THE SOCIAL CONTEXT OF ACTIVITY-SCHEDULING: A DISCRETE-CONTINUOUS MODEL OF THE RELATIONSHIP BETWEEN “WITH WHOM” AND EPISODE START TIME AND DURATION

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Transportation Research Record: Journal of the Transportation Research Board
Forthcoming 2008
Pre-print version

ABSTRACT

Activity-based approaches to travel demand modeling are increasingly moving from theoretical to operational models. In this context, agent-based micro-simulation models are a promising approach since they explicitly conceive travel as an emergent phenomenon from peoples' activity characteristics, and more explicitly, from their *activity scheduling processes*. Behaviorally, activity-scheduling processes are influenced not only by individuals' characteristics, but also by the other people with whom they interact. Thus, the activity scheduling process has an intrinsic *social context*. Using social activities as a case study, the objective of this paper is to empirically investigate the relationship between the social context (measured by with whom the respondents interacted) and two key aspects of activity scheduling: start time and duration. Econometric models of the combined decisions regarding "with whom" to participate and when to start or how much time to spend on are estimated to investigate the correlations between "with whom" and the start time / duration decisions. Data collected by a seven-day activity diary survey are used for the model developments. Findings suggest that the social context has a relevant role in activity scheduling processes. For example, the investigations indicate that it is "with whom" we socialize what influences the social activity scheduling processes more than the travel time or the distances to social travel. Overall, and additionally to the theoretical understanding of the questions posed to investigate in this paper, the models serve as an empirical support for agent-based microsimulation models that could incorporate the role of social networks in activity scheduling attributes.

1. INTRODUCTION

Activity-based approaches to model travel demand are increasingly moving from theoretical to operational models (*1*). In this context, agent-based microsimulation models are a promising approach since they explicitly conceive travel as an emergent phenomenon from peoples' activity characteristics, and more explicitly, from their *activity scheduling processes*. Behaviorally, activity-scheduling processes are not only influenced by individuals' characteristics, but also by the other people with whom they interact. Hence, the activity scheduling process has an intrinsic *social context*. In principle, agent-based microsimulation models have the capability of explicitly representing interactions among different actors, modeling their influence in their respective decision making processes (*2, 3*). However, current models in practice still rely heavily upon individualistic assumptions because of the lack of knowledge about how the social dimension affects activity-travel behavior in general, and activity scheduling processes, specifically.

The objective of this paper is to investigate how the social dimension – defined by "with whom" activities are performed – influences individuals' activity scheduling processes. The study explicitly focuses on social activities since these are the paradigmatic examples of the importance of "with whom" in activity-travel decision processes. Social activities are an understudied area that is becoming increasingly important from the policy perspective due to their relatively long trip lengths and aspects such as social cohesion and quality of life (*4*). However, simple statistical data analysis may not necessarily reveal the extensive behavioral details for such a complex phenomenon. This paper uses an advanced econometric method to investigate how "with whom" influences the start time and duration of social activity episodes, with the purpose of capturing the complex and multidimensional nature of people's behavior.

The study uses data from a Computerized Household Activity Scheduling Elicitor (CHASE) survey conducted in Toronto in 2002-2003 with 271 households, including 426 adults (*5*). CHASE focuses on capturing multi-day information on observed activity-travel patterns while tracing the underlying activity scheduling process (*6*). In addition, the data also includes information regarding temporal and spatial flexibility, and other key activity attributes, including "with whom" the respondent's activities were performed. Using these data, a discrete-continuous econometric approach is employed to explore the relationship between the social dimension and social activity scheduling attributes. The combined estimation of discrete-continuous models gives quantitative evidence of how "with whom" relates to start time and time allocation to social activity episodes. The models also use other socio-economic and activity attributes that give a better insight about these behavioral processes. In addition to behavioral understanding, it is expected that such a model can be useful to model activity scheduling-rescheduling processes in Toronto's operational activity-based model, TASHA (*7*). Replacement of *rules* used to resolve scheduling conflicts by econometric models should increase policy sensitivities of the overall model. The organization of the paper is the following: next section discusses the social dimension of activity scheduling behavior, followed by a description of data and methods, empirical model results, and conclusions.

2. THE SOCIAL DIMENSION OF ACTIVITY SCHEDULING BEHAVIOUR

Neglecting the social dimension in transportation modeling is one of the most crucial and critical shortcomings of existing activity-based models (*8*). Research in activity-based models has spread and focused on a variety of aspects, helping to understand better the different characteristics and attributes that constitute household and individual activity patterns. Modeling efforts have increasingly incorporated the insights gained by the greater understanding of activity patterns (*9*). However, there is still considerable room for improvements, especially in the scope and behavioral explanation these models give. In this context, understanding and modeling the influence of social interactions on activity-travel decisions is a crucial need (*10*). In order to incorporate formally the social dimension, researchers should take account of the existing structure of social relations represented in the *individual's social networks*, for it is within this structure that interpersonal interactions and social travel decisions are made.

The study of social networks in activity-travel behavior responds to "*the need to underpin our travel models with a better understanding of the social structures of daily life and, as we implicitly forecast/speculate about them when we predict travel behavior over long time horizons, anyway…*" as Axhausen (*11*: p.3), argues. This requirement is even more germane when a series of "possible transport questions" are considered, such as "*physical spatial-temporal coherence / overlap (constraints), replacement of physical and telecommunication-based contact, interaction frequency and spatial reach, and interaction and information / knowledge transfer*" (*11*: p.10). In addition, the focus in social activities is particularly interesting since interactions intuitively play a "motivator" role in the behavioral processes of those activities.

From a travel behavior perspective, the role of social networks has received increasing attention, tackling different questions, such as the social influence in travel related decisions (*12, 13*), social activity-travel generation (*14*, *15*), and the spatial distribution of social networks (*4, 16, 17*). However, little is known regarding the influence of the social context on activity-scheduling decisions, considering not only the intrinsic negotiation process that occurs in activities such as social, but also the importance of "with whom" in key scheduling decisions. For example, Goulias *et al.* (*18*) explicitly considered the role of "with whom", but mostly as a way of selecting different activity type groups rather than as studying the role of this attribute on the scheduling process. Closer to the analysis performed in this paper, Srinivasan and Bhat (*19*) study the companionship characteristics for leisure activities, using the American Time Use survey. Their results suggest "significant impacts of socioeconomics of individuals on companion type choices for leisure activities" (p.11) as well as an empirical relationship between scheduling attributes such as duration and day of the week, and "with whom".

This need for a better understanding of the social dimension in activity scheduling processes is even more crucial considering that, at least in principle, agent-based microsimulation approaches to model activity-travel have the capability of incorporating interaction somewhat explicitly (*2, 3*). For example, Miller argues that the social context of activity-scheduling processes need to be considered explicitly, even though social network formation processes may or may not be endogenously represented within an operational model (*3, 20, 21*). Furthermore, his agent-based theoretical framework explicitly defines "social projects", which encapsulates the key elements that define social activity-travel processes, and where social network attributes are an important part. Thus, in this approach, "with whom" activities are performed constitutes a potentially relevant piece of information to be used to condition scheduling attributes explicitly, such as start time, duration, and location.

3. DATA

The first wave of the Toronto Travel-Activity Panel Survey (TAPS, see *5*), which uses the CHASE instrument (*6*) was used in this study. TAPS provides important empirical data to support the activity scheduling process modeling pursued in Toronto's activity-based models (*3*). The specific survey was conducted in that city between 2002 and 2003, with 271 households (426 adults) participating in the weeklong survey. The CHASE instrument was designed to collect information about activities in both planning and execution stages. For this seven-day activity diary survey, the participants are required to record the individual activity information prior to the starting of the day. The CHASE program tracks the activity information that is *added* first, and then *modified*, *deleted* and *executed* over time. The first time *added* information represents the agenda formation, which undergoes *modification* or sometimes *deletion* for scheduling. The final scheduled observations include the information regarding scheduling pressure.

CHASE divides all activities into nine major groups, of which social is one; social activities in this paper are those self-classified by the respondents as well as those that correspond to "going to restaurants" and "having meals at home", were at least one non-household member participates. Further details about each of these categories can be found in Doherty *et al* (*5*). CHASE collects a variety of attributes related to the activity type, the actor of the activity and the household within which the actor resides. In addition to this general information, some specific information about the activity is collected by actively prompting the respondent in an *End of Week Review* (EWR). EWR systematically queries stated spatial and temporal flexibilities, normal duration, and frequency of the activity type of concern. A detailed description of this EWR component of CHASE is available in Doherty *et al.* (*5*).

In addition to socio-economic and activity specific variable, this paper incorporates variables regarding the social context where the activity-travel decisions occur. From an empirical perspective, an efficient way of addressing the impact of the social context is by considering the individual's *personal network* information. Personal networks constitute a useful approach to study the relevance of the social structure in activity-travel decisions. A personal network is "my network" for any given individual. In personal network analysis, the respondent individual is referred to as an "ego" and all of the people with whom he/she interacts are referred to as "alters". The number of "alters" within an ego's personal network indicates the size of the network. Measures of the size of a personal network vary according to the purpose of study. For example, McCarty, *et al.* (*22*) estimated networks of about 250 ties in an American sample. However, as scope conditions get more specific, the number of network members decreases.

There is a long tradition about methods to gather personal networks, mainly from sociology (*23, 24*), but also - more recently – from the travel behavior field (*4, 25, 26*). Most of these methods explicitly "elicit" the personal network from certain prompt questions, and then gather information about travel behavior patterns. However, an alternative method – even present in the social networks literature – consists of building the personal networks from the respondents' diary contacts (*27*) or, in other words, from with whom individuals interacted within a certain period.

Following that approach, personal networks are devised in this paper based on information of the people (alters) with whom a respondent (ego) socializes. Constructing these personal networks is feasible since the CHASE instrument records the specific persons with whom the respondent socialized in each episode. For the purposes of this paper, alters are divided in two categories: "family", which correspond to both close and extended family members; and the "friends", which correspond to all the other people who are not family members. At the same time, CHASE also records whether the alters are household members or not. The following personal network variables are studied in this paper:

- *Total number of family members*, *total number of friends, total number of alters* with whom the respondent socialized that week. All these variables measure the overall size of the respondent's personal network in the period studied.
- *Proportion of family members and proportion of friends*. This is the ratio between the number of friends and the total number of people with whom the respondent had social activities. These variables measure the relative importance of each role in the respondent's contact; that is, whether the respondent is more family- or friend-oriented, or whether there is a balance in the kinds of contacts s/he has.
- *Variability of with whom*. For each alter, a variability index is constructed calculating the ratio between the number of social episodes s/he had with the respondent and the total

number of episodes that the respondent performed during the week. The average variability index of all the alter members from the respondent's personal network corresponds to the *variability of the with whom* variable. This variable measures the "variety seeking" on social contacts, serving as a proxy of the fragmentation of the respondent's personal network. A number close to one involves a *low* variability of people, that is, the respondent tends to have social episodes mostly with the same people for all the episodes, whereas a number close to zero involves a *high* variability of people, where most of the social episodes involved different alters.

After cleaning some observations, 294 individuals in 208 households were selected for analyses. Total number of individual social episodes for these 294 people was 1223, 124 of the sampled persons are male, and 170 are female. For further details about these data the reader can consult Doherty *et al.* (*5*).

4. METHODS

As discussed before, the central question of this paper is how "with whom" influences the *start time* and *duration* of social activity episodes (see Figure 1). The "with whom" dimension is classified into four options:

1. Socialize with family members together with household members
2. Socialize with friends together with household members
3. Socialize with family members without any household member
4. Socialize with friends without any household member

Start time and duration are considered as continuous variables. The start time of an activity episode is expressed as the fraction of the twenty-four hours in a day, and the duration is expressed in terms of the total minutes spent. Thus, the hazard-based modeling approach is appropriate for such continuous start time and duration modeling. The overall method estimates jointly the effect of the discrete "with whom" choice, and the continuous start time and duration decisions. Joint estimation of these two types of decisions leads to the sample selection econometric structure proposed by several authors, notably Duncan (*28*) and Lee (*29*). Since the "with whom" decision option is more than binary, in both start time and duration decisions, the model becomes a continuous time hazard model with multinomial logit sample selection. The formulation of such a model is described below.

The specification for selecting "with whom" is defined by the utility function:

$$U_{wh} = V_{wi} + \varepsilon_{wi} = \beta_{wi} x_{wi} + \varepsilon_{wi} \tag{1}$$

Where V_{wi} indicates the indirect utility of alternative i (with whom), x_{wi} is the vector of explanatory variables, β_{wi} is the vector of corresponding coefficients, and ε_{wi} is the unobserved error term. The subscript w indicates each observation.

Alternative i (with whom) is chosen if and only if it gives maximum utility compared to all other alternatives:

$$\begin{aligned} U_{wi} &> \max_{j=1\ldots M, j\neq i} U_{wj} \\ V_{wi} &= \left\{ \max_{j=1\ldots M, j\neq i} U_{wj} \right\} - \varepsilon_{wi} \end{aligned} \tag{2}$$

If the error term has a Type I Extreme Value distribution, the choice model takes the form of multinomial logit model:

$$\Pr(wi) = F(\varepsilon_{wi}) = \frac{\exp(V_{wi})}{\exp(V_{wi}) + \sum_{j \neq i} \exp(V_{wj})} \tag{3}$$

In the case of the continuous component, the dependent variable is time. For the episode duration, it corresponds to the total time spent for the episode; for the start time, it corresponds to the time from midnight to the start time of the episode. Recognizing the inherent dynamics of the behavioral processes a continuous time hazard model is used for episode duration and episode start time. Two possible types of continuous time hazard specifications are: proportional hazard model and accelerated time hazard model. Although both of them are interchangeable, the proportional specification targets the hazard rate, where as the accelerated time specification targets the duration *per se.* An accelerated time hazard specification is the most appropriate approach in our case because it simplifies the likelihood function (*30*). Hence, the survival time, t of the events is expressed as follows:

$$\ln(t_i) = \gamma Z_i + \alpha_i \tag{5}$$

Where Z_i is the vector of covariates of the "with whom" alternative, γ is the vector of corresponding coefficients, and α_i is the unobserved error term.

The distribution function of this error term determines the different types of accelerated hazard model. In the case of the Normal distribution assumption, it takes the form of a certain lognormal accelerated time hazard model. Considering that α_i has a Normal distribution with mean and variance, it becomes:

$$f(\alpha_i) = N(\mu, \sigma_i) \tag{5}$$

The parameterization of the mean accommodates the covariate function:

$$\mu = \gamma Z_i \tag{6}$$

Then, the hazard function $h(t_i)$ of the accelerated time hazard model has the following expression:

$$\begin{aligned} h(t_i) &= \frac{f(t_i)}{S(t_i)} \\ f(t_i) &= h(t_i) * S(t_i) \\ f(t_i) &= \frac{1}{t_i \sigma_i \sqrt{2\pi}} \exp[\frac{-1}{2\sigma^2}\{\ln(t_i) - \gamma Z_i\}^2] \end{aligned} \tag{7}$$

Where $S(t_i)$ is the survival function and $f(t_i)$ is the first derivative of the cumulative distribution function with respect to time.

The joint estimation of these discrete and continuous decisions requires assuming that the error terms ε_{wi} and α_i are correlated. Given that these two error terms have different types of distribution, it is required to define the equivalent standard distribution for deriving the joint probability of discrete and continuous decisions. According to Lee (*29*), any random variable can be expressed as a standard normal distribution. Transforming the previous error terms in (1) and (4) to corresponding standard Normal distributed values, we get:

$$\begin{aligned} &\varepsilon_{wi}^{*} = J_1(\varepsilon_{wi}) = \Phi^{-1}F(\varepsilon_{wi}) \\ &\alpha_i^{*} = J_2(\alpha_i) = \Phi^{-1}F(\alpha_i) \\ &Where \\ &J_2(\alpha_i) = (\ln(t_i) - \gamma Z_i)/\sigma_i \end{aligned} \tag{8}$$

The combined decision process is modeled by assuming a bivariate distribution:

$$C(\varepsilon_{wi}, \alpha_i, \rho_i) = B[J_1(\varepsilon_{wi}), J_2(\alpha_i), \rho_i] \tag{9}$$

Where ρ_i is the correlation between the discrete choice alternative i and the corresponding continuous decision. For any individual i, the joint probabilities of observing a particular start time or duration and corresponding "with whom" can be written as (*29*):

$$\Pr(T = t_i \cap W = w_i) = \Pr(T = t_i \cap \varepsilon \le J_1(\varepsilon_{wi}))$$

$$= \frac{1}{\sigma_i t_i}\varphi\left(\frac{\ln(t_i) - \gamma Z_i}{\sigma_i}\right)\Phi\left(\frac{J_1(\varepsilon_{wi}) - \rho_i J_2(\alpha_i)}{\sqrt{1-\rho_i^{\,2}}}\right)$$

Therefore, for the lognormal accelerated hazard model assumption, the log-likelihood function of the combined estimation becomes:

$$\begin{aligned} LL = \sum_{s=1}^{N}\ \sum_{i=1}^{M} & D_i \ln(\ (\varphi(\ln(t_i) - \gamma Z_i)/\sigma_i) - D_i \ln(t_i\sigma_i) \\ & + D_i \ln(\ \Phi(\ (J_1(\varepsilon_{wi}) - \rho_i((\ln(t_i) - \gamma Z_i)/\sigma_i)))/\sqrt{(1-\rho_i^{\,2})}\ \ )\ ) \end{aligned} \tag{10}$$

where ϕ ( ) and Φ ( ) indicate the pdf and cdf of the Standard Normal distribution, respectively; σ_i is the variance or ancillary parameter of the accelerated time hazard component; s indicates the individual observations; i indicates the alternative in the discrete choice section; and D_i is the indicator variable of choosing alternative i.

The log-likelihood function is estimated with code written in GAUSS using the BFGS algorithm (*31*). The standard errors of the parameters are calculated using the inverse of Hessian procedure. The combined decision of "with whom" and duration or start time is shown in Figure 1. This modeling structure represents the sample selection model, where the duration of corresponding episode is only observed if the specific alternative of "with whom" is chosen for the social activity participation. The correlation coefficient and the alternate specific variance indicate the influence of the specific alternative of "with whom" on the corresponding episode duration. For mathematical identification purposes, one of the "with whom" alternatives is to be considered as the reference alternative.

The goodness of fit of the models is estimated using adjusted likelihood ratio test (*32*):

$$\text{Adjusted Rho-Square} = 1 - \frac{\text{Loglikelihood at Convergence - No. of Parameters}}{\text{Loglikelihood of the Null Model}} \tag{11}$$

where the null model has no explanatory variables and the number of parameters indicates the number of parameters in the fully specified model over the number of parameters in the null model. When the null model does not contain any alternative specific constant of the discrete choice component, then it becomes the adjusted likelihood ratio at zero. If the null model contains alternate specific constant of the discrete choice component, then it becomes the adjusted likelihood ratio index at sample share (*32*). In this paper, the null model contains only the constant for hazard model.

5. ESTIMATED MODELS

This section presents results of the estimated models; Table 1 corresponds to the model for episode duration and Table 2 corresponds to the model for episode start time. In both tables, ρ represents the correlation between the combined decisions of "with whom" and the total duration / start time. Also in these tables, σ represents the variance of the duration/start time model for specific option of "with whom" participation. Considering t values greater than or equal to 1.64 as the limit of statistical significance (i.e. at the 90% level), the models are discussed next.

The statistical significance of the error correlation parameter ρ indicates that the decision of "with whom" and start time/duration are not independent of each other. As per equation 9 and 10, it is clear that positive value of ρ indicates negative correlation and vice versa. The model for episode duration shows that the duration of social episodes is highly correlated with "with whom" if household members are not involved in the activity. This finding indicates that, when people participate in social activities without other household members, they tend to spend more time in social activities. When household members are involved in the social activities together, the activity episodes are usually shorter in duration. On the other hand, correlation coefficient of the model for episode start time with "with whom" indicates that involvement of more than one household member influences the social activity to start later in the day, possibly due to more intensive coordination constraints.

In terms of alternative specific variance of the duration and start time models, all parameters show high statistically significant results. According to the model formulations, the higher the value of the variance, the lower the duration and the earlier the start time of the social episode. In the case of duration, the minimum duration corresponds to the case when the respondent socializes with family members but without any household member. The second lowest duration corresponds to the case when the respondent socializes with friends but without any household member. Finally, the duration is higher if the respondent socializes with household members.

In the case of start times, later start times occur when the respondent socializes with family members but without any household member. The second latest start time occurs when the respondent socializes with friends but without any household member. Start time is the earliest if individual socialize with household members. In both of these cases, it is very clear that the involvement of household members in social activities significantly influences the time allocation decision. The higher statistical significance of σ in both models proves the necessity for combined estimation of such discrete-continuous decision structure.

In terms of decision regarding "with whom" to socialize, the models show the relevance not only of the personal attributes of the respondents, but also of the characteristics of their personal networks. The same variables enter into both duration and start time models with almost the same parameter values. Males prefer to socialize more with the friends than family members, compared with females. Household heads, either male or female, are less likely to socialize alone with the friends without any household members. In addition, adults with partners are more likely to socialize with friends together with household members, than in the case of single parents of adult children living in the household.

A higher proportion of friends in the social network increases the probability of participating in social activities with friends together with the household members. On the other hand, a higher total number of friends and a higher number of alters in the personal network increase the probability of participating in social activities with friends without any household members. Finally, a higher number of family members in the social network increase the probability of participating in the social activities with family members without any household members.

Overall, considering the alternate specific constant of the "with whom" selection model, it is clear that people prefer social activities with friends or family members but without household members. In the case of duration, the constant coefficient is very high with a high *t* statistic, indicating that there is still scope to incorporate more variables to explain the process. However, it is clear that the higher the number of people involved in the social activity, the longer the duration, although a higher number of household children tends to a shorter duration. A higher number of potential location for socialization influences longer duration episode. Duration flexibility of the activity also influences the duration positively. People tend to spend more time for the social activity that requires longer travel time to reach the activity location. Full time workers tend to spend more time in social activities than part time workers or people working at home. People with higher number of household automobiles are more likely to involve in longer duration social activities. Also, intuitively, is the relationship between higher weekly social activity frequencies and shorter durations for the individual activity episode.

In terms of start time, the constant coefficient indicates that people prefer the afternoon ($e^{-0.3593}$ = 0.698 = 4:45 pm) to start the social activities. However, when a higher number of people is involved, start times tend to be earlier. Similarly, start times tend to be earlier than 4:45 pm when there are a higher number of potential social activity locations and higher duration flexibility, as well as if the respondent has a relatively high number of children living at the household. On the other hand, a higher number of household automobile increases the options to travel and hence influences the activity to start later. It is important to note that neither the effect of distance to travel nor the travel time become statistically significant in the start time model. A possible explanation is that it is the "with whom" that defines the start time of the social activities and not the travel time to reach the activity location. Then, as the models explicitly integrated the "with whom" decision into the start time selection model, the variable indicating the travel time to reach the activity location becomes insignificant.

Both *with whom - duration* and *with whom - start time* models provide high goodness-of-fit (see Table 3 for a summary of their goodness-of-fit). The start time model has a higher goodness-of-fit than the duration model, although the number of statistically significant parameters is higher in the duration model. A possible explanation to this phenomenon is that the selection of "with whom" is more influential on the start time selection compared to that of duration. This also favors the argument that it is not the distance or travel time to define how to schedule the social activities but it is the "with whom" we socialize. This aspect also reaffirms the need of incorporating social dimension in activity scheduling model as well as treating the social activity separately than other activity types.

6. CONCLUSIONS

This paper investigates a critical issue in activity scheduling decision: the social dimension of activity scheduling. For prototype application, social activity episodes were selected for detailed analyses. The main objective was to identify how the "with whom" dimension influences scheduling decisions, specifically start time and duration of social activity episodes. CHASE survey data collected in Toronto were used for the investigation. The individual's social network is drawn from "with whom" respondents performed social activities in the seven-day survey period. Based on this social network approach, four classifications of "with whom" the individuals to participate the social activities are used to capture the social context of start time and duration of social activities.

Econometric models of combined decisions regarding "with whom" to participate and when to start or how much time to spend on were estimated to investigate the correlations between the “with whom” decision and these scheduling decisions: start time and duration. One of the key findings was that when the social dimension is incorporated explicitly in the start time model, the effect of travel time and travel distances becomes statistically insignificant. This finding bolsters the argument that it is “with whom” we socialize what defines the social activity scheduling process and not travel time or distance. The models also provide other profound insight into the behavioral process of activity scheduling and the social dimension. Significant correlations exist between “with whom” to participate and the start time as well as duration of the social activity episodes.

Overall, the contribution of this paper is two-fold. In addition to the theoretical understanding of the questions posed to investigate in this paper, the models are useful to advance empirically in previous theoretical ideas developed regarding activity scheduling modeling (*3*), which could serve to improve the existing operational activity scheduling model TASHA (*7*), integrated inside the ILUTE framework (*33*).

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LIST OF TABLES AND PICTURES

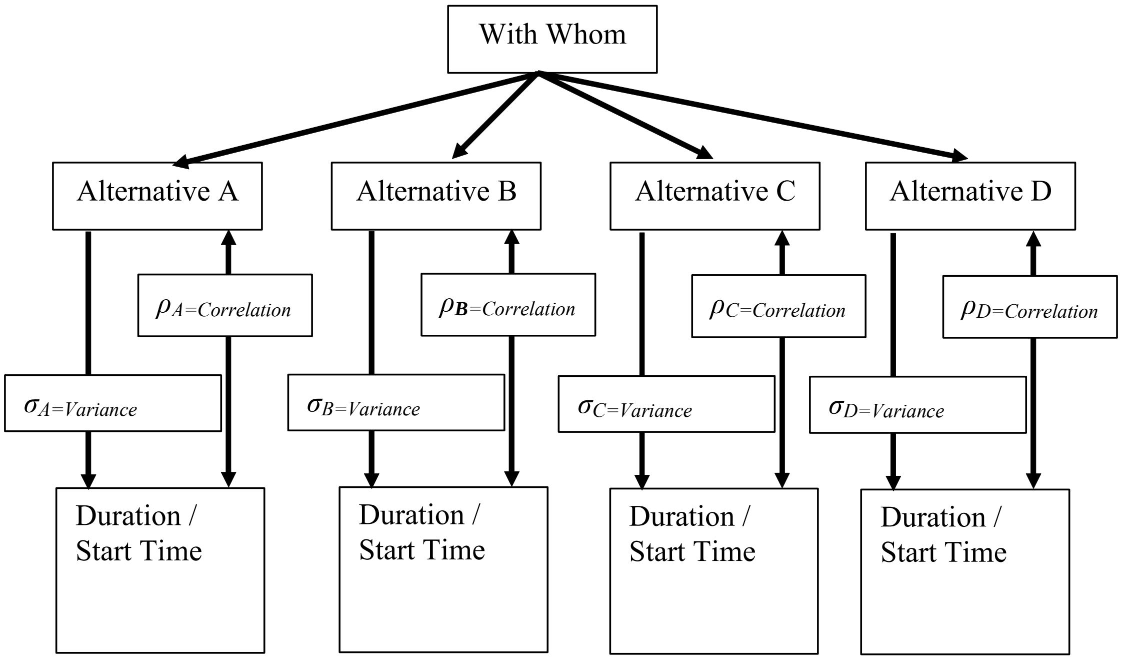

Figure 1: Graphical Presentation of Joint Decision Process

Table 1: Model for Episode Duration

Variable Name	Parameter	Std. Error	t
Base Alternative: With Family Members together with Household Members			
Correlation Between Discrete and Continuous Parts			
ρ_1	0.1155	0.1232	0.938
ρ_2	-0.2869	0.0936	*-3.066*
ρ_3	-0.1876	0.0786	*-2.385*
Variances of Continuous Hazard Model Part			
σ_1	0.4809	0.095	*5.061*
σ_2	0.8656	0.0245	*35.31*
σ_3	0.8738	0.0336	*26.025*
Utility Function of Multinomial Logit Components			
Alternative1: With Friends together with Household Member			
Male (Dummy)	0.9983	0.6343	1.574
Proportion of Friends in Network	3.1694	0.9499	*3.337*
Adult With Partner (Dummy)	1.5981	0.6238	*2.562*
Alternative2: With Family without any Household Members			
Constant	5.1642	0.9966	*5.182*
Total Family Members in Network	0.6535	0.1711	*3.819*
Variability of With Whom	1.1163	0.3886	*2.873*
Alternative3: With Friends without any Household Members			
Constant	5.8823	0.9925	*5.927*
Total Friends Members in Network	0.6632	0.1776	*3.734*
Total Alters in Network	0.0742	0.1646	0.451
HH Head (Dummy)	-0.3688	0.1954	*-1.888*
Covariates of Lognormal Hazard Model Component			
Constant	4.0337	0.1041	*38.738*
Total People Involved	0.1552	0.0259	*5.983*
No. of Potential Locations	0.0113	0.0088	1.286
Duration Flexibility(Dummy)	0.191	0.0568	*3.362*
Travel Time (Minutes)	0.0011	0.001	1.126
Total HH Children	-0.072	0.0324	*-2.224*
No. of HH Automobiles	0.0877	0.0386	*2.269*
Full Time Worker (Dummy)	0.0147	0.0543	0.271
Weekly Frequency	-0.033	0.0061	*-5.377*

Table 2: Model for Episode Start Time

Variable Name	Parameter	Std. Error	t
Base Alternative: With Family Members together with Household Members			
Correlation Between Discrete and Continuous Parts			
ρ_1	-0.4733	0.1254	*-3.773*
ρ_2	0.1551	0.1218	1.273
ρ_3	0.0507	0.0909	0.558
Variances of Continuous Hazard Model Part			
σ_1	0.2222	0.037	*6.00*
σ_2	0.5635	0.0154	*36.568*
σ_3	0.5494	0.0213	*25.841*
Utility Function of Multinomial Logit Components			
Alternative1: With Friends together with Household Member			
Male (Dummy)	0.9545	0.6233	1.531
Proportion of Friends in Network	3.1886	0.9517	*3.35*
Adult With Partner (Dummy)	1.6363	0.6124	*2.672*
Alternative2: With Family without any Household Members			
Constant	5.1866	0.9876	*5.252*
Total Family Members in Network	0.6836	0.1713	*3.991*
Variability of With Whom	1.0139	0.3919	*2.587*
Alternative3: With Friends without any Household Members			
Constant	5.8664	0.9861	*5.949*
Total Friends Members in Network	0.6332	0.1794	*3.53*
Total Alters in Network	0.1056	0.1652	0.639
HH Head (Dummy)	-0.3931	0.1997	*-1.968*
Covariates of Lognormal Hazard Model Component			
Constant	-0.3593	0.0645	*-5.572*
Total People Involved	-0.0407	0.0169	*-2.413*
No. of Potential Locations	-0.0109	0.0057	*-1.902*
Duration Flexibility(Dummy)	-0.0184	0.0361	-0.511
Total HH Children	-0.027	0.0211	-1.282
No. of HH Automobiles	0.034	0.024	1.419
Home Maker (Dummy)	-0.066	0.0803	-0.821
Weekly Frequency	-0.0047	0.0038	-1.229

Table 3: Summary of Goodness of Fit Measures

	Duration	**Start Time**
Loglikelihood of Null Model	-2865.93	-2607.41
Loglikelihood at Convergence	-1877.2	-1416.2
Number of Parameters to be considered for Adjustment	24	23
Number of Observations	1223	1223
Adjusted Likelihood Ratio Index	**0.35338**	**0.46566**