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A Need-Based Approach for Modeling Recurrent Discretionary Activity Participation Patterns for Travel Demand Analysis

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Abstract: As society advances and various technologies like AI and LLMs are further developed, the proportion of human labor contributing to the productivity of nations and societies is gradually decreasing. This has led to increased attention to the quality of life of individuals, and cases of implementing policies such as a four-day work week are on the rise. Therefore, the objective of this study was to analyze the patterns of how people are spending their increased leisure time amid this social trend and to identify the factors influencing these patterns. Building upon the need-based theory proposed in previous studies, this research analyzed people's recurrent discretionary activity patterns. Multiday analysis was conducted considering the characteristics of leisure activity patterns, and a hazard-based duration model was estimated for statistical analysis. The research results revealed that people's patterns of consecutive activities are influenced by various factors, such as socio-economic attributes, time–space budgets, previous activity experiences, and preferences for specific days of the week. Through this, we were able to confirm that socio-demographic and household characteristics, as well as attributes of time/space budgets, influence the growth speed and threshold of needs as suggested in need-based theory. Additionally, we observed a preference for specific days of the week for different types of activities. As a result, people tend to either postpone activities until specific days even when their need has accumulated sufficiently or engage in activities on specific days even when the need has not yet accumulated to the desired level. This study demonstrates novelty in that it utilizes the need-based theory proposed in prior research to identify factors influencing multiday activity participation patterns. Additionally, it presents the first study providing model estimation results from the perspective of need-based theory. The correlation between the time–space budget and discretionary activity patterns identified in this study is expected to serve as a guideline for future transportation-related policies, including regional balanced development. This study demonstrates a unique contribution compared to existing research in that it established that, with improvements in activity/travel conditions, there can be an induced demand for activities. This finding can contribute to the feasibility study of transportation projects and the establishment of policies related to regional balanced development.

Keywords: multiday analysis; need-based theory; hazard-based duration model; activity participation pattern; time use survey

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1. Introduction

Compared to earlier societies, modern society has evolved greatly due to advances in science and technology, including the emergence of AI (Artificial Intelligence) and LLMs (Large Language Models) and the widespread use of big data. Therefore, the contribution of human labor to the expansion of national economies is decreasing as more cutting-edge technology replaces human labor in various fields. Accordingly, many countries are implementing policies for reducing people's working hours, such as flextime and four-day working weeks, as a result of the paradigm shift in societies, which is anticipated to improve the flexibility of people's time use. In other words, as society becomes more developed and technologically advanced, people's quality of life can also be improved, allowing for more flexible and effective use of personal non-work time.

This improvement in the flexibility of the personal use of spare time seems to have the effect of expanding an individual's time–space budget, a concept that was initially suggested in transport geography, denoting the spatiotemporal range in which an individual can carry out a variety of activities [1–4]. According to this concept, an individual with a large time–space budget is less constrained in terms of activity/travel patterns by activity/travel conditions; this idea is commonly utilized in transportation equity studies. In other words, people's activity/travel patterns are affected by their time–space budget, and discretionary activity patterns are more affected than mandatory activity patterns due to the characteristics of the activity type. A mandatory activity refers to an activity that requires relatively compulsory participation, such as work or school classes, and a discretionary activity implies an activity with relatively little compulsion in determining participation in activities, such as leisure and social activities. The opportunity to participate in discretionary activities can be utilized as a proxy variable for evaluating an individual's quality of life because it means that a person who can freely participate in discretionary activity has a great deal of spare time and good accessibility to locations where this person can engage in discretionary activity. Despite the fact that discretionary activity patterns can serve as an indicator of people's quality of life, most studies have focused on peak-hour congestion relief, leading to relatively fewer studies on discretionary activity patterns.

Due to the tendency of discretionary activities to occur irregularly compared to mandatory activities, it is necessary to perform a multiday analysis, rather than a one-day analysis, in order to analyze the daily variation in activity/travel patterns. Multiday analysis has been widely used in various studies when analyzing the temporal variability of activity/travel patterns. Chow et al. (2015) extended activity-routing problems to consider 'needs' satisfaction over multiple days using an inventory-routing problem concept and proposed a Lagrangian relaxation-based algorithm to solve the model for multiple days [5]. Doherty et al. (2002) described a conceptual model of the household activity scheduling process based partially on empirical evidence gathered using a Computerized Household Activity Scheduling Elicitor (CHASE) survey and incorporated various modeling structures and decision rules in the conceptual framework [6]. Rasouli et al. (2014) sought to discuss the initial promises of activity-based models as an alternative to four-step and tour-based models and summarize the progress made in identifying still-unsolved issues that require further research [7]. Zhang et al. (2018) proposed generating multi-day activity-travel data through sampling through single-day household travel survey data considering interpersonal and intrapersonal variability [8]. Saneinejad et al. (2009) utilized multiple-sequence alignment methods for measuring similarities between the routine weekly activity sequences of surveyed individuals, categorizing their activity patterns into nine clusters [9]. Bhat et al. (1999) formulated a model for the allocation of the total weekly discretionary time of individuals between in-home and out-of-home locations and between weekdays and the weekend in the form of a continuous utility-maximizing resource allocation problem [10]. Axhausen et al. (2002) described the implementation of Mobidrive, a six-week continuous travel diary survey funded by the German ministry of Research and Education, and analyzed the rhythms in the behavior of the respondents [11]. Susilo et al. (2014) examined the degree of repetition of an individual's choices for their daily activity–travel–location combinations and discovered that the repetitiveness of an individual's activity–travel–location combinations is highly influenced by the individuals' out-of-home commitments, intra-household conditions, and the availability and accessibility of the activity's location [12]. Yamamoto et al. (1999) formulated a doubly censored Tobit model for analyzing the behavior of time allocation to two types of discretionary activities. Furthermore, the model was applied to examine individuals' allocation of time to in-home and out-of-home discretionary activities on working days and non-working days, using a weekly time use data set from the Netherlands [13]. Arentze et al. (2013) developed a model for predicting activity location choice sets and choices from these sets conditioned upon a varying activity schedule context and proposed a method for estimating the parameters of the involved utility functions, which do not require observations or the imputation of choice sets [14]. Arentze et al. (2011) extended and explored a method for creating dynamic models of activity generation based on 1-day travel diary data and applied the method to data from a national travel survey [15]. Lee et al. (2003) summarized an investigation of the structure of activity/travel patterns based on data collected from a pilot study of a computerized survey instrument that was developed to collect household-activity-scheduling data [16].

Another important characteristic of discretionary activity patterns is that the days when these activities predominantly occur can be specified, and subsequent activities can be influenced by the preceding activity. Since individuals can choose to participate in discretionary activities on days that are most convenient for them, they may engage in these activities on days that are influenced by their experiences from previous activities. Therefore, in order to analyze discretionary activity patterns, it is necessary to select a methodology that takes these characteristics into account and conduct research accordingly.

Most of the existing studies in the field of transportation planning have primarily focused on congestion alleviation, thus predominantly targeting travel behavior and mandatory activity patterns during morning and evening peaks. Furthermore, due to the significant temporal variation in and difficulty of data collection, discretionary activity patterns have not received much attention in this domain compared to their mandatory counterparts. Additionally, since most activity-based models analyze data based on a single day, they fail to adequately capture discretionary activity patterns. However, considering that with societal advancement, the proportion of discretionary activity demand within the total activity demand is expected to increase, identifying the factors influencing discretionary activity patterns and analyzing the potential changes in these patterns as cities develop could contribute to various related fields, including the expansion of activity-based models. Therefore, in this study, we have established the following research questions:

- What factors influence people's recurrent discretionary activity participation patterns?
- Would the multiday activity participation patterns change if the activity/travel conditions were improved?

Therefore, the purpose of this study was to investigate the factors influencing recurrent discretionary activity participation, which can reflect the quality of people's lives. Need-based theory was established as the theoretical framework for this study through a review of prior research. An online time-use survey was employed to collect multi-day activity participation information from the survey participants. Hazard-based duration models were applied to analyze the collected data. Based on the results of the analysis, the factors influencing people's multi-day activity participation were identified, and implications were provided. Based on a thorough review of prior studies, while there were numerous studies focusing on discretionary activity patterns, studies employing multiday analysis were limited. To the best of our knowledge, most studies employing multiday analysis primarily focused on analyzing the temporal (daily) variability of activity patterns or activity locations, and there were scarcely any studies identifying factors influencing activity participation. Since there were no studies considering the impact of changing activity/travel conditions on activity patterns due to urban development, this study seems to be distinct from prior research, and it offers contributions such as political implications. Moreover, the need-based theory utilized as the theoretical background in this study is expected to have greater applicability in various multiday analyses in future studies. Therefore, the methodology of this study is anticipated to have higher extensibility compared to other previous research.

The rest of this study has the following structure. Section 2 includes an introduction to the need-based theory and hazard-based duration model used in this study, as well as details on the data collection methods, and a basic statistical analysis of the collected data.

Section 3 encompasses the model estimation results. Section 4 contains the conclusions and provides a discussion of the results.

2. Materials and Methods

This study used the need-based theory proposed in prior research as a theoretical background and utilized a hazard-based duration model for statistical modeling. Additionally, a dataset suitable for application in the statistical model was constructed using a combination of time use survey and web-crawling techniques. The overall flow of the study is illustrated in Figure 1.

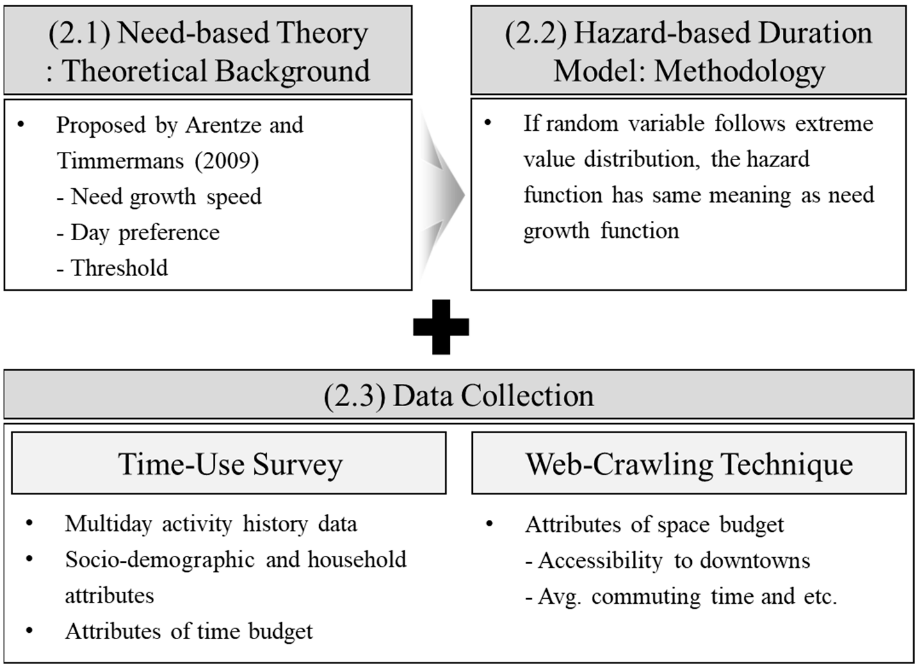

Figure 1. Research Framework [17].

2.1. Need-Based Theory

In this paper, the need-based theory introduced by Arentze and Timmermans (2009) was employed to examine multi-day discretionary activity patterns [17]. This theory operates on the premise that individuals decide to take part in an activity when the perceived need for it reaches a certain level. Moreover, it has proven highly valuable as it allows for the analysis of people's multi-day activity patterns using a proxy variable termed "need". The essential components of this need-based theory can be categorized into three parts, as outlined in Table 1. Need growth speed signifies the rate at which a need intensifies over time; a higher value indicates a swifter increase, prompting individuals to engage in activities more frequently. The threshold denotes the level of need that triggers activity participation. When this value is low, individuals tend to participate in activities more frequently since their need reaches the threshold swiftly. Day preference refers to one's inclination toward a specific day of the week for engaging in activities. This need-based theory has been applied in numerous previous studies that scrutinized multi-day activity participation patterns using various methodologies [17–21]. The concept of the need-based theory used herein is presented in Figure 2.

Table 1. The core components of need-based theory.

Component	Description
Need growth speed	• Speed at which need increases over time
Threshold	• Threshold value of need that determines participation in an activity
Day preference	• Preference for performing activities on specific days

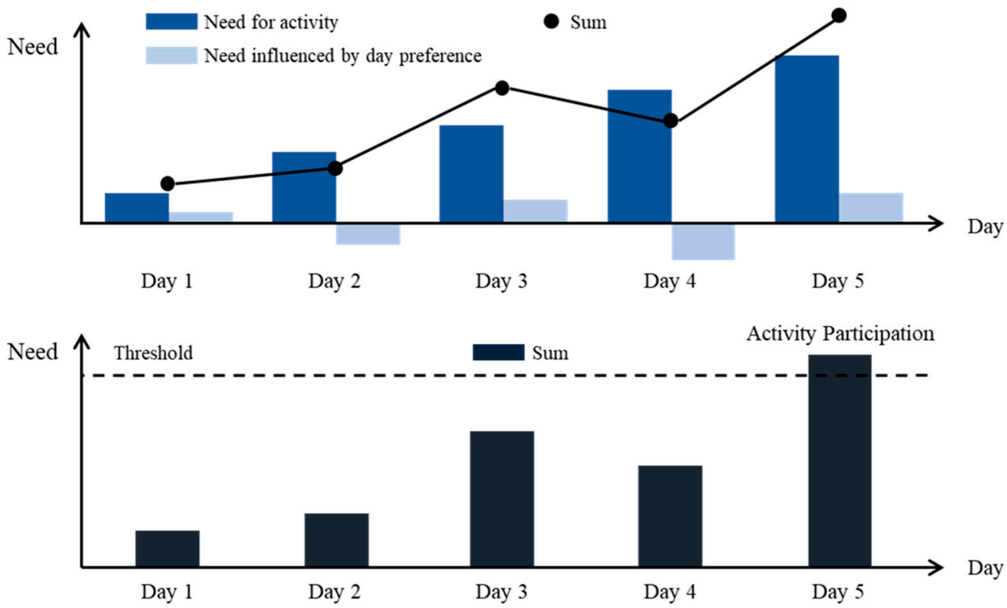

Figure 2. The concept of need-based theory.

2.2. Hazard-Based Duration Model

2.2.1. Introduction to Hazard-Based Duration Model

This research applied the hazard-based duration model to mathematically examine need-based theory as presented in prior studies. Originally utilized in fields like medicine and sociology, this model has become increasingly prominent in transportation studies [22–33]. Given its capacity to analyze the time until a particular event transpires or the duration of said event, the hazard-based duration model aligns well with the objective of this study, which is to scrutinize recurring activity patterns.

The datasets containing information on the time until a specific event occurs or the duration of that event are termed duration data. A notable feature of duration data is the presence of censored data. What sets the hazard-based duration model apart from other statistical models is its ability to effectively handle duration data (Table 2).

Having a grasp of one function among those mentioned above will unveil the mathematical relationship it shares with the others.

$$\mathrm{S(t)} = P(T \geq t) = 1 - F(t) = \int_t^{\infty} f(u)du = exp\{-H(t)\} \tag{1}$$

$$\mathrm{h(t)} = \frac{f(t)}{S(t)} = -\frac{S'(t)}{S(t)} = -\frac{d}{dt}log\{S(t)\} = \frac{d}{dt}H(t) \tag{2}$$

$$\mathrm{f(t)} = \frac{d}{dt}F(t) = -\frac{d}{dt}S(t) = \mathrm{h(t)S(t)} = \mathrm{h(t)}\exp\left\{-\int_0^t h(u)du\right\} \tag{3}$$

Table 2. Functions of hazard-based duration model.

Function	Description
cumulative distribution function	• Probability that an event occurs before time t $\mathrm{F(t) = P(T < t)}$
survival function	• Probability that an event does not occur until time t $\mathrm{S(t) = P(T \geq t) = 1 - F(t)}$
probability density function	• Probability that an event occurs at time t $\mathrm{f(t)} = \frac{d}{dt}F(t) = \lim_{\Delta t \to 0} \frac{P(t \leq T < t + \Delta t)}{\Delta t}$
hazard function	• Probability that an event does not occur until time t and then occurs between time t and t + dt $\mathrm{h(t)} = \lim_{\Delta t \to 0} \frac{P(t \leq T < t + \Delta t \mid T \geq t)}{\Delta t}$
cumulative hazard function	• Integrated function of hazard function with respect to time t $\mathrm{H(t)} = \int_0^t h(u)du$

2.2.2. Censored Data and Joint Likelihood Function

Since the hazard-based duration model includes censored data, a joint likelihood function was constructed to consider it, and the model was estimated using the maximum likelihood estimation method (Newton–Raphson method, Quasi-Newton method, EM algorithm, etc.). Assuming that there are n individuals and that the times until an event occurs for each individual are equal to $\mathrm{T_1,\ T_2,\ \cdots,\ T_n}$, the information that the researcher can observe is as follows:

$$\mathrm{t_i} = \min(T_i,\ C_i) \tag{4}$$

The terms above denote the following:

i = individual
$\mathrm{t_i}$ = observed information of individual i $(t_i > 0)$;
T_i = event time of individual i $(T_i > 0)$;
C_i = censoring time of individual i $(C_i > 0)$.

In this case, the indicator function is as follows.

$$\delta_\mathrm{i} = I(T_i \leq C_i) = 1, \quad if \quad T_i \leq C_i, \quad and \quad 0 \tag{5}$$

That is, when only right censoring is considered, if $\mathrm{t_i}$ is not right-censored data, $\delta_\mathrm{i} = 1$, and $\mathrm{t_i}$ is right-censored data, $\delta_\mathrm{i} = 0$; then, the researcher can obtain the following information:

$$\{t_i\ ,\ \delta_i\}\ ,\ \ i = 1,\ 2,\ \cdots,\ n \tag{6}$$

Assuming non-informative censoring is being applied, where the distribution of survival times provides no information about the probability distribution of censoring times, the joint likelihood function was constructed as follows based on the given data. If the information observed for individual i is event time, it is included in $\mathrm{f(t_i)}$, and if it is censoring time, it is included in $\mathrm{S(t_i)}$.

$$\mathrm{L(\theta)} = \prod_{i=1}^{n} \{f(t_i)\}^{\delta_i} \{S(t_i)\}^{(1-\delta_i)} = \prod_{i=1}^{n} \{h(t_i)\}^{\delta_i} exp\left\{-\int_0^t h(u)du\right\} \tag{7}$$

The terms given above denote the following:

$\mathrm{t_i}$ = observed time of individual I;
δ_i = censoring index of individual i.

2.2.3. Various Types of Hazard-Based Duration Models

Hazard-based duration models come in various types, depending on the specific analysis objectives. They can generally be categorized into four groups. The non-parametric model, represented by the Kaplan–Meier method, is the most straightforward, as it does not assume any distribution for the random variable, T, and does not account for covariates influencing T. The parametric distributional model assumes a specific distribution for the random variable, T, but does not incorporate covariates. It is used for estimating the baseline (underlying) function, denoted as $\mathrm{h}_0(t),\ f_0(t),\ S_0(t)$, representing the function of T itself when the effects of covariates are excluded. Among the semi-parametric models, Cox's proportional hazard model stands out as the most widely used. While it does not assume a specific distribution for T, it is considered semi-parametric because it estimates the regression parameters of the covariates to account for their effects on the random variable, T. Parametric regression models not only assume a distribution for T but also consider the impact of covariates. The parametric proportional hazard model and the parametric accelerated failure time model are prominent examples in this category (Table 3).

Table 3. Types of hazard-based duration model.

Models		Distribution	Covariate
Non-parametric model		X	X
Parametric distributional model		O	X
Regression model	Semi-parametric model	X	O
	Parametric model	O	O

In this study, we employed the parametric accelerated failure time model (AFT model). The association between the random variable, T; the covariate; and the baseline (underlying) function in each component of the AFT model can be described as follows:

$$\mathrm{h}(\mathrm{t};\mathrm{X}) = \mathrm{h}_0\{t\cdot \exp(\beta X)\}\exp(\beta X) \tag{8}$$

$$\mathrm{S}(\mathrm{t};\mathrm{X}) = \{\mathrm{S}_0(t)\}\exp(\beta X) \tag{9}$$

$$\mathrm{f}(\mathrm{t};\mathrm{X}) = \mathrm{f}_0\{t\cdot \exp(\beta X)\}\exp(\beta X) \tag{10}$$

As mentioned earlier, need steadily increases over time, and as need rises, the likelihood of participating in an activity also increases. Therefore, the hazard function, $\mathrm{h}_0(t)$, should exhibit a property of increasing as t becomes larger. To achieve this, in this study, it was assumed that the random variable T follows a Weibull distribution. When the shape parameter, P, of the Weibull distribution is greater than 1, the hazard function increases over time, and when P is less than 1, the hazard function takes on a decreasing trend as time progresses.

$$\mathrm{f}(\mathrm{t}) = \lambda\mathrm{P}(\lambda\mathrm{t})^{\mathrm{P}-1} exp\left\{-(\lambda\mathrm{t})^{\mathrm{P}}\right\} \tag{11}$$

$$\mathrm{S}(\mathrm{t}) = exp\left\{-(\lambda\mathrm{t})^{\mathrm{P}}\right\} \tag{12}$$

$$\mathrm{h}(\mathrm{t}) = \lambda\mathrm{P}(\lambda\mathrm{t})^{\mathrm{P}-1} \tag{13}$$

The terms above denote the following:

λ : rate parameter ($\lambda > 0$);
P : shape parameter ($\mathrm{P} > 0$).

When the random variable T follows a Weibull distribution, $\mathrm{y} = \log(\mathrm{T})$ follows an extreme value distribution, and in this case, the forms of the functions are as follows:

$$\mathrm{f}(y) = \frac{1}{\tau} exp\left\{ \frac{y-\alpha}{\tau} - exp\left(\frac{y-\alpha}{\tau} \right) \right\} \tag{14}$$

$$\mathrm{S}(y) = exp\left\{ -exp\left(\frac{y-\alpha}{\tau} \right) \right\} \tag{15}$$

$$\mathrm{h}(y) = \frac{1}{\tau} exp\left\{ \frac{y-\alpha}{\tau} \right\} \tag{16}$$

While there are various types of hazard-based duration models, in this study, we utilized the accelerated failure time model (AFT model). The AFT model is a parametric hazard-based duration model that assumes a probability distribution for the random variable T. It has the advantage of being able to analyze the influence of covariates on the random variable. When considering the functional form of the AFT model, it can be transformed into a log-linear regression model.

$$\mathrm{Y} = \log(T) = \beta_0 + \beta X + \tau W \tag{17}$$

The terms above denote the following:

$T =$ time to event;
$\beta_0 =$ location parameter;
$\beta =$ regression parameter;
$\mathrm{X} =$ covariates;
$\tau =$ scale parameter;
$\mathrm{W} =$ error term.

2.2.4. Accelerated Failure Time Model for Recurrent Event Modeling

A general hazard-based duration model analyzes the time until an event occurs assuming that an event occurs only once, but a hazard-based duration model for recurrent event modeling was developed in this study to analyze cases where one person experiences an event several times. For recurrent event modeling, the sequence of activities experienced by people was considered. In addition, the interval between consecutive activities is assumed to be the gap time, not the time until a specific event occurs. The mathematical formulation of the accelerated failure time model for recurrent event modeling proposed is presented in Equation (18).

$$\mathrm{Y_j} = \log(T_j) = \beta_{0,j} + \beta_j X_j + \tau_j W_j \tag{18}$$

The terms above denote the following:

$T_j =$ gap time to j th event;
$\beta_{0,\mathrm{j}} =$ location parameter of j th gap time model;
$\beta_{\mathrm{j}} =$ regression parameter of j th gap time model;
$\mathrm{X_j} =$ covariates of j th gap time model $(\mathrm{time} - \mathrm{variant})$;
$\tau_{\mathrm{j}} =$ scale parameter of j th gap time model;
$\mathrm{W_j} =$ error term of j th gap time model.

The joint likelihood function for estimation is expressed in Equation (19). $\mathrm{Y_{ij}}$ is an index introduced to consider the sequence of observed events, and $\mathrm{Y_{ij}}$ is equal to 1 if $\mathrm{t_{ij}}$ is the gap time of individual i for j th activity and 0 otherwise.

$$\mathrm{L} = \prod_{i=1}^{n} \prod_{j=1}^{J} \left[\left\{ f_j(t_{ij} \right\}^{\delta_{ij}} \left\{ S_j(t_{ij} \right\}^{(1-\delta_{ij})} \right]^{Y_{ij}} \tag{19}$$

The terms above denote the following:

$i =$ individual $(i = 1,\ 2,\ \cdots,\ n)$;
$j =$ stratum $(j = 1,\ 2,\ \cdots,\ J)$;

δ_{ij} = censoring index (1 if event observed and 0 otherwise);
Y_{ij} = stratum index $\left(1 \text{ if } t_{ij} \text{ is } j \text{ th gap time of inidivdual } i \text{ and } 0 \text{ otherwise}\right)$.

Using this model, multiday activity participations can be analyzed by modeling the intervals between recurrent activities. In addition, since X_j is a time-variant covariate, the model can be called a dynamic model because it can consider the day-to-day-variant activity/travel conditions whenever an activity is performed. Moreover, since the left-censored data can cause various problems in the hazard-based duration model, information on the first activity during the observation period was excluded from the analysis. Accordingly, only the activity histories of those who engaged in the same type of activity at least twice within the observation period were used for the study. Since the right-censored data were also excluded because the attribute of the day the activity was performed could not be considered, only activity data observed within the observation period were used in this study. The strata indicate the order of activity that took place during the observation period for one respondent. They were used as indices for recurrent event modeling, and models were estimated for each stratum. However, since people's activities were conducted before and after the survey period of the study, the strata in this study can be seen as a means of distinguishing activity history data for recurrent event modeling, and sample size for each stratum decreases as the value of stratum increases. In this paper, due to these limitations, research was conducted only for a total of three consecutive activities (Figure 3).

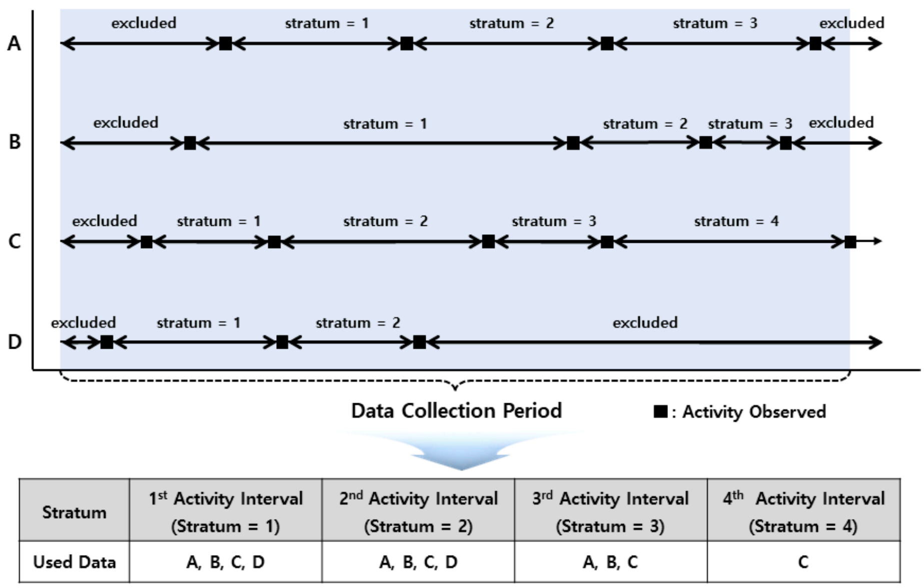

Figure 3. The classification of strata for recurrent event modeling. A–D represents the sample or survey respondents. For example, activity history of respondent A includes 3 activity intervals.

2.3. Data Collection

In this study, we aimed to model the need-based theory using a hazard-based duration model and to identify factors influencing consecutive activity patterns. For this purpose, data including multiday activity history of individuals was required. In addition, this study categorizes five major groups of variables that can influence multiday activity participation patterns. The first group consists of socio-demographic and household attributes. This category, commonly included in most activity/travel behavior-related studies, was incorporated in this study to analyze how multiday activity participation patterns differ among individuals based on their socio-demographic and household attributes. The second group corresponds to attributes of time budgets. Since discretionary activities are mostly carried out in the remaining time after mandatory activity/travel, it was anticipated that an individual's time budget would impact multiday activity patterns. Therefore, in this study, various variables representing time budget were included to determine which ones affect multiday discretionary activity patterns. The third group consists of attributes of space budgets. In this study, it was assumed, for example, that the multiday discretionary activity patterns of a person who lives 10 min away from downtown on foot would differ from those of a person who lives 30 min away from downtown on foot. Various variables representing space budgets were included in the analysis to determine which variables influence multiday activity patterns. The fourth group contains dummy variables for specific days of the week. In this study, these variables were included in the analysis to investigate whether people tend to engage in discretionary activities on specific days or prefer weekdays over weekends, or vice versa. Lastly, there is the group encompassing experience of previous activities. Since this study focuses on recurrent activity patterns, these variables were included in the research to analyze whether experiences and satisfaction from previous activities influence the timing of participation in subsequent activities.

In this study, we employed a time-use survey, among various survey methods, to collect these data. Utilizing a conventional survey approach for collecting multiday activity history data might lead to the collection of information that primarily relies on individuals' memory at the time of the survey, potentially neglecting the actual participation history. Therefore, in this study, we conducted a multiday time use survey, wherein participants responded to surveys daily for several days. However, it is worth noting that conducting a time use survey over multiple days necessitates sustained participation of survey respondents, potentially leading to increased respondent fatigue and a higher probability of errors due to reduced diligence in survey responses. Additionally, the data collection period of this study coincided with the widespread outbreak of COVID-19 in South Korea, making face-to-face surveys impractical. Taking these factors into consideration, we opted for an online time use survey to minimize respondents' fatigue and mitigate the risk of COVID-19 infection.

The time use survey was conducted over a period of 15 days, targeting respondents. This survey method, where respondents record their own consecutive activities and travels during a specific period to collect data, has been used in various fields of research. Data were collected from 306 individuals located in the Seoul metropolitan area, and respondents who faithfully participated in the survey for 15 days were recruited by offering points that could be used like cash in online shopping malls and other areas. While the daily routine survey has the advantage of collecting activity/travel history data from various people, on the other hand, respondents are required to respond to the survey continuously for more than 2 days, which may lead to respondent fatigue. This fatigue may result in inaccurate or omitted information. In this study, to minimize these disadvantages, the survey format was simplified as much as possible to make it as easy as possible for respondents to participate. In addition, the survey was conducted online instead of face-to-face, and every day, SMS messages including the URL of the survey site were sent to respondents to encourage their participation. Furthermore, to prevent data contamination due to dishonest responses, individuals who did not respond to the survey for more than 3 days were excluded from the survey, and new respondents were recruited to conduct the survey. Furthermore, in this study, the survey participants were limited to individuals with regular weekday activities, such as employees and students. The reason for this is that individuals without regular weekday activities do not face time–space constraints, and it was therefore deemed difficult to identify any trends in discretionary activity patterns for them.

Furthermore, in this study, assuming that the multiday discretionary activity patterns of people residing in relatively bustling areas would differ from those residing in less busy areas, accessibility data corresponding to the respondents' ability to travel from their residences to the major downtown area in the Seoul metropolitan area were collected. To gather accessibility data based on the respondents' places of residence for 68 downtown areas located in the Seoul metropolitan area, as reported by the Korea Real Estate Board's "Commercial real estate rental trend survey", automated data-mining techniques were employed. In this study, we utilized the OpenAPI provided by KakaoMap, one of the most widely used online navigation services in South Korea. The origin was set as the center of the administrative spatial unit where the respondents reside, and the destination was designated as the downtown area.

The independent variables constructed based on data collected through this method are presented in Tables 4–8. Moreover, the previously described time use survey and data-mining procedure were conducted in April 2021. However, it should be noted that this period was affected by restrictions on people's participation in discretionary activities due to the spread of COVID-19. Therefore, it is assumed that the activity patterns at present, with COVID-19 being endemic, may differ from those observed during that time.

Table 4. Socio-demographic and household attributes.

No	Variable	Description
1	gender	1 = male, 0 = female
2	age	
3	income	(million KRW/month)
4	educational level	1 = middle school graduated, 2 = high school graduated, 3 = bachelor's degree, 4 = master's degree, 5 = Ph.D
5	living alone	1 = yes, 0 = no
6	living with spouse	1 = yes, 0 = no
7	living with parents	1 = yes, 0 = no
8	living with child (ren)	1 = yes, 0 = no
9	household size	
10	number of children	
11	car ownership	1 = yes, 0 = no
12	commuting mode	1 = transit, 0 = personal mode
13	age dummy	1 = 40 years and older, 0 = younger than 40 years
14	income dummy	1 = more than 3 million KRW/month, 0 = otherwise

Table 5. Attributes of time budget.

No	Variable	Description
1	avg. activity duration	(hours)
2	avg. working time	(hours)
3	avg. commuting time	(hours)
4	number of days worked during data collection period	(days)
5	avg. working time dummy	1 = longer than 9 h, 0 = otherwise
6	avg. commuting time dummy	1 = longer than 45 min, 0 = otherwise

Table 6. Attributes of space budget.

No	Variable	Description
1	avg. travel time to access downtown areas (auto)	(hours)
2	avg. travel time to access downtown areas (transit)	(hours)
3	number of downtown areas accessible within 30 min (auto)	
4	number of downtown areas accessible within 60 min (auto)	

Table 6. *Cont.*

No	Variable	Description
5	number of downtown areas accessible within 30 min (transit)	
6	number of downtown areas accessible within 60 min (transit)	
7	dummy of avg. travel time required to access downtown areas (auto)	1 = longer than 1 h, 0 = otherwise
8	dummy of avg. travel time required to access downtown areas (transit)	1 = longer than 1.5 h, 0 = otherwise

Table 7. Attributes of the day of participating in an activity.

No	Variable	Description
1	working time on the day of participating in an activity	(hours)
2	commuting time on the day of participating in an activity	(hours)
3	the day of participating in an activity (Mon)	1 = Monday, 0 = otherwise
4	the day of participating in an activity (Tue)	1 = Tuesday, 0 = otherwise
5	the day of participating in an activity (Wed)	1 = Wednesday, 0 = otherwise
6	the day of participating in an activity (Thu)	1 = Thursday, 0 = otherwise
7	the day of participating in an activity (Fri)	1 = Friday, 0 = otherwise
8	the day of participating in an activity (Sat)	1 = Saturday, 0 = otherwise
9	the day of participating in an activity (Sun)	1 = Sunday, 0 = otherwise
10	the day of participating in an activity (Weekend)	1 = Weekend, 0 = otherwise
11	dummy of working time on the day of participating in an activity	1 = longer than average, 0 = otherwise

Table 8. Attributes of the previous activity.

No	Variable	Description
1	company of the previous activity	1 = alone, 0 = with others
2	the day of the previous activity (Mon)	1 = Monday, 0 = otherwise
3	the day of the previous activity (Tue)	1 = Tuesday, 0 = otherwise
4	the day of the previous activity (Wed)	1 = Wednesday, 0 = otherwise
5	the day of the previous activity (Thu)	1 = Thursday, 0 = otherwise
6	the day of the previous activity (Fri)	1 = Friday, 0 = otherwise
7	the day of the previous activity (Sat)	1 = Saturday, 0 = otherwise
8	the day of the previous activity (Sun)	1 = Sunday, 0 = otherwise
9	the day of the previous activity (weekend)	1 = weekend, 0 = otherwise
10	duration of the previous activity	(hours)

In this study, the activities performed by the survey respondents were broadly classified into four categories (shopping, social activity, recreational activity, and exercise), and separate models were estimated for each type of activity. The classification of activity types and the descriptive statistics of the collected data are as follows (Tables 9 and 10).

Table 9. Descriptive statistics.

Variable	Number of Observations	Min	Max	Mean	Std.dev
age	306	25	61	40.9	8.29
income		100	1700	388.46	199
household size		1	7	3.58	1.54
number of children		0	4	1.49	1.42
age of the youngest child		-	34	6.57	7.65

Variable		Number of observations	Portion (%)
gender	male	157	51.31
	female	149	48.69
educational level	high school graduate	32	10.45
	bachelor's degree	213	69.61
	master's degree	16	5.23
	Ph.D	45	14.71
car ownership	yes	271	88.56
	no	35	11.44
commuting mode	personal car	165	53.92
	transit	119	38.89
	walk, bicycle	20	6.53
	etc.	2	0.66
housing type	apartment	215	70.26
	studio	34	11.11
	apartment with commercial stores	17	5.56
	villa	22	7.19
	etc.	18	5.88

Table 10. Activity types.

Activity Type	Activities Included	
shopping	• shopping at a shopping mall • shopping at a supermarket	• shopping at a department store • shopping at a traditional market
social activity	• dining with acquaintances • inviting guests • attending a religious gathering	• visiting parents and/or other relatives • attending a party
recreational activity	• eating out with family members • watching musicals (theater) • visiting a concert, museum, art, gallery, fair, etc. • going on a picnic • driving for leisure • going out to take pictures	• watching a movie (at a theater) • studying at language school • watching professional sports game (at stadium) • attending volunteer activity • playing billiards, pool, etc.
exercise	• exercise at gym • individual indoor exercise - Pilates, yoga, etc. • indoor group exercise - CrossFit, squash, etc.	• playing golf • individual outdoor exercise - walking, running, etc. • outdoor group exercise - soccer, basketball, etc.

3. Results

3.1. Shopping

When excluding the influence of all the covariates, the consecutive shopping intervals were observed to be 4.66 days, 3.99 days, and 4.63 days, respectively. It was found that as the duration of the previous shopping trip increased, the interval until the next shopping trip also extended. This suggests that with longer durations of previous shopping trips, individuals are more likely to purchase a relatively greater number of items, leading to a longer interval until the next shopping trip. When interpreted from the perspective of need-based theory, this means that as the duration of the preceding activity increases, the growth speed of the need to shop until the next activity decreases. Additionally, the coefficients for the dummy variables "the day of the week (Wed)" and "the day of the week (Sun)" were found to be negative, indicating that activities were performed prior to these days in spite of an insufficiently cumulated need to shop. This implies a preference for Wednesday and Sunday, leading to engagement in shopping activities even when the need for it has not yet accumulated sufficiently. Moreover, it was observed that individuals with a higher income tended to shop more frequently. In addition, it was found that average commuting time and downtown accessibility via auto do not have statistically significant impacts on recurrent shopping intervals. This means that people's time/space budgets do not influence recurrent shopping patterns, as they must purchase essential items like groceries to maintain their livelihoods.

Income and preference for specific days of the week were found to be statistically significant only in specific strata, whereas, for the previous shopping duration, they were significant in both the first and second strata. Considering that these factors have a greater impact on multiday activity participation patterns as they exhibit statistical significance across more strata, it was observed that in the case of shopping patterns, they are more influenced by prior activity experiences than socio-economic attributes, preference for specific days of the week, and time/space budget (Table 11).

Table 11. Estimation results of AFT model (shopping).

Parameter	1st				2nd				3rd			
	Est	**SE**	**T-Stat**	***p*-Val**	**Est**	**SE**	**T-Stat**	***p*-Val**	**Est**	**SE**	**T-Stat**	***p*-Val**
β_0	**1.5396**	**0.2075**	**7.4212**	**0.0000**	**1.3840**	**0.2410**	**5.7428**	**0.0000**	**1.5322**	**0.4728**	**3.2411**	**0.0014**
τ	**0.5728**	**0.0442**	**12.9598**	**0.0000**	**0.5606**	**0.0563**	**9.9529**	**0.0000**	**0.5439**	**0.0720**	**7.5547**	**0.0000**
duration of the previous activity	**0.1210**	**0.0471**	**2.5686**	**0.0109**	**0.1521**	**0.0599**	**2.5387**	**0.0118**	0.0005	0.1125	0.0046	0.9963
the day of week (Wed)	−0.0427	0.2491	−0.1714	0.8640	−0.2713	0.2489	−1.09092	0.2768	**−0.5326**	**0.3156**	**−1.6876**	**0.0929**
the day of week (Sun)	−0.1886	0.1393	−1.3539	0.1771	**−0.4139**	**0.2040**	**−2.0287**	**0.0437**	−0.1456	0.2805	−0.5192	0.6041
income	**−0.0835**	**0.0359**	**−2.3272**	**0.0208**	−0.0714	0.0482	−1.4836	0.1393	−0.0961	0.0877	−1.0951	0.2746
avg. commuting time dummy	0.1049	0.1583	0.0624	0.50874	0.1054	0.1845	0.5712	0.5685	−0.0274	0.2734	−0.1003	0.9202
dummy of avg. time required to access downtown areas (auto)	0.0455	0.1385	0.3283	0.7430	0.7430	0.2148	0.1205	0.9042	0.3218	0.2749	1.1706	0.2430
Statistical Test	Number of observations according to stratum				110, 61, 34		Log-likelihood value			−204.6186		
	Goodness of fit (ρ^2)				0.0623		AIC, BIC			457.2372, 541.5595		

3.2. Social Activity

When all the covariates were excluded, the consecutive intervals between social activities were approximately 3.46 days, 3.23 days, and 2.78 days. The coefficient for the dummy variable "the day of the week (Tue)" was estimated to be positive, while the coefficient for "the day of the week (Sun)" was estimated to be negative. This suggests a tendency to postpone social activities until Tuesdays and further advance them to Sundays, indicating a preference for engaging in social activities on these days. When interpreting these results based on need-based theory, this means that due to the preference for Tuesday, individuals may postpone participation in activities even when the need has accumulated sufficiently and instead engage in activities on Tuesday. Similarly, due to the preference for Sunday, individuals may participate in activities on Sunday even when the need has not accumulated to the desired level. Additionally, it was observed that as accessibility to downtown areas via public transportation improved, the intervals between social activities shortened. This implies that since social activities are typically engaged in with others, individuals are more likely to participate in social activities in downtown areas with good accessibility. Furthermore, longer average commuting times were associated with longer intervals between social activities, indicating that social activities are influenced by individual time budgets. This means that as accessibility to downtown areas increases, the need growth speed also increases. Conversely, as the average commuting time lengthens, the need growth speed decreases. In summary, the model's estimation confirmed that recurrent social activity participation patterns are more influenced by attributes of time/space budget compared to socio-demographic and household attributes, and this finding contrasts with shopping behavior. This implies that the expansion of transportation infrastructure and advancements in land use may lead to changes in social activity participation patterns.

Accessibility to downtown areas via public transit was found to have statistically significant effects in two strata, unlike other factors like preferences for specific days or time budgets. This implies that social activity patterns are more influenced by accessibility to downtown areas than other factors. Moreover, this result suggests that if the service level of transportation infrastructure improves or land use around an individual's residence becomes more enhanced, the frequency of social activities may increase, indicating a potential increase in derived demand for social activities (Table 12).

Table 12. Estimation result of AFT model (social activity).

Parameter	1st				2nd				3rd			
	Est	**SE**	**T-Stat**	***p*-Val**	**Est**	**SE**	**T-Stat**	***p*-Val**	**Est**	**SE**	**T-Stat**	***p*-Val**
β_0	**1.2404**	**0.1341**	**9.2467**	**0.0000**	**1.1713**	**0.1416**	**8.2746**	**0.0000**	**1.0239**	**0.1355**	**7.5567**	**0.0000**
τ	**0.6335**	**0.036**	**17.6118**	**0.0000**	**0.5901**	**0.0382**	**15.4664**	**0.0000**	**0.5891**	**0.044**	**13.3966**	**0.0000**
the day of week (Tue)	0.0645	0.1566	0.4120	0.6805	**0.3756**	**0.1509**	**2.4883**	**0.0131**	0.1897	0.1617	1.1732	0.2412
the day of week (Sun)	−0.1637	0.118	−1.3869	0.1660	−0.1859	0.1189	−1.5633	0.1185	**−0.3729**	**0.1784**	**−2.0903**	**0.037**
commuting mode	0.1564	0.0987	1.5855	0.1134	0.0711	0.1104	0.6445	0.5195	0.1608	0.1385	1.1609	0.2462
number of downtown areas accessible within 60 min (transit)	**−0.0030**	**0.0033**	**−0.9271**	**0.3543**	**−0.0069**	**0.0033**	**−2.1041**	**0.0358**	−0.0036	0.0039	−0.9192	0.3584
dummy of working time on the day	0.0276	0.1179	0.2343	0.8148	0.1145	0.1209	0.9468	0.3441	0.2129	0.1317	1.6168	0.1065
avg. commuting time dummy	**0.2237**	**0.0965**	**2.3188**	**0.0208**	0.1669	0.1022	1.6329	0.1030	0.0538	0.1264	0.4259	0.6703
Statistical Test	Number of observations according to stratum				189, 143, 103			Log-likelihood value			−457.3659	
	Goodness of fit (ρ^2)				0.0398			AIC, BIC			962.7318, 1068.3778	

3.3. Recreational Activity

When excluding the influence of all covariates, the intervals between consecutive recreational activities were approximately 3.80 days, 2.62 days, and 4.21 days. It was observed that the variability in recreational activity intervals was relatively higher compared to that for shopping and social activities. There was no preference for specific days of the week for recreational activities, and individuals with a higher income appeared to engage in recreational activities more frequently. Furthermore, if the previous recreational activity was carried out on a Sunday, it was found that the interval until the next leisure activity was longer. This implies that, similar to shopping, recreational activity participation patterns are also influenced by the previous activity. This further implies that the day of engagement in the preceding activity and income both influence need growth speed. Generally, when engaging in recreational activities on holidays, the duration of the activities tends to be longer, leading to longer intervals until the next leisure activity. Additionally, it was found that as the average working hours increase, the frequency of leisure activities decreases.

Socio-demographic and household attributes such as income and household size were found to have no statistically significant impacts.

Similar to shopping, multiday social activity patterns were found to be more influenced by the characteristics of the preceding activity compared to other factors. However, unlike shopping, it was observed that the day of week on which the previous activity was conducted had a greater influence than the duration of the preceding activity. Most prior studies did not recognize that the characteristics of the preceding activity affect the timing of the subsequent activity, which can be considered a distinctive aspect of this study (Table 13).

Table 13. Estimation result of AFT model (recreational activity).

Parameter	1st				2nd				3rd			
	Est	**SE**	**T-Stat**	***p*-Val**	**Est**	**SE**	**T-Stat**	***p*-Val**	**Est**	**SE**	**T-Stat**	***p*-Val**
β_0	**1.3356**	**0.1927**	**6.9322**	**0.0000**	**0.9623**	**0.2688**	**3.5794**	**0.0004**	**1.4369**	**0.4157**	**3.4563**	**0.0006**
τ	**0.6858**	**0.0455**	**15.0792**	**0.0000**	**0.6616**	**0.0549**	**12.0459**	**0.0000**	**0.6113**	**0.0609**	**10.0446**	**0.0000**
the day of week (Sun)	−0.1016	0.1329	−0.7644	0.4451	−0.1063	0.1854	−0.5735	0.5667	−0.1929	0.2062	−0.9353	0.3503
income	**−0.0560**	**0.0331**	**−1.6915**	**0.0917**	−0.0324	0.0405	−0.7986	0.4251	−0.0425	0.0576	−0.7370	0.4616
household size	0.0636	0.0451	1.4094	0.1597	**0.1187**	**0.0590**	**2.0124**	**0.0450**	−0.1201	0.0762	−1.5770	0.1158
the day of the previous activity (Sun)	**0.4416**	**0.1666**	**2.6504**	**0.0084**	**0.2899**	**0.1753**	**1.6536**	**0.0992**	0.3044	0.2179	1.3971	0.1633
age dummy	−0.1033	0.1295	−0.7977	0.4256	−0.2138	0.1807	−1.1832	0.2376	−0.1432	0.2019	−0.7094	0.4786
avg. working time dummy	0.0875	0.1313	0.6669	0.5053	0.0189	0.1727	0.1092	0.9131	**0.4781**	**0.1885**	**2.5364**	**0.0117**
Statistical Test	Number of observations according to stratum				133, 85, 53		Log-likelihood value			−302.9391		
	Goodness of fit (ρ^2)				0.0516		AIC, BIC			653.8782, 746.7413		

3.4. Exercise

It was found that β_0, representing the intervals between successive exercises when all covariates were excluded, was not statistically significant. However, the coefficients for the dummy variables indicating exercise on Thursday ("the day of week (Thu)") and Friday ("the day of week (Fri)") were estimated to be negative. This implies a preference for exercising on Thursdays and Fridays, suggesting that individuals tend to exercise earlier in the week. Additionally, higher education levels were associated with lower exercise frequency, and longer average working hours were also linked to lower exercise frequency. In the case of exercise, we found that it was more influenced by an individual's time budget rather than their space budget, as constraints related to activity location were not as significant compared to other activities. This indicates a tendency to engage in exercise on Thursday and Friday, even when the need has not accumulated sufficiently, due to a preference for these days. This also means that education level, the day of engagement in the preceding activity, and average working hours influence the need growth speed until the next activity.

For exercise, it was observed that the model's goodness of fit was relatively higher compared to that of the other activity types, indicating that the multiday exercise pattern is influenced by the independent variables used in this study more than other activities. Specifically, the high preference for Thursday and Friday can be considered to be a result that accurately reflects reality, considering that individuals with full-time jobs were surveyed in this study. However, the lower statistical significance of the parameters determining the probability distribution compared to other activity types can be deemed an area to be clarified through future research (Table 14).

Table 14. Estimation result of AFT model (exercise).

Parameter	1st				2nd				3rd			
	Est	SE	T-Stat	p-Val	Est	SE	T-Stat	p-Val	Est	SE	T-Stat	p-Val
β_0	0.0469	0.3929	0.1193	0.9051	0.6222	0.5600	1.1111	0.2671	−0.3270	0.6744	−0.4848	0.6280
τ	**0.6100**	**0.0418**	**14.6085**	**0.0000**	**0.6086**	**0.0488**	**12.4693**	**0.0000**	**0.6459**	**0.0562**	**11.4968**	**0.0000**
the day of week (Thu)	**−0.9421**	**0.1576**	**−5.9786**	**0.0000**	**−0.4158**	**0.1947**	**−2.1358**	**0.0332**	−0.1938	0.2442	−0.7936	0.4278
the day of week (Fri)	**−1.0467**	**0.1954**	**−5.3558**	**0.0000**	**−0.6298**	**0.2392**	**−2.6332**	**0.0088**	−0.5046	0.5233	−0.9643	0.3354
education level	**0.3226**	**0.0926**	**3.4844**	**0.0005**	0.1217	0.1518	0.8016	0.4232	**0.3186**	**0.1626**	**1.9597**	**0.0507**
the day of the previous activity (Fri)	−0.1850	0.1859	−0.9949	0.3203	**−0.5448**	**0.2387**	**−2.2829**	**0.0229**	**−0.5031**	**0.2446**	**−2.0573**	**0.0402**
avg. working time	**0.0650**	**0.0312**	**2.0808**	**0.0380**	0.0373	0.0314	1.1862	0.2362	0.0535	0.0397	1.3474	0.1785
dummy of working time on the day	−0.2266	0.1405	−1.6132	0.1074	0.0907	0.1581	0.5738	0.5664	−0.1924	0.1634	−1.1779	0.2395
Statistical Test	Number of observations per stratum				124, 89, 73		Log-likelihood value			−300.7653		
	Goodness of fit (ρ^2)				0.1003		AIC, BIC			649.5307, 748.8361		

3.5. Summary and Remarks

In this study, discretionary activities were categorized into four activity types, and factors influencing the intervals between recurrent activities were identified by creating AFT models. The random variable was assumed to follow an extreme value distribution, and the coefficients determining the shape of the probability density function were statistically estimated. The model estimation results revealed that even after excluding the influence of covariates, the need growth speed for consecutive activities varied over time for all activity types. Furthermore, it was observed that there was a preference for specific days of the week across all activity types. For shopping, social activities, and recreational activities, there was a tendency for people to prefer engaging in these activities on the weekend, while for exercise, a preference for Thursday and Friday was noted.

Additionally, attributes of time/space budget were found to have statistically significant effects on recurrent activity participation patterns for most activity types. However, the consistency of such an influence was not entirely clear. For shopping, although it is a discretionary activity, it is also a necessary activity for livelihoods, and thus it was found to be less influenced by time/space budgets. This suggests that apart from shopping, other activity types may also exhibit changes in activity participation patterns due to factors like expanded transportation infrastructure and improved land use. This indicates that total activity demand may change due to the implementation of transportation and urban-related plans and projects.

Furthermore, for shopping and recreational activities, it was found that the experience of the previous activity influenced the need growth speed until the next activity. In the case of shopping, it was observed that the longer the duration of the previous shopping trip, the lower the need growth speed until the next shopping trip. As for recreational activities, the day of the week on which the preceding activity was performed was found to affect the need growth speed until the next activity. In addition, we consider the finding that the characteristics of the preceding activity influence the timing of the subsequent activity to be a unique quality of this study, as it has not been previously presented in existing research. While the overall goodness of fit of the models was not high enough, the fact that most model estimation results aligned with common sense implies a contribution to quantitatively analyzing the general knowledge presented in this paper.

4. Discussion

As society advances and various technologies are developed to enhance people's convenience in executing various tasks, the overall intensity of people's work has decreased. As a result, people's leisure time has increased. Due to these changes, people are now spending their extended time–space budgets in different ways compared to previous periods, leading to a shift in their activity/travel patterns. Therefore, this study analyzed the patterns of how people spend their leisure time and identified the factors influencing them. Data were collected through lifestyle surveys, utilizing a multi-day analysis method considering the characteristics of leisure activities. The need-based theory proposed in previous studies was set as the theoretical background, and a hazard-based duration model, which aligns with this theory, was employed. The research results showed that people's patterns of consecutive activity participation are influenced by socio-economic attributes, time–space budgets, and previous activity experiences. Additionally, preferences for specific days of the week varied depending on the type of activity. Shopping exhibited a different trend compared to other activity types, likely due to its necessity for livelihood. In more detail, the correlation between socio-economic attributes and multiday activity participation patterns can be explained as follows: It was found that multiday shopping and recreational activity participation patterns are influenced by socio-economic attributes, such as income and household size. Additionally, exercise patterns were observed to be influenced by educational level, while social activity patterns were not found to be influenced by socio-economic attributes. The correlation identified in this study between socio-economic attributes and multiday activity participation patterns may contribute to explaining variations in patterns based on the demographic composition of specific regions or communities.

The correlation identified in this study between time–space budgets and people's activity patterns is expected to be applied and utilized in various fields. At first, this study has demonstrated the correlation between the identified time/space budget and multiday activity participation patterns, establishing the presence of induced demand for activities. It is anticipated that this finding can be applied in the field of transportation demand forecasting and feasibility study of transportation projects. In this study, we have established that the time/space budget, i.e., activity/travel conditions, can influence multiday activity participation patterns. This contradicts the fundamental assumptions in most transportation projects' feasibility studies and travel demand forecasting. Typically, in most cases, it is assumed that even after a transportation project is completed, the total travel demand remains unchanged. However, the results of this study demonstrated the opposite phenomenon: if activity/travel conditions are improved, there can be an increase in activity frequency. Therefore, the findings of this study are expected to be applicable not only in research but also in practical applications. Furthermore, the correlation between time/space budgets and multiday activity participation patterns demonstrates potential applicability in establishing regional balanced development policies. The fundamental goal of regional balanced development is to enhance regional competitiveness through investment in small and medium-sized cities, a goal that recent paradigms like mega-cities also share. As suggested in this study, if improvements in activity/travel conditions lead to an increase in people's activity frequency, incorporating this insight into the establishment of policies related to regional balanced development could allow for a quantitative analysis of the effects on local economic development resulting from the facilitation of leisure activities within a city. This is expected to promote the implementation of transportation projects in suburban areas and enhance the impact of policies related to regional balanced development. Lastly, this study has demonstrated that experiences from previous activities influence subsequent activities, a finding that can directly inform panel data analysis. Furthermore, considering that most activity-based models are limited to analyzing daily activities, factors like preferences for specific days could contribute to extending existing activity-based models.

Nevertheless, we deem it necessary to consider additional factors in order to enhance the goodness of fit of the models estimated in this study. Firstly, people's social networks can be included. Since discretionary activities are often conducted in the company of others, it appears that individuals' social networks may have a relatively significant influence on recurrent discretionary activity participation patterns. To address this, collecting SNS-related data, commonly utilized in recent studies, and subsequently reconstructing or expanding the model to align with these data are necessary. Secondly, individual activity preferences might play a crucial role. As discretionary activities are not obligatory, the corresponding participation patterns may vary based on individual preferences. To account for this, conducting surveys on individual activity preferences and utilizing latent variable models, among other methods, seems promising. While these factors were not taken into consideration in this study due to limitations in the data collection methods, it is anticipated that incorporating these aspects into future research will enhance the reliability of further analyses.

As mentioned earlier, the data used in this study were collected in April 2021, and they suffer from limitations due to the spread of COVID-19, which might have led to differences in people's discretionary activity patterns compared to the current patterns. Future research that can complement this dataset and compare it with the results of this study is expected to provide broader insights. Additionally, due to limitations in the data collection period, this study only investigated three consecutive activities. This posed a limitation in that as a stratum increased, the sample size of this stratum decreased. Therefore, there is a need to devise data collection and processing methods that can address this issue. Furthermore, considering that obtaining reliable estimates in hazard-based duration models requires a large sample size, it is anticipated that conducting a study with a data set of an even larger sample size than what was collected in this research would lead to more dependable research results.

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