Flexible MDCEV Approach to Analyze Place-of-Visit and Time-Spent Behaviors of Visitors in Downtown Kumamoto

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Abstract: Accurate evaluation of a downtown-redevelopment program requires careful analysis of visitor behavior. This paper presents a flexible multiple discrete–continuous extreme-value (MDCEV) approach to analyze the place-of-visit and time-spent behaviors of downtown visitors. This approach was applied to smartphone-based survey data obtained from 825 people visiting downtown Kumamoto during the weekends of November and December 2013. The results reveal the effects of visitor attributes (age, gender, purpose, and travel mode) on their place-of-visit and time-spent behaviors. Compared to the conventional MDCEV model, the flexible model successfully describes the difference between the effect of these attributes on the discrete (place-of-visit) and continuous (duration-of-stay) preferences of visitors. Moreover, the flexible model provides a superior staying-time distribution, and it can be easily adapted to perform similar analyses for other cities around the world.

Keywords: Travel behavior, Flexible MDCEV model, Smartphone-based survey, GPS data

1. INTRODUCTION

Redevelopment programs for downtown areas in major provincial Japanese cities have attracted increased attention owing to the recent decline in visitor count therein. Accordingly, large-scale redevelopment of downtown Kumamoto was launched in the autumn of 2019. For accurate evaluation of such redevelopment plans, it is crucial to examine the changes in visitors' time-usage patterns in these areas before and after plan execution.

Traditionally, paper-based questionnaire surveys have been used to collect and examine visitor behaviors. However, this method has several limitations: it is difficult to collect accurate information regarding the visitors' time usage, places of visit, and route choices via paper-based surveys. To address this problem, global positioning system (GPS)- and smartphone-based surveys have been proposed and performed (Asakura *et al*., 2014; Chen *et al*., 2016; Gadziński, 2018; Wang *et al*., 2018). Accordingly, we performed a smartphone-based visitor-behavior survey in downtown Kumamoto during the weekends of November and December 2013 (Maruyama *et al*., 2015). Using the survey data, several studies have examined visitor behaviors and observed a certain behavioral pattern of visitors (Ishino et al., 2015; Sato & Maruyama, 2015, 2016). However, the unique methods suitable for analyzing these data need further development.

Several studies involving paper-based interviews have examined visitor behaviors in downtown Kumamoto. Araki *et al*. (2015) proposed a model for describing visitor behavior by sequentially combining a nested logit model of destination choice with an activity-duration model. Their model determines the visitors' destination and shop choices by considering the

street attractiveness (Mizokami *et al*., 2012) and shop size, respectively. Although these features holistically describe visitor behaviors, their implementation in practice requires further information, which might be unavailable.

Taketa *et al*. (2018) analyzed visitor behaviors in downtown Kumamoto using the conventional multiple discrete–continuous extreme-value (MDCEV) model. The model uses time-allocation data to describe the place-of-visit (zone) and duration-of-stay (time) behaviors of visitors simultaneously. The MDCEV modeling approach (Bhat, 2005; Bhat, 2008) is widely used for analyzing time-usage behaviors, and several applications have been previously reported (Chikaraishi et al., 2010; Fukuda & Chikaraishi, 2013; Jara-Díaz & Rosales-Salas, 2017; Abdul Rawoof Pinjari & Bhat, 2010; Watanabe *et al*., 2021). However, to the best of our knowledge, except for Taketa *et al*. (2018), this model has not yet been employed by any researcher to analyze the zone- and time-preference behaviors of people visiting downtown areas. However, this conventional model requires the zone and time choices to be modeled simultaneously using a single utility function. Thus, their proposed model might be extremely simple to represent the actual visitor behaviors.

A flexible MDCEV model was proposed by Bhat (2018) as an extension of the conventional model to overcome its issues. Subsequently, this study proposes the use of the flexible MDCEV model to analyze the place- and time-choice behaviors of visitors in downtown Kumamoto. The proposed model is based exclusively on GPS tracking data. The aims of this study were to 1) identify and understand the factors influencing the visitors' place- and time-choice behaviors in downtown areas using a flexible MDCEV model with smartphone-based survey data, and 2) to compare the performances of the conventional and flexible MDCEV models.

The remainder of this paper is organized as follows. Section 2 describes the model. Section 3 provides an overview of the study area and smartphone-based visitor survey. Section 4 presents and discusses the results obtained in this study. Finally, Section 5 lists major conclusions drawn from this study.

2. MODEL

This study analyzes the visitors' time-usage behaviors in downtown Kumamoto by examining their allocation of a 24-h duration to certain places within the downtown area. The conventional and flexible MDCEV models were employed to describe the visitors' place- and time-choice behaviors in the selected zones.

2.1 Conventional MDCEV Model

The conventional MDCEV model assumes individuals to choose the time $\boldsymbol{t} = (t_1, \dots, t_K)$ that they wish to spend in a given zone to maximize the total utility $U(\boldsymbol{t})$ under a given time constraint (i.e., $\sum_{k=1}^{K} t_k = T$) (Bhat, 2005, 2008). The utility function can be evaluated as

$$\begin{gathered} U(\boldsymbol{t}) = \frac{1}{\alpha_1}\psi_1 t_1^{\alpha_1} + \sum_{k=2}^{K}\frac{\gamma_k}{\alpha_k}\psi_k\left\{\left(\frac{t_k}{\gamma_k}+1\right)^{\alpha_k} - 1\right\}, \\ \psi_1 = \exp(\varepsilon_1), \\ \psi_k = \exp(\beta' z_k + \varepsilon_k),\ k = 2,3,\dots K, \end{gathered} \tag{1}$$

where ψ_k denotes the marginal utility, α_k and γ_k denote saturation parameters, ε_k denotes the error term and follows an independent and identically distributed (IID) Gumbel distribution with the scale parameter fixed to 1, z_k denotes a vector of explanatory variables corresponding to a given zone k with parameter vector β', and K denotes the total number of options. For computational efficiency, we considered $\alpha_k = 1$ and $\gamma_k = 0$ in this study. Therefore, the revised utility function can be expressed as

$$U(\boldsymbol{t}) = \psi_1 \ln t_1 + \sum_{k=2}^{K} \psi_k \ln(t_k + 1). \tag{2}$$

Equation (3) describes the resulting simultaneous choice probability when M zones are chosen from K zones and times $\boldsymbol{t}^*$ are allocated to these M zones. The corresponding utility function V_k is described in Eq. (4).

$$\mathrm{P}(t_1^*, t_2^*, \dots, t_M^*, 0, \dots, 0) = \left[\prod_{m=1}^{M} f_m\right] \left[\sum_{m=1}^{M} \frac{1}{f_m}\right] \left[\frac{\prod_{m=1}^{M} e^{V_m}}{\left(\sum_{k=1}^{K} e^{V_k}\right)^M}\right] (M-1)!, \tag{3}$$

$$f_m = \frac{1}{t_m^* + 1},$$

$$V_1 = -\ln(t_1^*)$$

$$V_k = \beta' z_k - \ln(t_k^* + 1), k = 2,3, \dots, K. \tag{4}$$

where $m\ (m = 1,2, \dots, M | M \in K)$ denotes the chosen zone.

The time allocation framework employed in the MDCEV models defines the time spent outside the downtown area as the time consumed for the outside good $(k = 1)$. Downtown Kumamoto is divided into six zones; thus, $K = 7$ (i.e., six zones plus the outside good). Note that the proposed-model framework neglects the order in which people visit the different zones and their behavioral changes over time. Additionally, the consideration of the IID error term ε_k implies the independence of the six zones.

2.2 Flexible MDCEV Model

Similar to its conventional counterpart, the flexible MDCEV model assumes individuals to maximize the following utility function within the time constraint (Bhat, 2018).

$$U(\boldsymbol{t}) = \psi_1 t_1 + \sum_{k=2}^{K} \gamma_k \left([\psi_{kd}]^{1(t_k=0)} \times [\psi_{kc}]^{1(t_k>0)}\right) \ln\left\{\left(\frac{t_k}{\gamma_k} + 1\right)\right\}. \tag{5}$$

where γ_k denotes the saturation parameter associated with the time t_k spent in zone k, ψ_{kd} denotes the discrete-choice component, and ψ_{kc} denotes the continuous-choice component. The index "$1(t_k = 0)$" equals 1 if $t_k = 0$; else, it equals zero. Similarly, the index "$1(t_k > 0)$" equals 1 if $t_k > 0$; else, it equals zero. The discrete- and continuous-choice components represent marginal utility so that, if zone k is not chosen, an infinitesimally small time is allocated to zone k. It is noteworthy that in the flexible MDCEV model, the conventional marginal utility ψ_k described in Eq. (1) is divided into two components, as defined in Eq. (6).

$$\psi_{kd} = \exp(\beta' z_k + \varepsilon_k), \quad \psi_{kc} = \exp(\theta' w_k + \xi_k), \tag{6}$$

where z_k and w_k denote the explanatory-variable vectors corresponding to zone k, while β' and θ' denote unknown parameters. The error terms ε_k and ξ_k follow the IID Gumbel distribution with scale parameter σ. The simultaneous choice probability of selecting M zones out of K options and allocating time t^* to these M zones can be evaluated using Eq. (7). Equation (9) describes the utility functions $\tilde{V}_{k,1}$ and $\overleftrightarrow{V}_{k,1}$.

$$\begin{aligned}
&P(t_1^*, t_2^*, \dots, t_{M+1}^*, 0, \dots, 0) \\
&= |J| \int_{\eta_2=\tilde{V}_{2,1}}^{\eta_2=\infty} \cdots \int_{\eta_{M+1}=\tilde{V}_{M+1,1}}^{\eta_{M+1}=\infty} \int_{\eta_{M+2}=-\infty}^{\eta_{M+2}=\tilde{V}_{M+2,1}} \cdots \int_{\eta_K=-\infty}^{\eta_K=\tilde{V}_{K,1}} f(\eta_2, \eta_3, \dots, \eta_K; \overleftrightarrow{V}_{2,1}, \overleftrightarrow{V}_{3,1}, \dots, \overleftrightarrow{V}_{M+1,1}) d\eta_K d\eta_{K-1}, \dots d\eta_2 \\
&= |J| \left[\sum_{S \subset \{2,3,\cdots M+1\}, |S| \geq 1} \begin{array}{c} G_{K-1}(\overleftrightarrow{V}_{21}, \overleftrightarrow{V}_{31}, \dots, \overleftrightarrow{V}_{M+1,1}, \tilde{V}_{M+2,1}, \dots, \tilde{V}_{K,1}) + \\ (-1)^{|S|} G_{K-1+|S|}(\overleftrightarrow{V}_{21}, \overleftrightarrow{V}_{31}, \dots, \overleftrightarrow{V}_{M+1}, \tilde{V}_{M+2,1}, \dots \tilde{V}_{K,1}, \tilde{\boldsymbol{V}}_{\boldsymbol{S},\boldsymbol{1}}) \end{array} \right],
\end{aligned} \tag{7}$$

where $|J| = \prod_{m=2}^{M+1} f_m$, $f_m = \frac{1}{t_m^* + \gamma_m}$,

$$G_{K-1}(\overleftrightarrow{V}_{21}, \overleftrightarrow{V}_{31}, \dots, \overleftrightarrow{V}_{M+1,1}, \tilde{V}_{M+2,1}, \dots, \tilde{V}_{K,1}) = \left(\frac{M!}{\sigma^M} \times \frac{\prod_{k=2}^{M+1} e^{\frac{-(\overleftrightarrow{V}_{k1})}{\sigma}}}{\left(1 + \sum_{k=2}^{M+1} e^{\frac{-(\overleftrightarrow{V}_{k1})}{\sigma}} + \sum_{k=M+2}^{K} e^{\frac{-(\tilde{V}_{k1})}{\sigma}}\right)^{M+1}} \right), \text{and}$$

$$\begin{aligned}
&G_{K-1+|S|}(\overleftrightarrow{V}_{21}, \overleftrightarrow{V}_{31}, \dots, \overleftrightarrow{V}_{M+1,1}, \tilde{V}_{M+2,1}, \dots \tilde{V}_{K,1}, \tilde{\boldsymbol{V}}_{\boldsymbol{S},\boldsymbol{1}}) \\
&= \left(\frac{M!}{\sigma^M} \times \frac{\prod_{k=2}^{M+1} e^{\frac{-(\overleftrightarrow{V}_{k1})}{\sigma}}}{\left(1 + \sum_{k=2}^{M+1} e^{\frac{-(\overleftrightarrow{V}_{k1})}{\sigma}} + \sum_{k=M+2}^{K} e^{\frac{-(\tilde{V}_{k1})}{\sigma}} + \sum_{m \in S} e^{\frac{-(\tilde{V}_{m1})}{\sigma}}\right)^{M+1}} \right).
\end{aligned} \tag{8}$$

In eqs. (7) and (8),

$$\tilde{V}_{k,1} = \beta' z_1 - \beta' z_k, \text{ and } \overleftrightarrow{V}_{k,1} = \beta' z_1 - \theta' w_k + \ln\left(\frac{t_k^*}{\gamma_k} + 1\right) \quad (k = 2, 3, \dots, K). \tag{9}$$

In the above equations, S represents a specific combination of selected zones while $|S|$ denotes its corresponding cardinality. The values of parameters $\beta', \theta', \gamma', \sigma$ could be estimated using the usual maximum likelihood estimation method because the choice probability is expressed in the closed-form, as described in Eq. (7). It is noteworthy that the values of the saturation and scale parameters (γ' and σ, respectively) were set to unity in this study to simplify the estimation.

In the conventional MDCEV formulation, the outside good was assumed satiated because the utility function in Eq. (2) contains the term $\ln t_1$. Contrarily, the flexible MDCEV model assumes no satiation of the outside good via the application of a linear utility function for the time spent on the outside good, as described in Eq. (5). In addition to the separated marginal utilities—ψ_{kd} and ψ_{kc}—because of no satiation of the outside good, the flexible MDCEV model can distinguish between the discrete- and continuous-choice components.

2.3 Validation Procedure

The conventional and flexible models were validated using the actual time-spent distribution. The conventional MDCEV model was validated using the forecasting algorithms proposed by Pinjari and Bhat (2012). The flexible MDCEV model was validated using one of the three forecasting models proposed by Bhat (2018). The following steps were performed for validation.

Step 1: Index all possible zone combinations by l $(l = 1, 2, \ldots, L)$, where $L = (2^{K-1} - 1)$.
Step 2: Draw K independent realizations for each alternative, including the outside good, from the extreme value distribution considering the location and scale parameter values of zero and unity (labeled as $\mathrm{EV}\ (0, 1)$), respectively.
Step 3: If $\varepsilon_1 < \varepsilon_k - \tilde{V}_{k,1}$, the selection of zone k is confirmed; else, zone k is not selected.
Step 4: Construct $W_{k,1}|\varepsilon_{1l} = \theta' w_k - \varepsilon_{1l}$ only for the selected zones using ε_{1l} and θ'.
Step 5: Draw another set ξ_{kl} of independent realizations for the selected zones in combination l while considering $\mathrm{EV}(0, 1)$.
Step 6: Simulate the time-spent levels for each selected zone in combination l using the relation $t_{kl}^* = \left(\exp(\xi_{kl}) \times \exp\left(W_{k,1}|\varepsilon_{1l}\right) - 1\right)$. For the realization set in combination l, confirm whether the total time spent is less than the time constraint T (24 h) considered in this study. Each time-spent component must exceed zero. If these conditions are not satisfied, reject the corresponding realization and repeat Step 5.
Step 7: Repeat Steps 2–6 for each combination l until all realizations are obtained.
Step 8: Calculate the discrete choice probability P_l for combinations of l using the below equation.

$$\begin{aligned} P_l(d_2 = 1, \ldots d_{M+1} = 1, d_{M+2} = 0, d_{M+3} = 0, \ldots\ d_K = 0) \\ = F_{K-M-1}\left(\tilde{V}_{M+2,1}, \tilde{V}_{M+3,1}, \ldots \tilde{V}_{K-1,1}, \tilde{V}_{K,1}\right) + \\ \sum_{S \subset \{2,3,\cdots M+1\}, |S| \geq 1} (-1)^{|S|} F_{K-M-1+|S|}\left(\tilde{V}_{M+2,1}, \tilde{V}_{M+3,1}, \ldots \tilde{V}_{K,1}, \tilde{\boldsymbol{V}}_{\boldsymbol{S},\boldsymbol{1}}\right). \end{aligned} \tag{10}$$

Step 9: The time spent in each zone k is forecasted using the relation $t_k^* = \sum_l P_l t_{kl}^*$.

3. DATA

3.1 Smartphone-based Survey

During the smartphone-based survey performed in this study, all participants were requested to install the designated application on their smartphones and activate GPS location tracking during their visit to downtown Kumamoto. The data collected from the participants include their gender, age, employment status, residential address, travel mode to downtown, and companion information. All participants were awarded a gift certificate equivalent to ¥500 for their participation in this study. The sample dataset comprised 1,086 survey entries collected in six days. After filtering for missing variables, the final dataset comprised 825 samples. The survey details, including the attribute distribution of survey participants, have been reported by Ishino *et al*. (2015) and Maruyama *et al*. (2015).

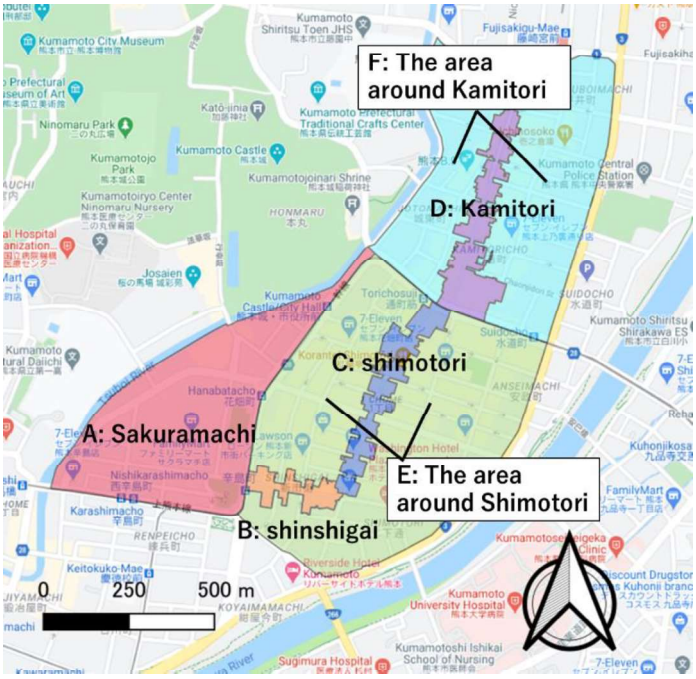


Figure 1. Target area and its zonal classification
Source: Google map

3.2 Study area

The target area of downtown Kumamoto was divided into six zones (Figure 1). This is less than the eight zones considered in our previous study (Taketa et *al*., 2018). Six zones were considered to reduce the computational complexity of the proposed flexible MDCEV model. Each zone illustrated in Figure 1 can be described as follows (all information provided is true as of 2013).

Zone A: "*Sakuramachi*" included a bus terminal and department store (*Kenmin Hyakkaten*) that was popular among the elderly population in 2013. In 2019, the bus terminal and department store were renovated, and a new shopping complex was inaugurated in this zone.

Zone B: "*Shinshigai*" included an arcade street offering several entertainment facilities, such as *pachinko* parlors and *karaoke* clubs. Moreover, it hosted the only movie theater in downtown Kumamoto.

Zone C: "*Shimotori*" was included the main arcades in downtown Kumamoto. It comprised fast-food outlets, fashion and clothing stores, and entertainment facilities, all of which are popular among young people.

Zone D: "*Kamitori*" hosted two arcades—*Kamitori* and *Namikizaka*—in the northern part of downtown Kumamoto. The *Kamitori* arcade is lined with clothing stores and well-established Japanese sweet stores. The *Namikizaka* Street has several small shops selling Japanese confectionery, stationery, and secondhand clothing.

Zone E: The area around "*Shimotori*" hosted a large department store (*Tsuruya*) and the Kumamoto City hall. While the western *Shimotori* area was mostly lined with office buildings, several restaurants operated on the east and west sides of the *Shimotori* Street. These restaurants attracted more business at night than during daytime.

Zone F: The area around "*Kamitori*" covered the northern part of downtown Kumamoto around the *Kamitori* Street. East *Kamitori* included restaurants, boutiques, beauty salons, banks, and large hotels, whereas west *Kamitori* comprised well-established hotels, live houses, and boutiques.

Because each above-described zone offers unique attractions to visitors, people are expected to visit downtown Kumamoto for different purposes and spend their time in different ways. We examined these trends in this study.

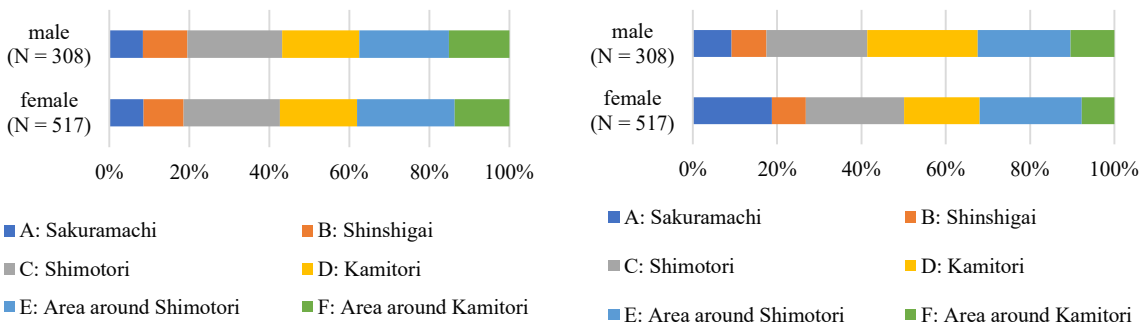
4. RESULTS AND DISCUSSION

4.1. Descriptive Analysis

This section describes the relationship between the total visitor count as well as their average time spent and individual attributes of each zone. This facilitates appropriate model selection and consideration of appropriate explanatory variable candidates in the model. In cases involving different trends of zone and time-spent behaviors, the use of the flexible MDCEV model, which can express the discrete and continuous preferences separately, is more beneficial. If no such difference is detected, the conventional MDCEV model may suffice to describe visitor behavior.

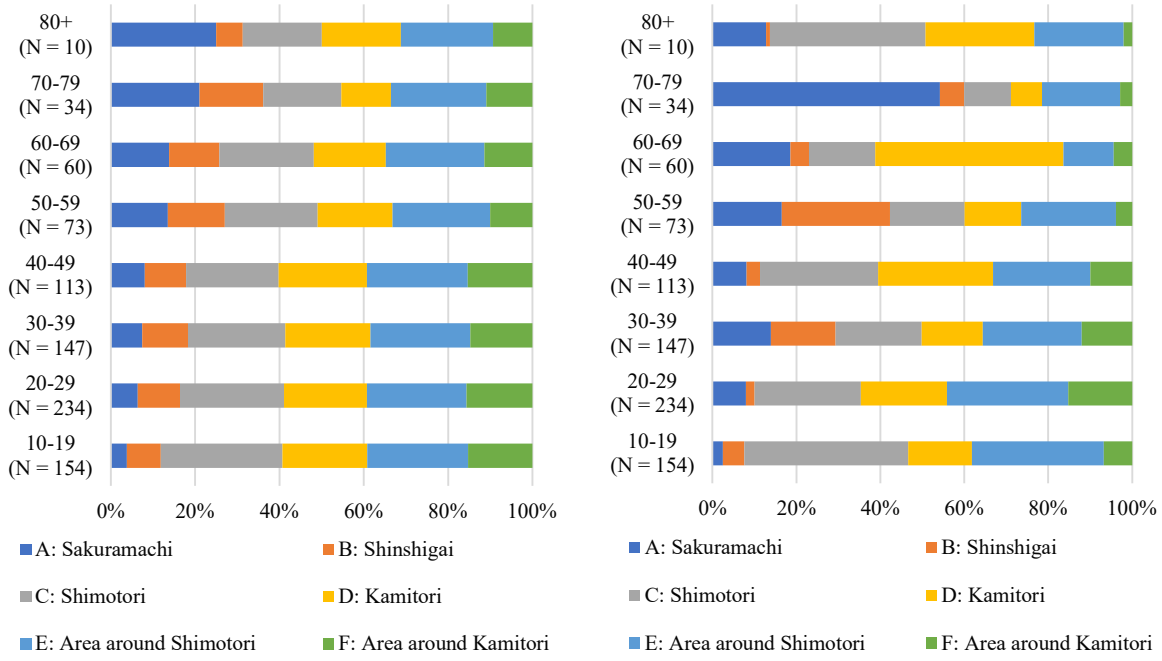
Figure 2 depicts the gender distribution of visitors to the different zones and their average time spent therein. Although the observed gender difference in terms of visitor count is negligible, the time spent by female visitors in zone A exceeds that in zone B. Meanwhile, male visitors spent more time in zone D. As observed, women spent more time in the department store in zone A while men stayed longer in the *pachinko* parlors in zone B.

Figure 3 depicts the age distribution of visitors to the different zones and their average time spent therein. As can be seen, visitors in their seventies, teens, as well as thirties and fifties spent more time in zones A, C, and B, respectively. Elderly visitors spent more time in the *Kenmin* department store in zone A. The youngsters (teens) spent more time in fast-food shops, cafes, and karaoke shops in zone C. Likewise, middle-aged visitors spent more time in the *pachinko* parlors in zone B. Figure 4 depicts the distribution of visiting-purpose. As observed, people visiting for entertainment purposes stayed longer in zones C and E to engage in activities available therein.



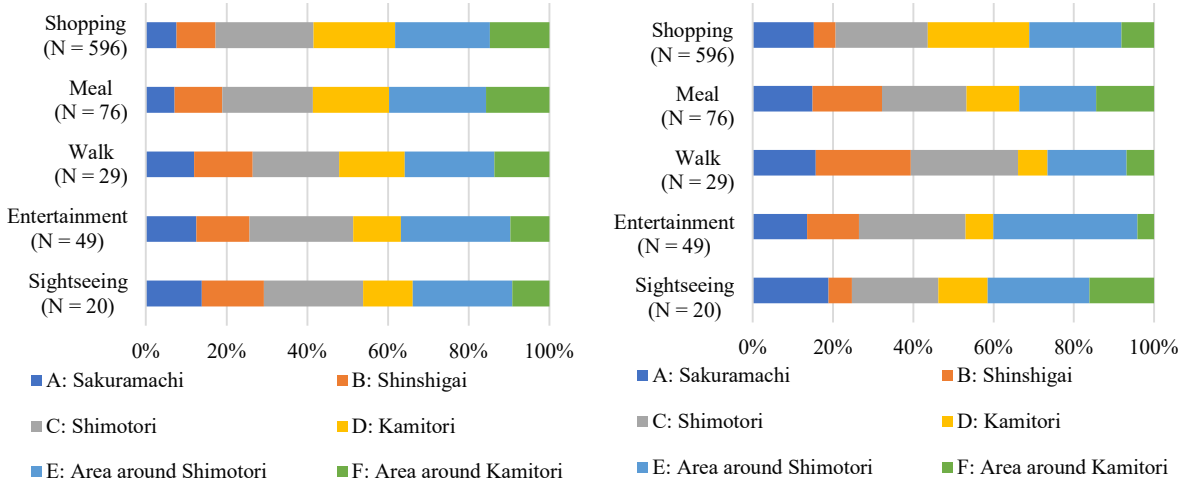
(a) Total visitor count (b) Average time-spent trend

Figure 2. Visitor gender distribution and average time spent in different zones



(a) Total visitor count (b) Average time-spent trend

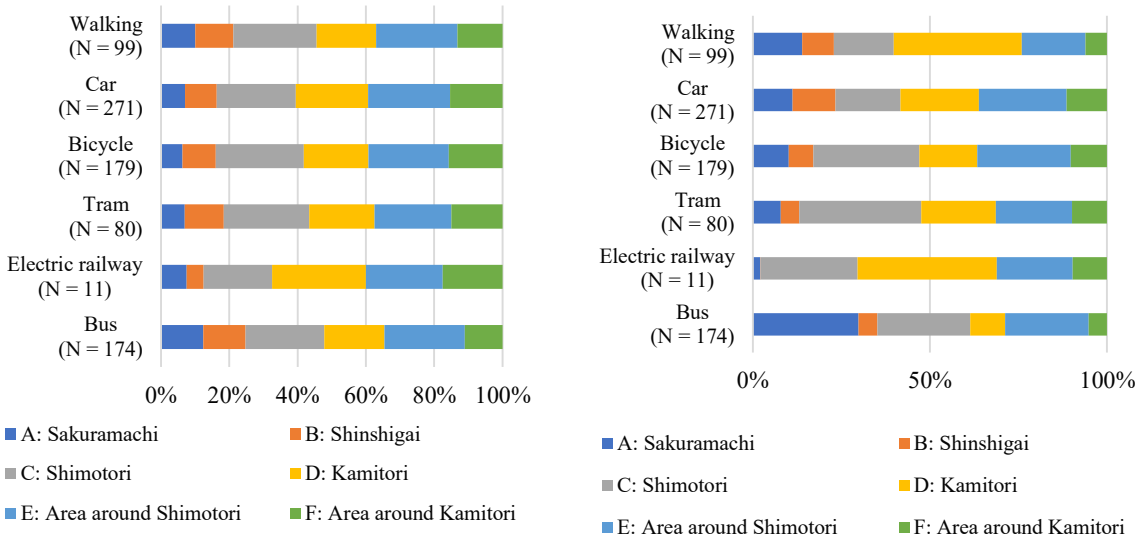
Figure 3. Visitor age distribution and average time spent in different zones



(a) Total visitor count (b) Average time-spent trend

Figure 4. Visiting-purpose distribution and average time spent in different zones

Figure 5 depicts the visitors' travel-mode distribution. As observed, bicycle riders, bus travelers, and pedestrians spent more time in zones C, A, and D, respectively. The availability of a bus terminal in zone A afforded greater convenience to visitors traveling by bus, thereby resulting in their greater time spent therein.



(a) Total visitor count (b) Average time-spent trend

Figure 5. Visitors' travel-mode distribution and average time spent in different zones

4.2. Estimation Results obtained using Conventional and Flexible MDCEV Models

The values of parameters pertaining to the conventional and flexible MDCEV models were estimated considering individual attributes, as shown in Table 1. Further, the estimation results are listed in Table 2. When employing the conventional model, the positive and significant parameter values indicate a higher preference of the corresponding zones among visitors and longer times spent therein. In the flexible model, the same inference can be drawn from similar values obtained for parameters corresponding to the discrete (zone) and continuous (time) components. To facilitate a performance comparison, the estimations of both models involved consideration of identical explanatory variables. The variables that were statistically insignificant in both models were excluded; thus, each zone had a different set of dummy variables.

In zone A, the values of the age- and bus-dummy variables remained significantly positive when employing both MDCEV models. The gender dummy was not statistically significant in the conventional model. Contrarily, in the proposed flexible model, the gender dummy was negative and significant only for continuous component. This indicates that the elderly visitors and those traveling by bus preferred zone A and stayed longer therein. Additionally, despite their low preference for this zone, females spent more time therein.

In zone B, the age-dummy variable remained positive and significant in the conventional model as well as both components of the flexible model. The entertainment dummy remained positive and significant in the continuous component of the flexible model. This indicates that elderly visitors demonstrated a higher preference for zone B and stayed longer therein. Moreover, entertainment seekers spent more time in zone B irrespective of their zone preference.

Zone C revealed negative values of the streetcar dummy (discrete component) and the student dummy (discrete and continuous components) when the flexible model was employed. Meanwhile, zone D revealed positive values for the shopping dummy (discrete and continuous components) and positive and significant values for electric-railway dummy (continuous component) when employing the flexible model. In zone E, the age dummy was positive and statistically significant in the conventional and flexible MDCEV models. Specifically, the results of the flexible model show that the age dummy affects both discrete and continuous components. Thus, the elderly appears to visit zone E and spend more time there.

Table 1. Explanatory variable definitions

Variable	Definition
Gender	1 if the participant is male and 0 otherwise
Age	Age of the participant
Student dummy	1 if the participant is a student and 0 otherwise
Tram dummy	1 if the travel mode is tram and 0 otherwise
Bus dummy	1 if the travel mode is bus and 0 otherwise
Electric railway dummy	1 if the travel mode is electric railway and 0 otherwise
Entertainment dummy	1 if the visiting purpose is entertainment and 0 otherwise
Shopping dummy	1 if the visiting purpose is shopping and 0 otherwise

Table 2. Estimation results obtained using the conventional and proposed MDCEV models

		Conventional MDCEV			Flexible MDCEV					
					Discrete choice			Continuous choice		
Zone	Explanatory variable	Coeff	t-stat		Coeff	t-stat		Coeff	t-stat	
A	Constant term	-10.19	-49.48	**	-2.66	-13.64	**	1.42	6.84	**
	Age/100	5.21	12.36	**	0.04	9.32	**	0.02	3.91	**
	Gender	-0.12	-0.82		0.02	0.15		-0.44	-2.86	**
	Bus dummy	0.87	5.53	**	0.60	3.84	**	0.42	2.55	*
B	Constant term	-8.58	-54.02	**	-1.36	-8.81	**	0.80	4.69	**
	Age/100	2.25	6.04	**	0.02	4.23	**	0.02	3.89	**
	Entertainment dummy	0.73	2.77	**	0.42	1.63		0.46	1.69	
C	Constant term	-5.63	-82.88	**	0.59	8.39	**	2.17	33.97	**
	Tram dummy	0.32	2.08	*	0.38	1.90		0.01	0.56	
	Student dummy	0.39	3.58	**	0.34	2.79	**	0.21	2.11	*
D	Constant term	-6.82	-64.15	**	-1.06	-1.01		1.78	16.86	**
	Electric railway dummy	2.61	5.82	**	6.44	0.19		1.01	2.55	*
	Shopping dummy	0.59	4.97	**	0.36	3.11	**	0.34	2.93	**
E	Constant term	-6.25	-51.48	**	0.39	3.00	**	1.77	15.52	**
	Age/100	2.04	6.89	**	0.01	2.76	**	0.01	3.78	**
	Entertainment dummy	0.41	1.94		0.25	1.09		0.15	0.74	
F	Constant term	-7.21	-112.41	**	-0.36	-5.56	**	1.49	22.81	**
	Electric railway dummy	0.83	1.81		0.66	1.47		0.30	0.68	
	Sample size	825			825					
Data fit measures for full model										
	Initial log-likelihood	-21 229.22			-17 686.19					
	Final log-likelihood	-15 266.29			-14 610.48					
	AIC	30 568.58			29 292.96					
Fit measures for continuous consumption										
	Predictive initial log-likelihood	-7 837.37			-6 149.63					
	Predictive final log-likelihood	-5 682.76			-3 778.83					
Fit measures for discrete consumption										
	Predictive initial log-likelihood	-8 631.61			-3 273.64					
	Predictive final log-likelihood	-3 064.88			-2 923.40					

Note–**1% significant, *5% significant, AIC: Akaike Information Criteria, initial log-likelihood: log-likelihood with all parameters fixed to 0. Fit measures for continuous and discrete consumption were calculated using the procedure proposed by Bhat (2018).

Results of the flexible MDCEV model reveal that not all the explanatory variables affect both discrete and continuous components, even if they are statistically significant in the conventional model. As shown so far, some variables were statistically significant in either the discrete or continuous components of the flexible MDCEV model. This implies that some visitors less frequently visit a given zone but spend more time there during each visit. Contrarily, some visitors preferred making frequent short-duration visits to certain zones. Therefore, the flexible model can reveal whether a variable affects zone choice and/or staying time choice.

Table 2 lists several data fit measures for model comparison. The full model's Akaike Information Criteria (AIC) of the flexible model is better than that of the conventional model. Moreover, the predictive final log-likelihood shows that the flexible model is better than the conventional model in discrete and continuous choices.

4.3. Prediction Results and Model-performance Comparison

Figure 6 depicts comparisons between the observed and predicted visitor stay times in the six zones. As observed, the flexible model exhibits superior performance compared to its conventional counterpart. Further, the result obtained using the flexible model demonstrates better agreement with the observed time distribution, particularly in zones A, B, and F. Comparatively, the conventional model prediction results show much worse performance in cases involving zero stay times; as a result, the predicted staying time distribution is considerably different than the observed one. In future endeavors, we intend to consider more explanatory variables for these cases with the aim of further improving the performance of the flexible model.

4.4. Discussion

The predictions result clearly demonstrates the superior performance of the flexible MDCEV model over the conventional MDCEV model. Additionally, the flexible model predicts the staying time distribution better than the conventional model. The conventional model performed poorly in the prediction of zone choice (discrete choice). Thus, the flexible MDCEV model appears to be useful for analyzing the visiting place and staying time distribution.

Several researchers have analyzed the zone- and duration-choice behaviors of individuals. These extant models include the dynamic discrete–continuous approach (Habib, 2011) and sequential model of destination and activity-duration choices (Araki et al., 2015). The sequential models describe detailed visitor behaviors, including their shopping preferences, by considering the dynamics of activity scheduling. These micro models are powerful. However, the availability of a large dataset pertaining to visitors in the target area (including shop data) is an essential prerequisite for their implementation. Such large datasets might not always be available. Meanwhile, the proposed macro approach is based on zone-level data; it can be readily applied to areas with limited data availability. In addition, the errors incurred when employing sequential models tend to accumulate; moreover, these models are difficult to calibrate. In contrast, the proposed approach is parsimonious and relatively easy to develop using GPS data exclusively. The dynamic discrete–continuous model (Habib, 2011) can be considered an extended version of our model. The dynamic model can describe visitors' sequential staying behavior, which could improve the prediction shown in this paper.

The limitations of the current study could be summarized as follows. In the current model, the saturation and scale parameters were set to unity for simplification. However, this assumption must be discarded in favor of a more detailed description of visitor behavior. Further,

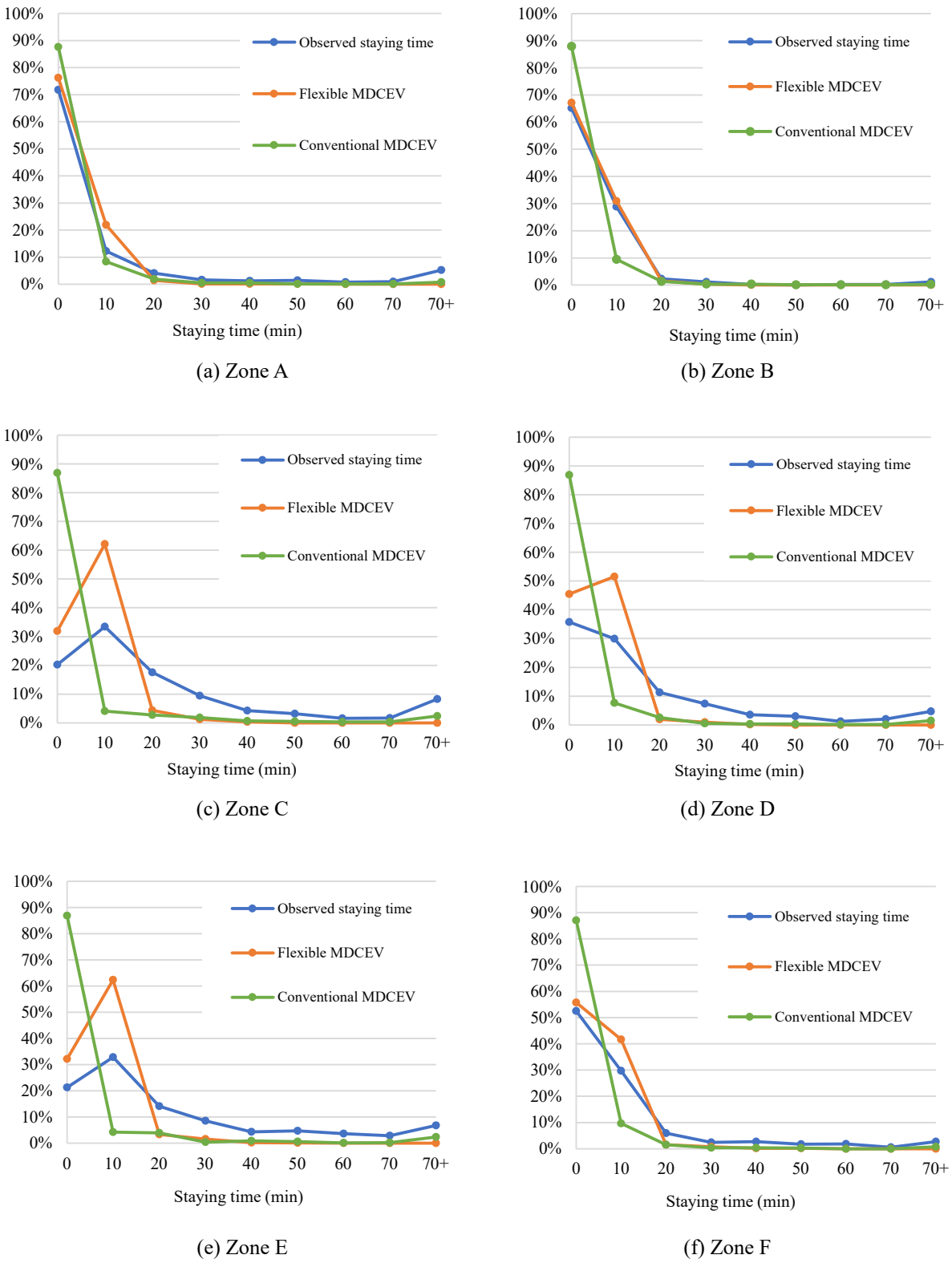


Figure 6. Comparison between observed and predicted visitor stay times obtained using conventional and flexible MDCEV models

the current model assumed no correlation between the error terms in the discrete component. This assumption should also be discarded. Because neighboring zones tend to have similar attributes, the correlation between them must be considered. In addition, the current model did not incorporate the spatial variables of each zone, such as shopping floor area and commodities available within the zone, owing to data unavailability. The inclusion of these variables is expected to improve the model and will be addressed in future work. Finally, the large-scale redevelopment of downtown Kumamoto that began in 2019 would change the visitors' behavior and therefore, in future work, we will elaborate on how the proposed model can better predict the changes in visitors' behavior.

5. CONCLUSIONS

This paper presents a flexible MDCEV approach to analyze the place-of-visit and time-spent behaviors of downtown visitors using GPS data. The proposed approach was applied to data obtained by conducting a smartphone-based survey involving people visiting downtown Kumamoto. The results obtained reveal the effects of visitor attributes—age, gender, purpose of visit, and travel mode—on their place-of-visit and time-spent preferences. Compared to its conventional counterpart, the proposed flexible model successfully describes the differences between the effects of these attributes on the discrete and continuous choices of visitors. Overall, the results obtained using the flexible model better match actual observations compared to the conventional model. The proposed model can be easily adapted for application to different cities around the world and is a useful tool to evaluate several urban policies including downtown redevelopment programs.

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