Modeling the Interactions between Activity Participation and Time Use Behaviors over the Course of a Day

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Abstract: Existing studies have shown that decision of activity participation and time allocation behaviors are interdependent. This study reconfirms this finding using a Japanese national time use data collected in 2001 by developing a joint discrete-continuous time allocation model to represent the interactions between activity participation and time use behaviors over the course of a day. A binary logit model is adopted to describe activity participation behavior, while a utility-maximizing time allocation model is established to calculate the time allocated to each activity. The estimation results show that personal attributes, household attributes, and external environment attributes have a significant impact on activity decision. The negative parameter for the above interaction suggests that competition of time allocation occurs across activities. Furthermore, it is also confirmed that individuals try to allocate available time on different activities equally in order to increase his/her utility.

Key Words: *Activity participation, Time allocation, Discrete-continuous choice model, Utility maximization*

1. INTRODUCTION

Activity-based approach has been applied to analyze travel demand for about three decades. The basis of this approach is that travel is derived from activity participation. The utility achieved from activity is affected by many factors, such as the type of activity, individual attributes, activity timing and duration while implementing the activity, available travel mode and so on. Time allocation is an important dimension of the activity-based approach. Bhat (2005) argued that individuals' travel patterns are a result of their time use decisions.

Activity-based travel demand analysis approach usually assumes that an individual makes decision on time allocation to different types of activities by maximizing his/her own utility

considering the influences of personal attributes, household attributes, socio-environment attributes and physical-environment attributes. Different time allocation patterns might result in great difference in utility achieved from activity participation. Consequently, analysis of time use patterns not only contributes to the understanding of travel generation mechanisms, but also to the better measurement of the value of time, well-being, and quality of life. The studies in social science have examined these connections. For example, Harvey (1995) analyzed time use behavior of some special activities focusing on the involvement degree of activity participation. Zuzanek (1998) used a large-scale time use data to investigate social interaction to reveal the quality of life. Easterlin (2005) argued that "the happiness can be increased" if more time is allocated in domains where "hedonic adaptation and social comparison is less important (p.54)", such as accompanying families and friends, doing physical exercises.

Recently, activity participation has been explored in the field of time use analysis. Individuals have to decide what kinds of activities to participate and how long time is allocated if the activity is performed. Existing time use studies always assume that no utility can be obtained if an individual does not participate in an activity (Zhang and Fujiwara, 2006). In fact, daily time allocation involves discreteness, which means that the decision of activity participation is a part of the time allocation decision processes. Kitamura (1984) mentioned the nonnegative of the activity time, and employed Tobit model to describe the choice of activity time. Bhat and Misra (1999) studied the discretional activity time allocation between weekdays and weekends, which distinguished work activity participation and other activities. Chikaraishi *et al.* (2007) combined the censored Tobit activity choice model proposed by Kitamura (1984) under the time allocation modeling framework proposed by Zhang and Fujiwara (2006) to account for the non-participation of activities. In line with the above studies, this study attempts to explicitly incorporate activity participation into the processes of time allocation, aiming to improve the understanding of interrelationship among those two decision aspects.

The remaining part of this paper is organized as follows. Section 2 provides a brief review about time use research, especially in the field of transportation. The joint discrete-continuous choice model developed in this study is described in section 3. Section 4 introduces the data used in this study. Finally, model estimation results are analyzed in section 5 and the study is concluded in Section 6.

2. LITERATURE REVIEW

The methodologies focusing on time use analysis can be classified into two major categories: random utility theory based approach with disaggregate pattern, and probability distribution function based approach with aggregate pattern. The earliest application of microeconomic theory, based on the assumption that an individual derives the utility from the time allocated to an activity, was formulated by Evans (1972). Many researchers subsequently concentrated their efforts on random utility maximization approach to analyze time use behavior (e.g., Yamamoto and Kitamura, 1999; Zhang *et al.* 2002). The central basis of the second approach is to develop some joint probability distribution functions of activity frequency, starting time and duration from large sample surveys and subsequently draw activity time allocation patterns (e.g., Millera *et al.* 2004; Roorda *et al.* 2008). Moreover, it is easier to apply probability distribution function based approach to simulate the activity episode and time expenditure; however it suffers from the drawback of being not behaviorally-oriented

approach, though the original goal of activity-based time use analysis is to predict travel demand in a behaviorally-oriented way. The activity time use model proposed in this study belongs to the behaviorally-oriented random utility maximization approach.

Time allocation modeling based on random utility maximization theory at a household level (husband and wife), developed by Zhang *et al.* (2002, 2005, and 2006), is one of the representatives. This time allocation model deals with time allocation patterns among different types of activities. A multi-linear function is adopted as a household utility function in the basic model, which simultaneously represents relative importance of activities, the interactions of different types of activities, behavioral interdependency between weekday and weekend, intra-household interaction, and relative influences of different household members.

There are also some studies dealing with activity participation when the times allocated on some activities are zero. Tobit model is one of the main methods due to the censoring of the time duration variable. Lee *et al.* (2007) adopted a simultaneous doubly-censored Tobit model to describe the household time allocation behavior, with upper tail censoring for total household out-of-home activities and "0" for lower tail censoring. Chikaraishi *et al.* (2008) also applied a one-tailed Tobit model to represent the activity participation with time allocation behavior simultaneously. Discrete choice model is another method to represent the activity participation behavior. In addition, the time allocated to an activity is considered as continuous choice model, therefore a joint discrete-continuous choice model developed in econometrics is adopted to describe the time use behavior as well as activity participation. Habib *et al.* (2008) used this approach to investigate the relationship between activity time duration with continuous time hazard model and social context (with whom when participate in an activity) with multinomial logit model. Our proposed model is in line with Habib *et al*'s approach, which will be described in detail in the next section.

3. METHODOLOGY

For the time allocation model, a multi-linear function developed by Zhang *et al*. (2005) is adopted to represent individual time allocation behavior by assuming that an individual attempts to allocate his/her available time to various activities so that the total utility is maximized (note that suffix for the individual is omitted).

$$\textit{Maximize} \quad u = \sum_j \gamma_j u_j + \sum_j \sum_{j' \succ j} \delta \gamma_j \gamma_{j'} u_j u_{j'} \tag{1}$$

$$\textit{Subject to} \quad \gamma_j \geq 0, \sum_j \gamma_j = 1 \tag{2}$$

$$U_j = \rho_j \, ln(t_j) \tag{3}$$

$$\rho_j = exp\left(\sum_r \beta_r \chi_r + \xi_j\right) \tag{4}$$

$$\sum_j t_j = T_i \tag{5}$$

where, u_j is utility of activity j,

γ_j is weight parameter of activity j, reflecting the relative interest of this activity, or the relative importance in all the activities,

δ is inter-activity dependency parameter for the individual,

ρ_j is heterogeneous preference for activity j, reflecting the influences of age,

education, income and so on,

t_i is the allocated time to activity j, and

T_i is available time for the individual.

Lagrange function is used to maximize the utility, and the time allocated to activity j can be derived, as showed below:

$$t_j = \frac{\gamma_j \rho_{j[}[1+\sum_{j'\neq j}\delta\gamma_{j'}\rho_{j'}\ln(t_{j'}+1)]}{\sum_{j'}\gamma_{j'}\rho_{j'}[1+\sum_{j''\neq j'}\delta\gamma_{j''}\rho_{j''}\ln(t_{j''}+1)]}T = \kappa_j T \tag{6}$$

Here, it should be mentioned that the error term ξ_j is included in ρ_j in equation (4), which reflects the influence of unobserved factors on activity decision. For ease of model estimation, equation (6) is further transformed as follows:

$$t_j = \kappa_j T + \eta_j \tag{7}$$

where η_j is a new error term reflecting the influence of the original error term. It is assumed that η_j follows a normal distribution, $\eta_j \sim N(0,\sigma_j^2)$ and $\frac{t_j - \kappa_j T}{\sigma_j} \sim N(0,1)$.

As discussed before, the objective of this paper is to explicitly incorporate the activity participation into the processes of individual time allocation. The participation choice is binary, and therefore a binary Logit model is adopted to represent the activity participation choice behavior. We define the utility of systemic part V_{j1} as 0 for non-participation, w_{j1} represents the participation of activity j, and w_{j2} represents non-participation. If the error term ε_{j1} in equation (8) has a Gumbel distribution, then we can get the probalility of participation in activity j as shown in equation (9):

$$U_{j1} = V_{j1} + \varepsilon_{j1} \tag{8}$$

$$\Pr(w_{j1}) = F(\varepsilon_{j1}) = \frac{\exp(V_{j1})}{\exp(V_{j1})+1} \tag{9}$$

$$\Pr(w_{j2}) = 1 - \Pr(w_{j1}) \tag{10}$$

Up to now, we have built two types of models to reflect the time allocation decision processes: a binary logit model which represents whether to participate in an activity or not, and the continuous time allocation model which represents the duration in that activity. Therefore the model becomes a joint discrete-continuous choice model. The joint estimation assumes that two error terms ε_{j1} and η_j are correlated. According to Lee (1983), with the completely specified arbitrary marginal distribution function $F(\varepsilon_{j1})$ and $G(\eta_j)$ of ε_{j1} and η_j, each of them can be transformed into a standard normal random variable with zero means and unit variances.

$$\varepsilon_{j1}* = J_1(\varepsilon_{j1}) = \varphi^{-1}(F(\varepsilon_{j1})) \tag{11}$$

$$\eta_j* = J_2(\eta_j) = \varphi^{-1}(G(\eta_j)) \tag{12}$$

where φ^{-1} represents the inverse of the standard normal cumulative density distribution function. Then, a bivariate distribution having the marginal distribution $F(\varepsilon_{j1})$ and $G(\eta_j)$ can be specified as:

$$C(\varepsilon_{j1}, \eta_j; \mu_{j1}) = B(J_1(\varepsilon_i), J_2(\eta_j); \mu_{j1}) = N(0,0,1,1, \mu_{j1}) \tag{13}$$

where μ_{j1} refers to the correlation of error terms for time allocation part and participation part. In our study,

$$J_1(\varepsilon_{j1}) = \varphi^{-1}(F(\varepsilon_{j1})) = \varphi^{-1}(\Pr(w_{j1})) \tag{14}$$

$$J_2(\eta_j) = \frac{t_j - \kappa_j T}{\sigma_j} \tag{15}$$

Finally, for the joint probabilities of participation and corresponding time allocation can be written in equation (16), which has the same format with Habib *et al.* (2008) and Chikaraishi *et al.* (2007). Different from Habib *et al*'s hazard-based model, we derive the time allocation model based on the utility-maximizing principle, and different from Chikaraishi *et al'*s Tobit-based model, we adopt the logit-based modeling approach.

$$\Pr(t_j \cap w_{j1}) = \frac{1}{\sigma_j}\phi(\frac{t_j - \kappa_j T}{\sigma_j})\varphi(\frac{J_1(\varepsilon_{j1}) - \mu_{j1}(\frac{t_j - \kappa_j T}{\sigma_j})}{\sqrt{1-\mu_{j1}^{\ 2}}}) \tag{16}$$

where ϕ represents the standard normal probability density distribution function.

For any individual the probability of non-participation:

$$\Pr(t_j = 0 \cap w_{j2}) = \Pr(w_{j2}) = 1 - \Pr(w_{j1}) \tag{17}$$

Therefore, the log likelihood function of the joint discrete-continuous choice model is:

$$LL = \sum_{j=1}^{J}\left\{\begin{array}{l} D_j[-\ln(\sigma_j) + \ln(\phi(\frac{t_j - \kappa_j T}{\sigma_j}))] + D_j \ln(\varphi(\frac{J_1(\varepsilon_{j1}) - \mu_{j1}(\frac{t_j - \kappa_j T}{\sigma_j})}{\sqrt{1-\mu_{j1}^{\ 2}}})) \\ + (1 - D_j)\ln(1 - \Pr(w_{j1})) \end{array}\right\} \tag{18}$$

where D_j is a dummy variable to indicate participation in activity *j* ("1" means participation and "0" for non-participation). The maximum likelihood estimation method is applied in this study, the details of the estimation results will be discussed in Section 5.

4. DATA

The data used in this paper is the survey data on Time Use and Leisure Activities collected by the Ministry of Internal Affairs and Communications in Japan in 2001. The original datasets include time use survey data both on weekdays and weekends, since some of the employee don not have to participate in work activity, and the activity in weekends are more unrestricted and personal, relatively. Hence, data on Tuesday and Thursday are selected as the sample data due to only the typical weekdays' time use behavior are focused in this study. There are 20 types of activities altogether in the original datasets, and they are classified into 5 types of activities according to previous research (Xu *et al.* 2008): in-home activity, work activity, maintenance activity, discretionary activity and shopping activity. In-home activity include sleeping, body cleaning and dining; work activities include work, studying in school and related activities; maintenance activity include cleaning house, taking care of child, nursing and seeing a doctor; discretionary activity include sport, meeting friends, studying for interest, rest and so on. Table 1 show the average time distribution for 5 types of activities. As can be seen from the data in table 1, the minimum of the last four activities are zero, which means these activities are not participated for some individuals. Hence, we introduce the participation selection model to represent such situation. For the in-home activity, we assume that all individuals participate in this activity because of the necessity of life support, therefore the participation selection is not considered for in-home activity.

Table 1 Average time allocated to different activities (minutes)

	Mean	Std Dev	Minimum	Maximum	Variance
in-home activity	629	119	180	1440	14278
work activity	281	263	0	1125	69014
maintenance activity	201	197	0	975	38792
discretionary activity	248	189	0	990	35860
shopping activity	20	39	0	405	1485

5. ESTIMATION RESULTS

Table 2 corresponds to the estimation results of activity participation selection part. The base alternative is non-participation in that activity. Based on a preliminary analysis, four factors are adopted to describe individuals' activity participation selection: gender, age, marital, and education. Those four attributes are the most significant symbols that distinguish individuals' life styles and corresponding activity engagement. The gender parameter for work activity is positive while the others is negative, which means that males have higher participation preference than females in work activity, while females have higher participation preference than males in maintenance, discretionary and shopping activities. This is consistent with the role function for male and female in Japan society especially in household situation. For age parameter, it is only significant in work activity with negative signs, it can be explained that the participation of work activity is decreased as people get old. In terms of the marital attribute, it is a not significant factor to influence the participation in work and maintenance activities according to the estimation results. Moreover, it can also be concluded that higher education level contributes to the participation in work activity.

Table 3 shows the estimation results of time allocation part with in-home activity as base

alternative. The highest value of infrastructure attribute is discretionary activity, which indicates the significant fundamentality of infrastructure in personal time use behavior and thereby the utility achieved from this activity. For the shopping activities, the utility achieved from this activity in rainy days will decrease compared with no rain days, furthermore, it also make sense that unemployed individuals will allocate more time in shopping activity than employed individuals.

Table 2 Estimation results of activity participation part: Base alternative (non-participation)

Parameter	work activity	maintenance activity	discretionary activity	shopping activity
constant	1.9117*	3.2993 *	2.1986 *	-0.7116*
gender (1: male, 0: female)	1.5744 *	-2.4211 *	-0.2886 *	-0.8707*
age	-0.0523 *	0.0044	0.0006	-0.0018
marital (1: married, 0: single)	0.0898	0.3176	0.3388 *	0.3451+
education (1: low ~ 5: high)	0.2403 *	-0.2094 *	-0.0691*	0.0829
sample size: 1038	*: 95% statistical significant, +: 90% statistical significant			

Table 3 Estimation results of time allocation part: Base alternative (in-home activity)

work activity	
income level (1, low~12, high)	0.0044*
occupation (1 for employed, 0 for not employed)	0.0809*
infrastructure	1.0000
maintenance activity	
number of room	0.0028
income level (1, low~12, high)	0.0100*
infrastructure	0.4372
discretionary activity	
income level (1, low~12, high)	-0.0019
rain (1 for yes, 0 for no)	0.0034
infrastructure	1.6961*
shopping activity	
number of room	-0.4505*
rain (1 for yes, 0 for no)	-0.3622+
occupation (1 for employed, 0 for not employed)	-0.7146*
infrastructure	1.3030
infrastructure attributes (unit: per 1000 persons in prefecture level) Data source: “Minryoku” by Asahi Press 2001	
length of expressway	-0.0233
number of hospitals	-0.0965
number of libraries	0.0773
number of supermarkets	-0.4400*
number of restaurants	-0.0173*
number of parks	0.0004
sample size: 1038	*: 95% statistical significant, +: 90% statistical significant

Table 4 shows the estimation results of joint discrete-continuous time use model on weekdays.

As can be seen, the correlation between activity participation and time allocation are significant, which proved the assumption that the two error terms for activity participation selection part and time allocation part have interaction during the time use decision processing. Moreover, the correlation for discretionary and shopping activity is higher than maintenance and work activity, which shows the relatively fixed work duration, employment status and also low interaction between those two factors compared with other activities on weekdays. In terms of the variance of time allocation model part, discretionary activity have the highest value which represents the individuation of free time expenditure; the variance of work time is the lowest which can also be explained by relatively fixed work duration. The sorting order for relative importance of activity is consistent with previous studies (Xu *et al.* 2008), however, the values trend to be balance and the difference is smaller, which suggest the equally important role of those five different activities in utility function. Considering the negative parameter of interaction of activities, it is consistent with previous studies, which implies the competition of time allocation among activities. Table 3 also shows the measurement of goodness of fit, as revealed in the data, the joint discrete-continuous time use model provides relatively high goodness of fit with adjusted likelihood ratio index 0.27.

Table 4 Estimation results of joint discrete-continuous time use model

	correlation between activity participation and time allocation	variance of time allocation model part	relative importance of activity
in-home activity	-	124.2660*	-
work activity	0.4699*	104.6570*	0.2220*
maintenance activity	0.7462*	138.4860*	0.1833*
discretionary activity	-0.9990 *	173.2850*	0.2314*
shopping activity	-0.9155*	61.8435*	0.1368
interaction of activities		-0.2577*	
log-likelihood of Null Model		-34881.4	
log-likelihood at convergence		-25366.1	
number of variables to be considered for adjustment		47	
number of observations		1038	
adjusted McFadden's rho-squared		0.27	
sample size: 1038	*: 95% statistical significant, +: 90% statistical significant		

6. CONCLUSIONS

Existing studies have shown that decisions of activity participation and time allocation are interdependent. Using the survey data on Time Use and Leisure Activities collected by the Japanese government in 2001, this study reconfirmed this finding and also found out that the correlation for maintenance and work activity is lower due to their relatively fixed activity type, duration and corresponding low interaction between participation and time allocation, especially compared with discretionary and shopping activity on weekdays. In order to represent the interdependency in time use decision processes, a joint discrete-continuous time use model was developed, in which a binary logit choice model was used to describe activity participation and a continuous time allocation model was adopted to describe the activity duration. Since the interaction parameter is negative, the competition of time allocation

among different types of activities is confirmed. Furthermore, the relative importance of activity trends to be balanced and the difference is smaller, suggesting that an individual tries to allocate available time to different activities equally to increase the total utility.

The estimation results clarified the assumption that personal attributes, household attributes, socio-environment attributes and physical-environment attributes have an impact on activity participation and time use behaviors. Gender show significant differences of participation preference among activities: males have higher participation preference in work activity, while females have higher participation preference in maintenance, discretionary and shopping activities. Marital status could influence the participation in shopping activity, and the probability for married individuals participate in shopping activity is higher because of purchasing the necessaries for the household level. Infrastructure attribute contributes to the time allocation in discretionary activity, which indicates the significant fundamentality of infrastructure in personal time use behavior. The utility achieved from the time allocation in shopping activity influenced by physical-environment decreases in rainy days compared with no rain days.

This study should be further improved in the future. One of the limitations is that only a limited set of variables are used. There might exist some other more effective factors, further studies should be done by exploring a comprehensive set of factors to describe the complicated decision-making mechanisms for activity participation.

REFERENCES

Bhat，C. R. and Misra, R. (1999) Discretionary activity time allocation of individuals between in-home and out-of-home and between weekdays and weekends, **Transportation, Vol. 26, No. 2**, 193–209.

Bhat, C. R. (2005) A multiple discrete–continuous extreme value model: formulation and application to discretionary time-use decisions, **Transportation Research Part B: Methodological, Vol. 39, No. 8**, 679-707.

Chikaraishi, M., Zhang, J. and Fujiwara, A. (2007) Time allocation model incorporating self-selection biases of activity choice and inter-activity interactions, Presented at the 42nd Annual Conference of the City Planning Institute of Japan, Tokyo, November 2007.

Easterlin, R. A. (2005) Building a better theory of well-being, In Bruni L. and Porta P. L. (eds.), **Economics & Happiness--Framing the Analysis**. Oxford University Press, New York.

Evans, A. (1972) On the theory of the valuation and allocation of time, **Scottish Journal of Political Economy, Vol. 19, No. 1**, 1-17.

Harvey, A. S. (1995) Canadian time-use in a cross-national perspective, **Statistics in Transition, Vol. 2, No. 4**, 595–610.

Habib, K. M. N., Carrasco, J. A. and Miller, E. J. (2008) The social context of activity scheduling: a discrete-continuous model of the relationship between "with whom" and episode start time and duration, **Compendium of Papers CD-ROM, the 87th Annual Meeting of the Transportation Research Board**, Washington D.C., January 13-17.

Kitamura, R. (1984) A model of daily time allocation to discretionary out-of-home activities and trips, **Transportation Research Part B: Methodological, Vol. 18, No. 3**, 255–266.

Lee, L.-F. (1983) Generalized econometric models with selectivity, **Econometrica, Vol. 51, No. 2**, 507-512.

Lee, Y., Hickman, M. and Washington, S. (2007) Household type and structure, time-use

pattern, and trip-chaining behavior, **Transportation Research Part A: Policy and Practice, Vol. 41, No. 10**, 1004-1020.

Millera E. J., Hunt J. D., Abraham J. E. and Salvini P. A. (2004) Microsimulating urban systems, **Computers, Environment and Urban Systems, Vol. 19, No. 1-2**, 9–44.

Roorda M. J., Miller E. J. and Habib K. M. N. (2008) Validation of TASHA: A 24-h activity scheduling microsimulation model, **Transportation Research Part A: Policy and Practice, Vol. 42, No. 2**, 360-375.

Xu, L., Zhang, J., Hizume, Y. and Fujiwara, A. (2008) Capturing the long-term changes in time use behavior based on time allocation model, presented at Infrastructure Planning 37th Spring Conference, Hokkaido, June 2008.

Yamamoto, T. and Kitamura, R. (1999) An analysis of time allocation to in-home and out-of home discretionary activities across working days and non-working days, **Transportation, Vol. 26, No. 2**, 211-230.

Zuzanek, J. (1998) Time use, time pressure, personal stress, mental health, and life satisfaction from a life cycle perspective, **Journal of Occupational Science, Vol. 5, No. 1**, 26-39.

Zhang, J., Timmermans, H. and Borgers, A. (2002) A utility-maximizing model of household time use for independent, shared and allocated activities incorporating group decision mechanisms, **Transportation Research Record: Journal of the Transportation Research Board, No. 1807**, 1–8.

Zhang, J., Timmermans, H. and Borgers, A. (2005) A model of household task allocation and time use, **Transportation Research Part B: Methodological, Vol. 39, No. 1**, 81–95.

Zhang, J. and Fujiwara, A. (2006) Representing household time allocation behavior by endogenously incorporating diverse intra-household interactions: A case study in the context of elderly couples, **Transportation Research Part B: Methodological, Vol. 40, No. 1**, 54–74.