

An Empirical Investigation of the Underlying Behavioral Processes of Trip Chaining

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ABSTRACT

Trip chaining is a phenomenon that has a significant impact on urban transportation and activity systems. This paper argues that an appropriate representation of the underlying behavioral processes in models of trip chaining is crucial to the capability and reliability of the models. To examine the behavioral processes, data on the complete processes of activity scheduling and trip chaining were collected with a computerized survey instrument, REACT!. The scheduling horizons of sojourn activities were analyzed with contingency tables. The results of this analysis indicate that some of the decision elements entailed in trip chaining were opportunistically formed within constraints set by previously planned activities. While engaged in earlier activities, individuals might see opportunities of carrying out certain activities at different locations occurring later in the day. The decisions as to whether to take these opportunities or not would depend on their evaluation of scheduling feasibility (e.g., the travel time required to reach these activities). However, the analysis also illustrates that some trip chains were indeed executed as planned, suggesting optimality and potential routine behavior. Based on the empirical evidence, transactional opportunistic planning within a constrained environment is viewed as a potential behavioral model for trip chaining behavior.

Keywords: trip chaining, activity scheduling, underlying decision processes

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INTRODUCTION

During the past three decades, as the number of two-worker households increased, the way people travel has significantly changed from the days when the four-step travel models were developed (Weiner and Ducca, 1996). The average number of home-to-work trips per household has nearly doubled and the conventional definitions of trip purposes (e.g., home-based work or home-based other) can no longer describe a major portion of intra-urban trips that serve for more than one purpose. It is necessary and common for modern-day household heads to stop by more than one location on a single out-going travel (e.g., drop-off children on the way to work). The need to incorporate such a “trip chaining” behavior in travel models was first noted in the 1970s. Adler and Ben-Akiva (1979) noted that approximately 30% of non-work trips were components of travel tours that consisted of more than one non-home sojourn. Strathman and Dueker (1995), summarizing results from more recent empirical studies, indicated that 10 to 20 percent of all non-work trips were linked to work commute. Since the 1990s, with enactment of policies that aim for control of air quality and transportation efficiency, the assessment of trip chaining phenomenon in an urban area has become more important in evaluation of policies (Stophor, 1993). For example, the number and duration of vehicle trips made during the cold start mode affect the amount and composition of vehicle emission. Trip chaining has direct impacts on the number of trips, trip length, and the fraction of trips made in cold start mode. In addition, models that lack the representation of trip chaining may over-estimate the effect of Transportation Control Measures set to reduce the use of single occupancy vehicles by workers (Karash and Schweiger, 1994).

A trip chain, sometimes referred to as a “tour”, connects sojourns each meant for participation of specific activities in one out-going travel. Models of trip chaining need to account for a wide spectrum of decisions such as the number of sojourns in a tour, the combination and sequencing of sojourn activities, and the duration of each activity. Conventional trip-based modeling methodology cannot incorporate trip chaining since it is limited by the oversimplified assumption that each trip of a single purpose starts and ends at the same zone without intermediate stops. Recognizing that the salient features of a tour are the activities conducted at sojourns, most of the existing models of trip chaining were framed within the activity-based paradigm, in which travel is explicitly viewed as a derived demand, with consideration of how a trip is related to a specific activity, and when, where, with whom, and for how long this activity is conducted. Early applications of activity-based models were focused on explanation of behavior rather than its prediction, and very often they were targeted to find empirical evidence on the conventional approach's fallacies. The research on trip chaining behavior can be seen as the epitome of this era. By the 1980s, researchers began to take the much-needed step toward the integration of all partial theories. On the center of the integrated view of activity and travel is the process, often termed activity scheduling, that links all the segmental behavior to a cohesive decision stream. Assessment of trip chaining behavior has since been incorporated in models of activity scheduling, with trip chains being the out-of-home components of a person's daily activity schedules.

Although various theoretical and analytical methods have been proposed to model trip chaining and activity scheduling behavior, "consensus" has yet to be reached due to the complex nature of the problem. Two general approaches have been applied to the modeling of trip-chains. The first one follows the random utility maximization (RUM) framework rooted in the economic theory of consumer choice (McFadden, 2000). Models of trip chaining (e.g., Adler and Ben-Akiva, 1979; Kitamura, 1984) 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 trip chaining, the behavioral fallacy of the RUM approach is manifested, as Ben-Akiva et al. (1998) noted that 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. Moreover, the assumption that there is a tour optimizing one's utility implicitly asserts that all the decisions related to the tour are determined at the same time before departure. In reality, the scheduling and execution of activities often involve a dynamic adjustment of unexpected opportunities and constraints (Hayes-Roth and Hayes-Roth, 1979).

The second approach of trip chain modeling 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.

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 take advantages of these advanced techniques and tools, work is urgently needed to reveal the underlying decision processes needed for models of activity scheduling and trip chaining,

as Simon (1990) suggested that, 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 behavioral processes of 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 sojourn activities, the decision dynamics of tour formation can be identified. If decision elements entailing in making a tour were determined dynamically rather than simultaneously, it can be further hypothesized that sojourns in the later part of a tour were more likely to be dynamically determined, because opportunities to engage in these activities could be recognized during previous engagement. In addition, it is reasonable to expect that if one of the sojourns in a tour requires a longer travel time, the activity occurring at the sojourn is likely to be planned earlier. Similarly, an opportunistically determined sojourn is more likely to occur if it is close to the current location. It is expected that answers to these questions can help illuminate the underlying behavioral processes that results in the revealed patterns of trip chaining.

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 behavioral model 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.

In the process of searching for behavioral models of everyday activity participation, Gärling and Garvill (1993) cautiously noted that analyzing the performance of activities with the aim of defining all conceivable preceding decisions may lead to overemphasizing the role of decision-making. Both intuition and empirical evidences suggest that, after acquiring some experience on a specific task, people do not seem to deliberate to the same extent, especially in everyday activities. Verplanken et al (1997) analyzed the effect of habit in the process of making travel mode choices. It was found that, compared to subjects with weak habit, those who possessed strong habit towards

choosing a particular travel mode acquired less information and showed signs of employing less elaborate choice strategies. One particular cognitive theory of routinization suggests that routine activities are performed automatically with information retrieved from memory, as opposed to relying on conscious information processing with general algorithms (Logan, 1988). As experience amasses, specific solutions are learned and become available for retrieval from memory. However, even if an activity has become a routine, a person is still able to consciously control its performance with algorithmic information processing. The difficulty of distinguishing the consciously controlled activities and routine activities lies in the question of when a person would choose to take conscious control over an activity. It is noted here that the routinization process can be approximated by the aforementioned transactional opportunistic view of problem solving, since the model acknowledges the feedback effect from previous execution of plans (i.e., learning from experiences). In addition to the remaining question of whether or not an activity should be classified as automatic, the process of learning is another key issue of incorporating routinization in behavioral models of activity participation.

Most of the existing theories and models directly examining activity scheduling and trip chaining (see Kurani and Kitamura, 1996 for a review) were conducted with the aim of describing revealed behavioral patterns. Data on activity and travel choices rather than on the scheduling of these activities were used in the formation and validation of these theories. One of the notable exceptions is Cullen and Godson (1975), which involves a unique time budget tailored for the authors' hypothesis about the structure of individuals' activity patterns. The term structure refers to a wide range of decisions that detail the ways that people conduct their daily activities. At a minimum, structure can be interpreted as the sequence by which various activities enter one's daily activity scheduling process. They formulated the renowned activity-peg theory hypothesizing that certain activities in one's daily schedule tend to act as pegs around which the ordering of other activities is arranged and shuffled according to their flexibility. Any periods of time that are left free are either scheduled in a later, shorter planning period, or are ultimately occupied by spur-of-the-moment activities (or simply left unused). The authors test their hypotheses using a data set that contains information about the priority and flexibility of activities for 336 respondents drawn from the academic staff and students of a college of London University (as part of a more applied study of university contact and location factors). The instrument was based on a recalled, one-day time budget administered by interviewers on weekdays, but a set of specially designed questions were attached to each activity record.

Using the technique of verbal protocols (Svenson, 1989), Chen (2001) conducted another experiment investigating activity scheduling and rescheduling behavior. Subjects were randomly assigned a day in the week to fill out an activity diary. Before the day began, subjects were asked to record activities they intended to do on the diary day. On the night following the diary day, telephone interviews were conducted to obtain from subjects the executed activities of the day. Subjects were also asked to schedule for a hypothetical day in a laboratory setting while thinking silently, and then talking aloud.

Hypothetical unexpected events were then described to the subjects. Subjects were asked to think and talk aloud about the revision they would make if they do encounter such events in real life. Results from the experiment indicate that initial activity schedules are often incomplete. Individuals would usually schedule a selected number of activities. In the process of executing these activities, they would engage in more activities. It was also shown that activities with relatively fixed starting times and durations are more likely to be scheduled before other activities.

It is noted that both Cullen and Godson and Chen's findings generally support the transactional view of problem solving, with certain activities working as scheduling anchors around which other activities would dynamically fit in.

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! was divided into three self-completing data entry stages: initial interview, pre-travel, and post-travel. 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.

Weekly diaries of 72 adults are included in the analysis. The sample of voluntary participants (with compensation) was derived from a regular apartment complex and a complex of graduate student housings. There were 12 single adult households (one with a child), 19 couples without children, and 11 couples with one to two children. There are 34 male and 38 female respondents. The average age of the respondents is 28.54 (the oldest is 55 while the youngest is 20). All out-of-home activities recorded by the participating adults were organized into tours to investigate the mechanism of tour formation. 802 tours were identified from all out-of-home activities, except for jogging and recreational biking that started and ended at home and did not serve for purposes other than exercises. A tour is composed of a sequence of out-of-home sojourns (activity

locations). If more than one activity occurred at the same location consecutively, the location is counted as one single sojourn. The counting of sojourn sequence increases only when the person went to another location for a different activity. For each sojourn, an ordinal variable with four levels, indicating how far in advance the decision of participating in the activity was made, was derived from the REACT! data:

1. Before week planning
2. Within week planning
3. Within day planning
4. Spur of the moment

Underlying the categorization of the planning levels is a continuous variable measuring the time interval between an activity's first entering the overall scheduling flow and its final execution. Activities labeled as "Before week planning" are those known and entered on the beginning Sunday. Such activities were recognized and scheduled prior to other activities. Activities counted as "Within week planning" were those known at least one day before they were performed, but not on the first Sunday. The above two levels correspond to activities that were known at least one day in advance. When an activity record was entered to the program on the evening after it was done, REACT! would question respondents about the decision timing for undertaking this activity. The "Within Day planning" level corresponds to decision timing of "earlier in the day", while the "Spur of the moment" level contains activities scheduled "during the previous activity" or "right before the previous activity". Although the "Within day planning" and "Spur of the moment" were both performed within the same day, the difference between the two is that one is rather spontaneous and the other might have minimal level of planning and organization involved.

To reduce the amount of data entry, respondents participating in pilot were instructed that they did not need to enter meal activities in their pre-travel plans. In the following analyses, meal activities were not labeled with specific planning horizons.

THE DECISION DYNAMICS OF TOUR FORMATION

Table 1 shows the contingency table of tours in terms of when the decision to participate in activity at each sojourn was made. Tours of more than four sojourns were not presented in this table, since they rarely occurred during the survey. Within each column of planning horizon, there are two numbers presented. The one on the left is the number of activities falling in that category. The proportion on the right is computed by dividing the cell count by the corresponding row sum.

For two-sojourn tours, approximately 60% of the activities occurring at the first sojourn were planned (before-week and within-week), but only 19% were determined dynamically (within-day and spur). The planned and dynamic proportions are almost identical at the second sojourns. Among three-sojourn tours, the cell counts of the first

two sojourns are similar to those of the two-sojourn tours. However, at the second and third sojourn, the dynamic portions are higher than those of the planned. The Pearson goodness-of-fit statistics (χ^2) is large enough to reject the null hypothesis that the observed cell counts are the same as those produced by chance (Wickens, 1989), which essentially indicates that the two factors (planning horizon vs. sojourn sequencing) in this table are not independent of each other.

Based on the patterns of tour planning horizon shown in Table 1, it can be inferred that the decisions of stopping by sojourns are not necessarily pre-determined at the same time prior to departure. There are a certain number of sojourns that were dynamically determined. While engaged in previously planned activities, individuals might see opportunities of carrying out certain activities at different locations coming up later in the day. The decision of undertaking these activities would be based on their evaluation of feasibility. It is reasonable to expect that travel time required to reach the activity locations would come to one's mind as an evaluation criterion. Table 2 (utilizing the same set of our-of-home sojourns as Table 1) shows the three-way contingency table of types of activities (work/non-work) conducted at the sojourns, travel time required to reach the sojourns, and the planning horizon of the activities. In both work and non-work groups, the spur-of-the-moment proportion descended as travel time increased. Within the work group, the proportion of before-week planning increased as travel time increased. Test statistics indicate that the observed relationships are valid, since no independence of planning horizon and travel time can be concluded. It is interesting to note that, in both work and non-work groups, the within-day proportion increases as travel time increases. This suggests that, if one suddenly came up with the idea of participating in activities elsewhere, it is more likely to be undertaken if the location is very close. If it was of a certain distance, the chance for a short-term scheduling on the later part of the day would increase. Inherent in the relationship between travel time and spontaneous sojourns is the bounding effect of constraints in one's space-time prism (Hägerstrand, 1970). It can be hypothesized that the feasibility (e.g., travel time required) of moving to another sojourn has been evaluated when making the decision.

Table 3 crosses the modes used to get to the activity locations with planning horizons. The "No travel" category contains successive activities that occurred at the same locations. It should not be surprising to see that these activities were relatively impulsive. The "Non car" category contains walk, bicycle, car pool, and bus, but majority of them were walk trips to school. This directly explains its high proportion of before-week planning. It seems that if a person could use a car (i.e., better mobility), the propensity of opportunistically participating in activities elsewhere would increase. However, the difference between the opportunistic proportions of car and non-car categories is not significant, because most respondents lived in an apartment complex where a variety of activities could be reached within non-auto modes.

OPPORTUNISM IN TRIP CHAINING

To understand the fractions of tours that were determined simultaneously or opportunistically, tours themselves were used as the units of analysis in the following analyses. Among the 802 tours, 616 are single-sojourn trips and 186 multi-sojourn tours. The high percentage of single-sojourn trips is likely a special feature of the sample. Most student respondents lived within 10 to 20 minutes of walking distance to school. Many would go directly back home before they would go out again for other activities. There were also many activities being conducted at the same location, since many workers did multiple activities (e.g., work and meals) in their work locations. As a result, there were substantially more single-sojourn work trips than multi-purpose, multi-sojourn tours. Table 4 summarizes the planning horizon of single-sojourn trips. The "planned prior to the day" category combined activities with scheduling horizons of "before-week" and "within-week". If there were more than one activities occurring at the sojourn, the planning horizon for the trip is based on the activities with the most distant horizon among these activities. For example, if an individual went out and did one planned activity and one spur-of-the-moment activity at the sojourn, the trip is counted as planned. Out-of-home meal trips were separated, because respondents were not questioned about the planning horizon for meal activities. Work/school trips were mostly known before the day. Especially, when there were other activities happening at the work places, the multi-purpose trips were all planned before the day. Non-work or non-school trips were more likely to be spontaneous or planned within the day. Overall, single-sojourn trips were often planned prior to the day. The propensity for the respondents to impulsively make an out-going trip was pretty low.

For multi-sojourn tours, a sojourn is counted as planned if there was at least one activity at the sojourn being decided either before-week or within-week. Because the decision horizons for meal activities were not questioned, two separate sets of statistics were created: one counts meals as planned activities and the other counts them as not planned (see Table 5). A planned tour is one in which all the sojourns were planned at least one day in advance. A "pure opportunistic" tour represents one that does not contain any planned sojourns. That is, decision of visiting each sojourn is either made within-day or spur-of-the-moment. A transactional opportunistic tour is one between completely planned and pure opportunistic. It contains at least one planned sojourn but not all of them were planned. The definition of transactional opportunistic follows Meyer and Rebok, reflecting the fact that a tour often starts with a few pre-determined sojourns before the tour unfolds. The executed tours are the results of transaction between the planned ones and unexpected constraints and opportunities.

Depending on if meals are counted as planned or not, approximately 25% to 40% of all tours made by survey respondents were completely planned. Decision timing for these tours complies with the RUM-based trip chaining models. That is, participation in all the activities in these tours was determined simultaneously prior to departure. These patterns may contain routines activities. However, there is also a substantial portion of tours that

were not purposefully chained together at the same time horizon. 44% to 51% of all tours were combinations of plans and improvisation and 6% to 13% of them were opportunistically formed throughout the day. Overall, 50% to 60% of tours made by the respondents do not comply with the behavioral assumption of RUM theory. These tours were made progressively as opportunities for activity participation occasionally being evaluated and realized throughout the day.

SUMMARIES AND CONCLUSIONS

Data collected from naturalistic settings of everyday activity scheduling and trip chaining were used to examine the decision dynamics of tour formation. The analyses of tour structure show that the propensity of visiting un-planned 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. Simple statistics of the planning horizons of tour sojourns indicate that the transactional opportunistic view of trip chaining is a valid one, since a certain portion of tour sojourns were not completely elaborated prior to the execution and short-term planning did occur in these cases. However, the analysis also illustrates that some tours were indeed executed as planned, suggesting optimality and potential routine behavior.

The results of this analysis provide a empirical evidence on the behavioral processes behind trip chaining. Based on the empirical evidence, 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, 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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Number of sojourns in tour	Sojourn Sequence	Spur		Within day		Within week		Before week		Missing		Meals		Total
One	1st	142	17%	48	6%	143	18%	374	46%	32	4%	75	9%	814
One-sojourn total		142	17%	48	6%	143	18%	374	46%	32	4%	75	9%	814
Two ¹	1st	20	13%	11	7%	33	21%	64	41%	10	6%	20	13%	158
	2nd	43	29%	16	11%	14	10%	44	30%	11	7%	19	13%	147
Two-sojourn total		63	21%	27	9%	47	15%	108	35%	21	7%	39	13%	305
Three ²	1st	10	15%	3	4%	10	15%	35	51%	5	7%	5	7%	68
	2nd	12	23%	10	19%	5	9%	13	25%	2	4%	11	21%	53
	3rd	12	25%	10	21%	8	17%	7	15%	6	13%	5	10%	48
Three-sojourn total		34	20%	23	14%	23	14%	55	33%	13	7%	21	12%	169
Four	1st	1	11%	0	0%	3	33%	4	44%	0	0%	1	11%	9
	2nd	2	22%	3	33%	1	11%	1	11%	0	0%	2	22%	9
	3rd	2	18%	2	18%	3	27%	1	9%	1	9%	2	18%	11
	4th	3	27%	0	0%	4	36%	4	36%	0	0%	0	0%	11
Four-sojourn total		8	20%	5	13%	11	28%	10	25%	1	3%	5	13%	40
<p>1. Test for independence of all factors of two-sojourn tours: $\chi^2 = 20.26$, d.f.= 4 (p=0.0004). Missing records were excluded in the estimation of test statistics. The total cell count of first sojourn does not equal to that of the second sojourn, because multiple activities could be conducted at a single sojourn.</p> <p>2. Test for independence of all factors of three-sojourn tours: $\chi^2 = 27.67$, d.f.= 8 (p=0.0005). Missing records were excluded in the estimation of test statistics.</p>														

Table 1 Scheduling Structure of Tours

Activity 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
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
Non 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
Test for the hypothesis of complete independence of all three factors: $\chi^2 = 131.43$, d.f.= 17 (p=0) Test for the hypothesis that planning horizon is independent from the other two factors: $\chi^2 = 129.52$, d.f.= 15 (p=0) Test for the hypothesis that planning horizon is independent from activity type: $\chi^2 = 94.49$, d.f.= 9 (p=0) Test for the hypothesis that planning horizon is independent from travel time: $\chi^2 = 47.71$, d.f.= 12 (p=0) Hypothesis testing omitted missing records and meals														

Table 2 Three-way Table of Work, Travel Time, and Scheduling Horizon

Mode used	Spur		Earlier in the day		Within Day		Before Week		Missing		Eat		Total
No Travel	64	22%	6	2%	45	16%	92	32%	14	5%	64	22%	285
Non Car	53	16%	23	7%	70	21%	178	52%	5	2%	12	4%	341
Car (as driver)	112	17%	76	12%	99	15%	265	40%	47	7%	62	9%	661
Missing	22	32%	3	4%	13	19%	25	36%	1	1%	5	7%	69
Total	251	19%	108	8%	227	17%	560	41%	67	5%	143	11%	1356

Test for the hypothesis of complete independence of the two factors: $\chi^2 = 99.69$, d.f.= 8 (p=0)
Missing records omitted, but meals included

Table 3 Two-way Table of Mode and Scheduling Horizon

Single-sojourn Trip purpose	Spur		Earlier in the day		Planned prior to the day		Meals		Missing		Total
Work/school only	12	6%	13	6%	174	85%	0	0%	5	3%	204
Multi-purposed (mixed)	0	0%	0	0%	76	100%	0	0%	0	0%	76
Non-work/school only	71	21%	27	8%	194	58%	27	8%	17	5%	336
Total	83	13%	40	6%	444	72%	27	4%	22	5%	616

Table 4 Scheduling Horizon of Single-sojourn Tours

Multi-sojourn tour purposes	Pure opportunistic		Transactional opportunistic		Planned		Missing		Total
Meals counted as unplanned									
Work Only	0	0%	1	33%	2	67%	0	0%	3
Work/Non work (mixed)	4	5%	51	62%	20	24%	7	9%	82
Non Work Only	21	21%	44	44%	25	25%	11	11%	101
Grand Total	25	13%	96	52%	47	25%	18	10%	186
Meals counted as planned									
Work Only	0	0%	1	33%	2	67%	0	0%	3
Work/Non Work	4	5%	37	45%	34	41%	7	9%	82
Non Work Only	8	8%	44	44%	38	38%	11	11%	101
Grand Total	12	7%	82	44%	74	40%	18	10%	186

Table 5 Scheduling Horizon of Multi-sojourn Tour