:

$$P(y \leq m \mid x) = F(\mu_m - \beta'_m x) \quad \textit{for } m = 1 \quad \textit{to } J - 1$$

The $\beta$'s are allowed to differ across the equations. For the parallel regression to hold, the coefficient estimates of $\beta_1$, $\beta_2$, ..., $\beta_{J-1}$ should be relatively "close". A special Wald test by Brant (1990) tests the parallel regression assumption for each variable individually. If the parallel regression assumption is rejected, alternative models that do not impose restrictions on $\beta$'s should be considered. The formulation of a generalized ordered logit model (Long and Freese, 2001) follows the above equation, which allows $\beta$ to differ for each of the *J - 1* comparisons, and assumes a logistically distributed $\varepsilon$ with a mean 0 and a variance of $\pi^2/3$. The predicted probabilities of observing $y = j$ are computed as:

$$\begin{aligned} P(y = 1 \mid x) &= \frac{\exp(\mu_1 - \beta'_1 x)}{1 + \exp(\mu_1 - \beta'_1 x)} \\ P(y = j \mid x) &= \frac{\exp(\mu_j - \beta'_j x)}{1 + \exp(\mu_j - \beta'_j x)} - \frac{\exp(\mu_{j-1} - \beta'_{j-1} x)}{1 + \exp(\mu_{j-1} - \beta'_{j-1} x)} \quad \textit{for } j = 2 \textit{ to } J - 1 \\ P(y = J \mid x) &= 1 - \frac{\exp(\mu_{J-1} - \beta'_{J-1} x)}{1 + \exp(\mu_{J-1} - \beta'_{J-1} x)} \end{aligned}$$

To ensure that the P($y$=$j$ | $x$) is between 0 and 1, the following condition must hold:

$$(\mu_j - \beta'_j x) \geq (\mu_{j-1} - \beta'_{j-1} x)$$

A total number of 3223 activities recorded by the 72 adults throughout the surveying week were used for this analysis. For modeling tractability, the five activity categories are further aggregated into three distinct types: Work, maintenance, and discretionary. Here the category of maintenance activities includes maintenance and shopping/services in Table 1 and discretionary category consists of recreation/entertainment and social events. Brant's Wald test for parallel regression is first applied to test if regular ORM are valid for the data. Table 2 summarizes the Brant test of parallel regression assumption. The results of the Brant test suggest that the parallel regression assumption for the entire model can be rejected at the 0.01 level. In addition, all the individual variables significantly violate the assumption. The rejection of parallel regression assumption justifies the use of generalized ordered logit models for the weekly activity data set. The model is estimated by the maximum likelihood method, which produces coefficient estimates that have the greatest likelihood of generating the observed sample of data if the assumptions of the model are true (see Greene, 1997 for a comprehensive review of maximum likelihood estimation). Table 3 summarizes the estimation results.

With the dependent variable of four planning levels, the generalized ordered logit model estimates three binary regressions, each with a distinct set of coefficient estimates $\beta$. All of the variables are significant in all three sub-models, except for PARTY and NCHILDN, which are not significant in the regression of PLANHORI 3. The first two binary (PLANHORI 1 and PLANHORI 2) regressions are identical in terms of the sign of each individual coefficient. The regression of PLANHORI 2 corresponds to the separation of structured events (expected at least a day in advanced) versus those planned and executed on-the-fly (planned earlier in the day plus spontaneous activities). The regression of PLANHORI 1 corresponds to the partition of activities with a minimal level of planning (at least a few hours before the execution) vs. the essentially spontaneous activities. In these two sub-models, the association between planning horizon and each independent variable is generally in the expected direction. For example, work and maintenance activities generally have more advanced planning horizon than discretionary activities. In-home activities are mostly of spontaneous nature. Shorter activities do tend to be more spontaneous than their counterparts. The longer the events are the more likely they would be expected and planned earlier in the week. When persons other than family members are involved in an activity, the activity also tends to be planned early. In addition, persons with children may expect more activities than those with no children. The survey data also show that female respondents tend to be more structured in terms of how the weeks are planned. The binary regression of PLANHORI $\leq 3$ corresponds to the question of what activities are expected before the week begins. In this model, the variables PARTY and NCHILDN are not significant, suggesting that activities expected on the first Sunday evening are not necessarily related to engagement with family members or appointments with other persons outside of the household. However, the other four independent variables remain significant and consistent with those in the other two sub-models.

## 5. ANALYSIS OF TRIP CHAINING PROCESSES

In this section, the out-of-home portion (i.e., trip chain or tour) of an activity schedule is analyzed with the same approach. A tour is defined as a sequence of out-of-home stops (i.e., activity locations). If more than one activity occurred at the same location consecutively, the location is counted as a single stop. Stop sequence increases only when the person went to another location for different activities. A total of 700 tours were identified from 1083 out-of-home activities (i.e., excluding jogging and recreational biking that started and ended at home and did not serve a purpose other than exercise). Generalized ordered logit models are applied to the tour stop data for identification of factors associated with planning horizons of trip chains. Table 4 summarizes the results.

In addition to the variables used in the model of activity patterns, two new variables are included in the tour stop model: stop sequence (STOPSEQ) and travel time (TRAVELTM) used to reach the stop. For all three binary regression models, stop sequence is significantly associated with planning horizon of an out-of-home activity. The probability for the occurrence of spontaneous stops increases as stop sequence increases, which suggests that the earlier stops in a tour are often planned and, from these stops, people tend to make spontaneous decisions to go somewhere else. While engaging in planned activities, individuals may see opportunities to complete certain activities at different locations. The decision whether to undertake these activities would be based on the evaluation of feasibility. It is reasonable to expect that travel time required to reach the activity locations would be considered as an evaluation criterion. Such a hypothesis is supported in the regression of PLANHORI 1, in which the probability for the occurrence of spontaneous stops decreases as travel time increases. However, travel time is not a significant factor for the other two binary regressions, when the binary thresholds (PLANHORI 2 and PLANHORI 3) are set at higher planning horizons. A potential reason for such a phenomenon is that, for activities with more advanced planning level, other attributes such as activity category, duration, and involved persons may play a more decisive role than travel time in these activities' being recognized earlier. For example, routine work activities are almost always expected and planned earlier than other activities. The effect of travel time on the planning horizon of an out-of-home activity can be further elaborated with a three-way cross table (Table 5) of activity type (work/non-work), travel time to reach the event location, and the event's planning horizon. The spur-of-the-moment proportion clearly decreased as travel time increased in both work and non-work groups. Within the work group, the proportion of before-week planning also increased as travel time increased. Attention should also be directed to the within-day column, which increases as travel time increases in both groups. This suggests that if one suddenly think of doing something at a different location, it is more likely to be undertaken if the location is close. If the location were off a certain distance from one's current position, the likelihood of its being scheduled later in the day would increase.

When both in-home and out-of-home activities are considered, gender and the number of children of the actors are relatively significant factors of the activities' planning horizons (see Table 3). However, when only out-of-home activities are considered (see Table 4), these two demographic variables do not appear as significant factors, suggesting that people react in a similar way to spontaneous decisions in a tour. Difference in actors' role in the family does not appear to affect how the actors plan their out-of-home activities.

## 6. SUMMARY AND CONCLUSIONS

Data collected from naturalistic settings of everyday activity scheduling and trip chaining were used to examine the decision dynamics of the processes. The series of analyses proves that the "activity-peg" phenomenon does exist. Activities with shorter duration are more likely to be opportunistically filled in a schedule already anchored by their longer duration counterparts. The analyses of tour dynamics show that the propensity of visiting unplanned sojourns increased during later part of the day. These results suggest that some of the decision elements of trip chains were opportunistically formed within constraints set by previously planned activities. While engaged in planned activities, individuals might see opportunities of carrying out certain activities at different locations occurring later in the day. The decision of undertaking these activities would be based on their evaluation of feasibility. The chance of making an unplanned sojourn would increase, if the travel time required to reach this location were substantially short.

The need to improve the behavioral credibility of travel demand models has been a continuing theme in transportation research for over 30 years (Polak, 1998). The results of this analysis provide an empirical evidence on the dynamic processes behind activity scheduling and trip chaining. Based on the results, transactional opportunistic planning within a constrained environment is viewed as a potential behavioral model for trip chaining. As mentioned previously, advancement of the understanding is urgently needed in order to utilize advanced tools of behavioral modeling. It is noted here that the cognitive model of planning by Hayes-Roth and Hayes-Roth did not end with the aforementioned prototype. Barbara Hayes-Roth and her colleagues continued the work in late 70s and developed several other architectures for intelligent agents, rendering artificial agents in real-time systems (Hayes-Roth, 1993; Hayes-Roth *et al.*, 1994; Morignot and Hayes-Roth, 1995). These architectures accommodate real-time improvisation and affiliation with other agents, two of the most important features in human everyday activities. One particular framework of interest integrates the goal achievement orientation of the traditional AI with the survival instinct of new AI, so the agents could act autonomously within a given environment with specific opportunities (Hayes-Roth *et al.*, 1994). This work postulates the use of motivation as (1) a control mechanism for internal and external goal selection, and (2) an internal mechanism for goal generation. A motivation is generated based on the functional state of the agent (e.g., its battery level, the time, and its estimated activity) that produces a need (i.e., the strength of the motivation). An agent designer can program the agents in a way that they recognize the features of the environment (e.g., opportunities for achieving its goals), and accordingly adjust its own motivational profile that in turn determines the agents' immediate goals and ensuring action. Because its resemblance with human thinking, the architecture is flexible enough to accommodate human decision rules governing the formation of daily activity patterns.

The review of the updated AI models shows that many of the psychological elements of human behavior can be represented in new AI. A potential way to utilize these models is to take these psychological elements as the building blocks and set up empirical investigation to examine the dynamics of how these elements interact within the context of everyday activity participation. In deed, the need for a better understanding of the behavioral processes does not apply exclusively to the AI modeling approach, as McFadden (2000) noted:

> "The major scientific challenge to development of a psychological model of choice that can be used for travel demand applications is to find stable scales for attitudes, perceptions, and other psychological elements and establish that these scales can be used to forecast travel behavior more reliably than "reduced form" systems that map directly from experience and information to behavior."

The set of "stable scales" is in line with what Simon (1990) termed "invariants" of human behavior. Thus, continuing research along the line of this study is influential for modeling activity scheduling and trip chaining from either a "quantitative" (i.e., parametric) or a "qualitative" (i.e., heuristic) approach.

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**Table 1 Activity Functional Classes**

| Class | Activities | Class | Activities |
|---|---|---|---|
| Work/School | Work | Recreation/ Entertainment | Jogging, biking, roller-skating |
| | School (only if you are a student) | | Fitness center |
| Maintenance | Meals | | Golf |
| | Meal preparation | | Spectator sports |
| | Shower/dress | | Bars |
| | Cleaning/Maintenance (at home) | | Movies in theaters |
| | Pick-up/drop-off kids | | Watching videos |
| | Pick-up/drop off others | | Regular TV programs |
| | Attending to children (at home) | | Browsing Web sites |
| Shopping/Services | Major Grocery (10+ items) | | Relaxation/Rest |
| | Minor Grocery (<10 items) | | Hobbies at home (crafts, gardening, and others) |
| | House wares/clothing/personal items | | Pleasure driving |
| | Drug Store | Social | |
| | Mostly browsing | | |
| | Convenience store | | |
| | Medical care | | Visiting |
| | Personal services (Hair, nails ...) | | Hosting visitors |
| | Professional services (dry clean, auto repair…) | | Phone/email (over 10 minutes) |
| | Banking/ATM | | Church and other religious events |
| | Post office/Shipping | | Volunteer work |
| | Library | | |
| | Gas station | | |
| | Video rental store | | |

**Table 2 Results of Brant's Wald Test for Parallel Regression**

| Variable* | $chi^2$ | $P > chi^2$** | Degree of freedom (df) |
|---|---|---|---|
| All | 97.040 | 0.000 | 12 |
| TOTMIN | 5.920 | 0.052 | 2 |
| INHOME | 16.370 | 0.000 | 2 |
| PARTY | 6.880 | 0.032 | 2 |
| ACTCATE | 20.140 | 0.000 | 2 |
| NCHILDN | 27.800 | 0.000 | 2 |
| GENDER | 9.640 | 0.008 | 2 |

* See Table 3 for variable definition

**A significant test statistic indicates that the parallel regression assumption has been violated.

## Table 3 Generalized Ordered Logit Model of Activity Scheduling

| | Coefficients | Std. Err. | z | P>z | [95%Conf. Interval] | |
|---|---|---|---|---|---|---|
| PLANHORI 1 | | | | | | |
| ACTCATE | 0.570 | 0.053 | 10.750 | 0.000 | 0.466 | 0.674 |
| INHOME | -1.279 | 0.087 | -14.663 | 0.000 | -1.450 | -1.108 |
| TOTMIN | 0.004 | 0.001 | 7.958 | 0.000 | 0.003 | 0.005 |
| PARTY | 0.167 | 0.059 | 2.814 | 0.005 | 0.051 | 0.283 |
| NCHILDN | 0.240 | 0.061 | 3.907 | 0.000 | 0.120 | 0.360 |
| GENDER | 0.233 | 0.077 | 3.009 | 0.003 | 0.081 | 0.385 |
| CONSTANT | -1.063 | 0.208 | -5.116 | 0.000 | -1.470 | -0.655 |
| PLANHORI 2 | | | | | | |
| ACTCATE | 0.511 | 0.052 | 9.776 | 0.000 | 0.409 | 0.614 |
| INHOME | -1.063 | 0.083 | -12.851 | 0.000 | -1.225 | -0.901 |
| TOTMIN | 0.003 | 0.000 | 6.844 | 0.000 | 0.002 | 0.004 |
| PARTY | 0.151 | 0.058 | 2.605 | 0.009 | 0.038 | 0.265 |
| NCHILDN | 0.189 | 0.059 | 3.181 | 0.001 | 0.073 | 0.306 |
| GENDER | 0.320 | 0.077 | 4.142 | 0.000 | 0.169 | 0.472 |
| CONSTANT | -1.463 | 0.205 | -7.132 | 0.000 | -1.865 | -1.061 |
| PLANHORI 3 | | | | | | |
| ACTCATE | 0.316 | 0.055 | 5.695 | 0.000 | 0.207 | 0.425 |
| INHOME | -1.083 | 0.087 | -12.484 | 0.000 | -1.254 | -0.913 |
| TOTMIN | 0.002 | 0.000 | 5.750 | 0.000 | 0.002 | 0.003 |
| PARTY | -0.013 | 0.060 | -0.214 | 0.830 | -0.131 | 0.105 |
| NCHILDN | -0.044 | 0.063 | -0.704 | 0.482 | -0.168 | 0.079 |
| GENDER | 0.474 | 0.084 | 5.653 | 0.000 | 0.310 | 0.638 |
| CONSTANT | -1.746 | 0.220 | -7.947 | 0.000 | -2.176 | -1.315 |

**Fit Statistics of Maximum Likelihood Estimation**

Number of observations = 3223
Log likelihood at convergence= -3542.4524658
Model $chi^2(18)$ = 768.03 (i.e., likelihood ratio chi-squared for the test of the null hypothesis that all of the coefficients associated with independent variables are simultaneously equal to zero)
Prob > $chi^2$ = 0.0000 (i.e., *p*-value)
Pseudo $R^2$ = 0.0978 (i.e., McFadden's $R^2$)

**Variable Definition**

| Variable | Description | Value | Definition |
|---|---|---|---|
| PLANHORI | Planning horizon | 1 | Spur of the moment (right before the activity) |
| | | 2 | Earlier in the day |
| | | 3 | Within week (at least a day before it took place) |
| | | 4 | Before week (entered on the beginning Sunday) |
| ACTCATE | Activity types | 1 | Discretionary |
| | | 2 | Maintenance |
| | | 3 | Work |
| INHOME | Activity location: in-home or out-of-home | 0 | Out-of-home |
| | | 1 | In-home |
| TOTMIN | Total activity duration in minutes | | |
| PARTY | Involved persons | 1 | Alone |
| | | 2 | Household members |
| | | 3 | Other persons |
| NCHILDN | Number of children | | |
| GENDER | Gender | 1 | Male |
| | | 2 | Female |

## Table 4 Generalized Ordered Logit Model of Trip Chaining

| | **Coefficients** | **Std. Err.** | **z** | **P>z** | **[95%Conf. Interval]** | |
|---|---|---|---|---|---|---|
| PLANHORI 1 | | | | | | |
| TOTMIN | 0.004 | 0.001 | 4.466 | 0.000 | 0.002 | 0.006 |
| ACTCATE | 0.733 | 0.109 | 6.709 | 0.000 | 0.519 | 0.947 |
| PARTY | 0.349 | 0.113 | 3.082 | 0.002 | 0.127 | 0.571 |
| STOPSEQ | -0.310 | 0.112 | -2.781 | 0.005 | -0.529 | -0.092 |
| TRAVELTM | 0.022 | 0.006 | 3.728 | 0.000 | 0.010 | 0.033 |
| GENDER | 0.121 | 0.158 | 0.765 | 0.444 | -0.188 | 0.430 |
| NCHILDN | 0.131 | 0.114 | 1.152 | 0.249 | -0.092 | 0.354 |
| CONSTANT | -1.377 | 0.458 | -3.007 | 0.003 | -2.274 | -0.479 |
| PLANHORI 2 | | | | | | |
| TOTMIN | 0.004 | 0.001 | 5.594 | 0.000 | 0.003 | 0.005 |
| ACTCATE | 0.673 | 0.100 | 6.733 | 0.000 | 0.477 | 0.868 |
| PARTY | 0.323 | 0.098 | 3.285 | 0.001 | 0.130 | 0.516 |
| STOPSEQ | -0.516 | 0.102 | -5.071 | 0.000 | -0.715 | -0.317 |
| TRAVELTM | 0.002 | 0.004 | 0.557 | 0.578 | -0.006 | 0.010 |
| GENDER | 0.188 | 0.142 | 1.323 | 0.186 | -0.091 | 0.467 |
| NCHILDN | 0.049 | 0.099 | 0.492 | 0.623 | -0.145 | 0.243 |
| CONSTANT | -1.293 | 0.414 | -3.125 | 0.002 | -2.104 | -0.482 |
| PLANHORI 3 | | | | | | |
| TOTMIN | 0.003 | 0.001 | 4.911 | 0.000 | 0.002 | 0.004 |
| ACTCATE | 0.522 | 0.095 | 5.498 | 0.000 | 0.336 | 0.708 |
| PARTY | 0.214 | 0.087 | 2.470 | 0.014 | 0.044 | 0.385 |
| STOPSEQ | -0.381 | 0.103 | -3.685 | 0.000 | -0.583 | -0.178 |
| TRAVELTM | 0.000 | 0.004 | 0.072 | 0.943 | -0.007 | 0.007 |
| GENDER | 0.420 | 0.133 | 3.160 | 0.002 | 0.159 | 0.680 |
| NCHILDN | -0.066 | 0.094 | -0.704 | 0.481 | -0.249 | 0.118 |
| CONSTANT | -2.020 | 0.402 | -5.019 | 0.000 | -2.808 | -1.231 |

**Fit Statistics of Maximum Likelihood Estimation**

Number of observations = 1083
Log likelihood at convergence= -1213.7317743
Model $chi^2(21)$ = 222.80 (i.e., likelihood ratio chi-squared for the test of the null hypothesis that all of the coefficients associated with independent variables are simultaneously equal to zero)
Prob > $chi^2$ = 0.0000 (i.e., $p$-value)
Pseudo $R^2$ = 0.0841 (i.e., McFadden's $R^2$)

**Variable Definition***

| Variable | Description | Value | Definition |
|---|---|---|---|
| STOPSEQ | Sequence number of the stop in tour | | |
| TRAVELTM | Travel time | | |

*Rest of the variables are the same as those in table 3

**Table 5 Three-way Table of Work, Travel Time, and Scheduling Horizon**

| Event Type | Travel time ( t ) | Spur | | Within day | | Within week | | Before week | | Missing | | Meals | | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Non - Work | t < 10min | 70 | 24% | 11 | 4% | 38 | 13% | 78 | 27% | 16 | 6% | 78 | 27% | 291 |
| | 10 <= t < 30 min | 90 | 23% | 44 | 11% | 55 | 14% | 128 | 33% | 26 | 7% | 43 | 11% | 386 |
| | t >= 30 | 22 | 17% | 21 | 16% | 21 | 16% | 40 | 31% | 7 | 5% | 17 | 13% | 128 |
| | Missing | 21 | 36% | 2 | 3% | 8 | 14% | 22 | 37% | 1 | 2% | 5 | 8% | 59 |
| Non-work total | | 203 | 24% | 78 | 9% | 122 | 14% | 268 | 31% | 50 | 6% | 143 | 17% | 864 |
| Work | t < 10min | 28 | 18% | 5 | 3% | 41 | 26% | 76 | 48% | 10 | 6% | 0 | 0% | 160 |
| | 10 <= t < 30 min | 18 | 7% | 19 | 7% | 46 | 18% | 168 | 65% | 6 | 2% | 0 | 0% | 257 |
| | t >= 30 min | 1 | 2% | 5 | 8% | 13 | 20% | 45 | 69% | 1 | 2% | 0 | 0% | 65 |
| | Missing | 1 | 10% | 1 | 10% | 5 | 50% | 3 | 30% | 0 | 0% | 0 | 0% | 10 |
| Work total | | 48 | 10% | 30 | 6% | 105 | 21% | 292 | 59% | 17 | 3% | 0 | 0% | 492 |
| Grand total | | 251 | 19% | 108 | 8% | 227 | 17% | 560 | 41% | 67 | 5% | 143 | 11% | 1356 |

Goodness of fit statistics[1]

| Models | Independent factor | Pearson $^2$ | Degree of Freedom | $p >$ $^2$ |
|---|---|---|---|---|
| Complete independence | NA | 131.43 | 17 | < 0.001 |
| Independence of one factor | Planning horizon | 129.52 | 15 | < 0.001 |
| | Work | 96.02 | 11 | < 0.001 |
| | Travel time | 49.93 | 14 | < 0.001 |
| Conditional independence | Work – Planning horizon | 94.49 | 9 | < 0.001 |
| | Work – Travel time | 13.96 | 8 | < 0.001 |
| | Planning horizon – Travel time | 47.71 | 12 | < 0.001 |
| Homogeneous association | NA | 11.45 | 6 | 0.075 |

1 The hypothesis testing omitted missing records and meals