Preferences for electric scooter sharing in Japan

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Abstract

We analyze the preferences of older adults and the Japanese population as a whole for electric scooter sharing (ESS) using a discrete choice experimental method (best–worst scaling [BWS]). A nationwide web-based survey was conducted in Japan in May 2023 to collect data. Multiprofile BWS was used to compare the effects of user fees, insurance premiums (or compensation), parking access time, and waiting time for use. Although e-scooters are expected to become an essential means of transportation for elderly people after they return their driving licenses, we could not find that ESS is an attractive means of transportation for elderly people. Furthermore, e-scooter users are discouraged by the burden of accident compensation. People with low safety awareness were less willing to pay compensation than those with high safety awareness. However, this study does not present adverse selection, in which riskier (less safety-conscious) respondents are unwilling to pay premiums. In addition, people want e-scooter parking lots to be located some distance away from the station.

Keywords: Electric scooter sharing; Last-mile problem; Stated preference method

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1 Introduction

Since the 2010s, the call for climate change prevention and implementation of the Mobility-as-a-Service (MaaS) scheme have stimulated the demand and supply of the sharing economy in transportation. The global need to combat climate change requires not only switching to electric and fuel-cell vehicles but also curbing dependence on automobiles.

In this study, as a new sharing economy trend in transportation, we focus on services that enable the sharing of electric scooters (e-scooters). These are simple two-wheeled vehicles powered by an electric battery and equipped with a standing deck and handlebars. Using smartphone applications, users can easily rent and return e-scooters anywhere within a designated service area. One-way use is available. E-scooter sharing (ESS) is an eco-friendly alternative to other modes of transportation and has become popular in several developed countries such as the United Kingdom, Germany, France, Spain, the United States, Australia, and Singapore. Besides reducing carbon emissions (Hwang, 2010), ESS presents many social benefits, including tourism and regional development, new urban and regional transportation options, and mobility assistance to the elderly (May et al., 2010).

However, in some countries where ESS has been introduced, it has been partially banned despite government promotion initiatives. One reason for this is death and injury from accidents involving pedestrians and cyclists caused by e-scooters (Cloud et al., 2023). The second is the intentional vandalism of e-scooters: users do not own the scooters and, therefore, treat them roughly (Useche et al., 2022; Turoń et al., 2023). These problems can be caused by information asymmetries between users and operators, which is a disincentive for the diffusion of ESS. Therefore, it is necessary for countries introducing ESS to implement policies to mitigate these problems.

This study considers how (potential) users in Japan perceive ESS and which factors affect users' preferences for ESS.[1] In other words, our study investigates the extent to which different factors affect users. In particular, we consider insurance fees and compensation burdens to reduce the above two problems: accidents and intentional vandalism. We chose Japan for several reasons. First, Japan is in the early stages of ESS adoption, so it is necessary to study people's perceptions of ESS to examine the challenges associated

[1] See, for example, Teixeira et al. (2023) for a survey of non-users of ESS.

with its adoption and find solutions. Second, in Japan, deregulation in 2023 made it possible to use e-scooters without a driver's license; therefore, e-scooters are expected to become more widespread throughout society in the near future. The Japanese government, which faces a nationwide aging population problem, has encouraged the elderly to return their driver's licenses owing to the increase in traffic accidents caused by elderly drivers. However, returning driver's licenses may cause a last-mile problem for elderly people, potentially leading to inconveniences in terms of shopping and thus isolating them from the community. ESS combined with MaaS offers an inexpensive solution to this problem. Deregulation may promote the sharing of e-scooters among elderly people after they return their driver's licenses.

We focus on two factors that can restrain the diffusion of ESS: *adverse selection*, in which people do not use ESS because of accident risk, and users' *moral hazard*, which results in increased external costs, such as intentional vandalism. For the former, we set insurance premiums to be paid in advance; for the latter, we use compensation fees to be paid in case of vehicle damage. In addition, to examine the effect of deregulation that eliminates the need for a driver's license, we set the respondents' willingness to return their driver's license as an attribute.

Because ESS in Japan is in its early stages, empirically revealed preference data from actual use cases have not been adequately accumulated. Therefore, we adopted stated preference (SP) data obtained from users' responses to hypothetical choices. The SP method has often been used in studies on the demand for clean fuel vehicles in transportation.[2] This study is not the first to examine ESS using the SP method.[3] Baek et al. (2021) estimated the number of people who saw value in e-scooters as a last-mile transportation option. Brezovec and Hampl (2021) investigated individuals' preferences for sustainable transport modes using MaaS, including ESS. Abouelela et al. (2021) estimated a choice model between carsharing and ESS using an SP method targeting young individuals in

[2] For early literature on the potential demand for clean-fuel vehicles, see Beggs et al. (1981) and Calfee (1985). Studies using the SP methods in this century include Axsen et al. (2009), Hidrue et al. (2011), Ito et al. (2013), Jung et al. (2022), Khan et al. (2020), Potoglou and Kanaroglou (2007), Qian and Soopramanien (2011), and Tanaka et al. (2014).

[3] Other studies of ESS that use methods other than SP have been published recently; see, for example, Eccarius and Lu (2020), Sanders et al. (2020), and Younes et al. (2020).

Munich. Cao et al. (2021) conducted an SP survey on e-scooter users in Singapore to analyze the factors affecting the choice of e-scooters and short-distance transit trips. The contribution of this study is to consider how adverse selection, such as accident risk, and moral hazard, such as vandalism, affect ESS preferences.

Several ESS-related studies have analyzed the substitutability or complementarity with public transportation (Aarhaug et al., 2023; Luo et al., 2021; Ziedan et al., 2021). Button et al. (2020) considered regulatory approaches that guide ESS. McQueen and Clifton (2022) found that e-scooters are less preferred than private cars. This study examines whether ESS can replace private cars for the elderly and the location of parking spaces for e-scooters; these issues have not been examined in previous studies.

Several recent studies have investigated regulations and safety measures for e-scooters. For example, Kutela and Mwekh'iga (2023) examined the regulatory priorities in Bloomington City, Indiana. Szemere et al. (2024) showed that the categorization of e-scooters is extremely important for regulation. Younes et al. (2023) found that e-scooter users are less likely to use bike lanes or wear helmets. Based on these studies, our study examines user safety measures by considering potential users' safety awareness of ESS.

The following conclusions can be drawn: ESS as an attractive means of transportation for elderly people remains unexplored. Next, the burden of accident compensation is a deterrent for e-scooter users. People with low safety awareness were less willing to pay compensation than those with high safety awareness. This is due to the moral hazard associated with being less careful when paying less for compensation. However, adverse selection, in which riskier (less safety-conscious) respondents were unwilling to pay premiums, was absent. The simulation analysis showed that the full cost of insurance is not preferred; however, the more the people are willing to use ESS, the more willing they are to accept payment for insurance. In addition, people want e-scooter parking lots to be located some distance away from the train station.

The remainder of this paper is organized as follows. Section 2 explains the methodology and the SP data. Section 3 describes the basic model. The results are presented in Section 4. In Section 5, we discuss how to promote ESS among the elderly people and simulate our results. Section 6 concludes the paper.

2 Methodology

2.1 Analysis Method (Best-Worst Scaling)

This section explains the SP method and the experimental design. SP experiments, which measure people's preferences using hypothetical choice situations, are widely used in transportation choice research.

We adopted best-worst scaling (BWS) as the analytical method for the consumer experiments (Louviere et al., 2015). In standard choice experiments such as conjoint analysis, only the best option (best) or the worst option (worst) is selected. However, "best" and "worst" are irreversible. This means that the characteristics of respondents who do not consider a certain option the most attractive differ from those who do not consider it the least attractive. So, the BWS is used to determine preferences for a wide range of questions by asking respondents to indicate the best and worst among available items or options. In BWS, two choices can be obtained for one hypothetical experimental question. The goal is to obtain a complete ranking of the items in a manner that is easy for respondents and can then be analyzed in various ways. BWS is less psychologically burdensome for respondents than a method that ranks all alternatives and provides more information than one that asks respondents to choose a single alternative.

There are three types of BWS methods: object case (case 1), profile case (case 2), and multi profile case (case 3). In this study, we adopt the BWS multi profile case (case 3) to make comparisons that include the price attributes of ESS. The multi profile case (case 3) can be used to obtain the marginal valuations of product characteristics by presenting multiple profiles consisting of multiple product characteristics and selecting the best and worst profiles.

2.2 Survey Design

The survey consists of 10 basic questions and 13 profile-based BWS questions. First, the basic questions include gender, age, location, marital status, occupation, and awareness of the July 2023 amendment to Japan's traffic law, which makes a driver's license unnecessary for e-scooter users over 16 years of age. Respondents are also asked about their awareness that e-scooters with a maximum speed of 6 km/h can be used on sidewalks, road shoulders, and bicycle lanes. In addition, respondents are asked about the type of driver's license they hold, whether they plan to surrender their driver's license within the next year, and whether they wear a helmet while cycling. According to Zhou et al. (2022), as the helmet-wearing rate increases, the accident rate decreases. So the question about wearing a helmet while cycling measures the respondent's safety awareness while driving. Those who answer "yes" are assumed to have a high level of safety awareness in their daily lives and a lower risk of having an accident.[4]

Next, the BWS questions are discussed. In the BWS questions, each attribute related to ESS is examined to see if it influences the choice of ESS type. In this survey, we assumed a situation in which the respondents themselves use the ESS service to travel from the nearest train station to their final destination (e.g., work or shopping mall), and they are allowed to return their vehicles at any rental/return point located in the assigned area, and this information was presented before the BWS questions. At the same time, it was predicted that information about e-scooters was not well known in Japan at the time of the survey, so the following three main features were presented to enhance respondents' understanding of the topic.

(i) ESS is a service where an e-scooter (maximum speed: 15 km/h) can be rented and returned at designated parking lots in various locations. (ii) The service has a low environmental impact, is suitable for short-distance travel, and is expected to be used for commuting to work, school, and sightseeing. (iii) Conversely, in some foreign countries where e-scooters have become popular, collisions with pedestrians and other vehicles have increased.

Respondents choose the best and worst profiles from each choice set, each containing random levels of four attributes. Table 1 shows the levels for each attribute.

We explained these attributes in detail in the survey questionnaire before starting with the discrete choice questions. The description is as follows. "Usage fee (yen)" means the monthly payment for using an e-scooter. "Compensation burden (%)" means the

[4] Vanparijs et al. (2015) argue that there is no correlation between helmet-wearing and a decrease in accident rates. The debate regarding the decrease in accident rates due to helmet-wearing continues. We adopt the findings of Zhou et al. (2022), but whether we make this assumption or not does not affect our conclusion. This is because we only define safety awareness assuming that those who wear helmets when riding bicycles have a high level of safety awareness.

Table 1: Attributes and attribute levels

Attributes	Level			
Fee/month(¥)	¥500	¥1,000	¥5,000	¥10,000
Compensation burden(%)	10%	50%	100%	
Insurance premiums(%)	10%	50%	100%	
Time to park (min)	1	3	5	
Waiting time to use (min)	10	30	60	

percentage of the repair cost to be paid if the e-scooter is damaged while using the sharing service. (Not included in the usage fee). "Insurance premiums (%)" means the percentage of the cost of voluntary insurance to be paid before using the sharing service (not included in the usage fee). "Time to park (minutes)" means the time it takes to travel to the designated parking space. "Waiting time (minutes)" means the time from reserving the e-scooter until it is available.

In the survey, respondents were divided into two subgroups, and each group evaluated different scenarios. One scenario included the burden ratio of insurance premiums for e-scooters (paid in advance), and the other scenario included the burden ratio of repair costs in case of an accident (paid after the fact). The two survey questionnaires differ only in the attribute names of the burden ratio of insurance premiums for e-scooters and the burden ratio of repair costs in the case of an accident. All levels are identical.

Respondents made their choices based on the entire scenario, not on a single factor. Table 1 shows each attribute and its level. We set one four-level attribute and three three-level attributes. Figure 1 illustrates an example of the choice set in this study. An orthogonal plan is used since the number of attributes becomes too large and unwieldy when all possible combinations are considered. Therefore, we create a set of 13 alternatives using the orthogonal plan and compared four profiles with four attributes. We then design a choice situation using a balanced incomplete block design (BIBD). The multi profile includes all the factors and one level per factor, and the respondent is assumed to make deliberate choices based on the level presented for each factor.

The question about wearing a helmet while driving measures the respondent's safety awareness while cycling. In other words, those who answer "yes" are assumed to have a strong awareness of safety in their daily lives and a lower risk of accidents.

Plan	1	2	3	4
Fee (per month, ¥)	10000	500	1000	10000
Compensation burden(%)	50	10	100	10
Time to park (minutes)	5	5	5	3
Waiting time to use (minutes)	30	30	10	10

Please select the most and least attractive plans for you by clicking on each box.

Most attractive	Plan	Least attractive
☑	1	☐
☐	2	☐
☐	3	☑
☐	4	☐
☐	I would choose none	

Figure 1: E-scooter choice survey BWS question

3 Model Specification

This section describes the estimation model in detail. In this study, we use a conditional logistic (CL) model that incorporates both individual-specific and case-specific parameters to evaluate the diversity of individual attributes. However, this assumes independence of irrelevant alternatives (IIA), which does not consider the impact of preferences for irrelevant choices (McFadden et al., 1977). Therefore, we adopt a mixed logit (ML) model to assess consumers, preference diversity for each attribute of ESS.

The standard case 3 BWS modeling approach uses three major selection models: maximum difference (MaxDiff), sequential, and marginal sequential (rank-ordered), depending on the choice method used by each individual to maximize utility (Marley and Pihlens, 2012; Louviere et al., 2015). The MaxDiff model is based on the assumption that the most attractive and the least attractive options are generated to maximize the difference in utility between them. On the other hand, the sequential (or marginal sequential) model assumes making selections in a specific order from the options. For example, the former assumes selecting the best from a choice set of n items, then selecting the worst from the remaining $n-1$ items, and finally selecting the best from the remaining choices. Certainly, since the MaxDiff model assumes comparing any combination of alternatives, it may not necessarily be more appealing compared to other models. However, it possesses theoretically and empirically more attractive properties, including consistency with random utility model used in traditional discrete choice analysis. Therefore, the MaxDiff model was used in this study.

Let V be the systematic component, and the unobserved random terms ϵ be i.i.d extreme value distributions. The utility function of individual n from alternative s, in linear form, can be expressed as (Brownstone et al., 1998; Train, 2009)

$$U_{ns} = V_{ns} + \epsilon_{ns}. \tag{1}$$

The MaxDiff method assumes that the utility difference $U_{ni} - U_{nj}$ is the largest among any set of alternatives S when $i, j \in S$ are chosen as best and worst, respectively. In this case, the probability of selecting i, j is expressed as follows:

$$\begin{aligned} P_{nij} &= Pr[U_{ni} - U_{nj} \geq U_{np} - U_{nq}, \forall p, q \in S, p \neq q] \\ &= Pr[V_{ni} - V_{nj} + \epsilon_{ni} - \epsilon_{nj} \geq V_{np} - V_{nq} + \epsilon_{np} - \epsilon_{nq}, \forall p, q \in S, p \neq q] \\ &= Pr[\epsilon_{np} - \epsilon_{nq} \leq \epsilon_{ni} - \epsilon_{nj} + V_{ni} - V_{nj} - (V_{np} - V_{nq}), \forall p, q \in S, p \neq q] \end{aligned} \tag{2}$$

In the usual CL model, a systematic component is defined as $V_{ij} = \beta x_i - \beta x_j$, where x_i and x_j are the vector of attributes, so the selection probability in the CL model is defined as

$$P_{ij} = \frac{\exp[\beta(x_i - x_j)]}{\sum_{p,q \in S, p \neq q} \exp[\beta(x_p - x_q)]}, \tag{3}$$

where β is the utility coefficient.

The ML model is an extension and applied model of the CL model. The ML is one of the selection models in which the coefficients of the explanatory variables are treated as random coefficients, and the selection probability for each individual n is generally expressed as follows (Cerwick et al., 2014; Train, 2009):

$$P_{nij} = \int L_{nij}(\beta_n) f(\beta_n \mid \theta)\, d\theta, \tag{4}$$

where $f(\beta_n \mid \theta)$ is the density function for multiple mixed distribution (uniform, normal, or exponential) of β_n; μ is the mean of the probability distribution; and θ is parameters of this distribution (e.g., mean, covariance). Now, L_{nij} denotes the logit selection probability:

$$L_{nij} = \frac{\exp(\bar{\alpha}_{nij} + \mu_n x_i - \mu_n x_j)}{\sum_{p,q \in S, p \neq q} \exp(\bar{\alpha} + \mu_n x_p - \mu_n x_q)}, \tag{5}$$

where $\bar{\alpha}_{nij}$ is a vector of alternative specific constants (ASC). In the current study, these ASCs are applied to the option "I would not choose." Since the error term contains a probability density function, the coefficients cannot be determined to be one. Therefore, we use the Halton sequence method, which is used as quasi-random numbers a sequence of numbers that equally cover the distribution range and are not mutually correlated, and the selection probabilities are derived by simulation (Monte Carlo method).

Our objective is to calculate the willingness to pay (WTP) for a one-unit change in the level of each attribute of the ESS. Now βx is expressed as a linear function of the vector of attributes x and their coefficients as $\beta x = \beta_{x_c} x_c + \beta_{x_a} x_a$, where x_c is the cost attribute (fee) and x_a is another attribute. Assuming that the marginal utilities of each alternative and choice set are the same, WTP is calculated using the following formula (Gaudry et al., 1989).

$$WTP = \frac{\partial V / \partial x_a}{\partial V / \partial x_c}. \tag{6}$$

Predictions are often used to interpret the results of regression models (Aguinis et al., 2013). Marginal effects describe how changes in the independent variable of interest may affect the predicted value of the outcome while holding the other variables constant. There are several types of marginal effects. We can calculate the average marginal effect (AME) over other covariates; the average marginal effect at the mean (MEM), where all other covariates are set to these means; or the marginal effect at representative values (MER), where other covariates are set to specific values of interest (median or mean). For simulations, we compute the effect of discrete changes with respect to x at representative values x_k. We can calculate the MER when the variable of interest x changes from an initial value x_k to a certain value x'_k as follows:

$$MER_X = \beta(x = x'_k, x_{-1} = \bar{x}_{-1}) - \beta(x = x_k, x_{-1} = \bar{x}_{-1}), \tag{7}$$

where the other variable x_{-1} is fixed at a certain $\bar{x}_{-1}$, and x'_k denotes an exogenous variables. We set the explanatory variable of interest to X and the other independent variables (including covariates) to x_{-1}.

4 Data Description and Results

4.1 Data Collection

The survey was conducted online in May 2023. The survey selected a sample of individuals living in Japan who can respond to Japanese-language questionnaires provided by the research company (MyVoice Communications, Inc). The analysis utilizes data from 1,300 samples after cleaning for any fraudulent responses. Of these, 650 responded to the BWS questions with four evaluation attributes (usage fees, compensation burden, access time to private parking, and waiting time for availability). The other 650 respondents answered BWS questions with four evaluation attributes (usage fees, insurance burden, access time to parking lot, and waiting time). Table 2 presents descriptive statistics on the characteristics of the respondents.

Since there are some categorical variables, including “relicense” and “helmet,” these variables were coded into binary variables as follows. If the respondent will or has already returned their license within the next year, “relicense” is coded as 1; otherwise, it is coded as 0. In the same way, if the respondent wears a helmet while riding their bicycles, the variable “helmet” is coded as 1, otherwise; it is coded as 0.

Table 2 shows the descriptive statistics of respondents (socioeconomic variables).

Data from the BWS multi profile type (case 3) were analyzed using CL and ML models.

Table 2: Respondents characteristics

Variable	Option	Questionnarie(%) 1	Questionnarie(%) 2
Gender(male)		50.0	50.0
Age	16-49	50.0	50.0
	50-90	50.0	50.0
Marital status	Married	39.3	38.5
Knowledge about deregulation of e-scooter regulation			
Have knowledge of when the regulation begin	Yes	34.2	38.8
Have knowledge about speed limits	Yes	20.2	26.8
Driver's license(multiple choices allowed)	Not have or handed over	14.6	16.9
	Ordinary motor vehicle	83.7	82.0
	Ordinary two-wheeled motor	11.1	13.4
	Scooter	17.5	17.4
Handing over driver's license	Not have	12.5	13.2
	Returned	3.1	3.5
	Have a mind to return	1.7	1.7
	Have no mind to hand over	82.8	81.6
Bicycle helmet	Usually wear	6.6	5.5
	Have a mind to wear	19.3	17.4
	Have no mind to wear	30.2	28.5
	Not use a bicycle	43.9	45.5
		N = 650	N = 650

4.2 Results with Conditional Logit Model

This section briefly describes the data used in this study and the distribution of respondents, and then provides the estimation results for each model. Table 3 shows the CL results for Questionnaires 1 and 2. The first column lists the attributes of the BWS study. This column is followed by the coefficients and willingness to pay (WTP) for each attribute. The values in the parentheses represent standard errors.

Here, ASC is an alternative specific constant (error component). Its positive value indicates that these five attributes cannot explain the preference for e-scooters, and another attribute influences selection: the quality of fit of the CL model is measured by the residual deviance and Akaike's information criterion (AIC) values. Lower residual deviance and AIC values indicate a good fit to the data and good prediction accuracy of the model, respectively.

The analysis results for Questionnaire 1 (left-hand side column in the table), all mean parameters are significant at the 1% level. In addition, the estimates ("coefficient") of the burden rate for the usage fee, the compensation fee paid by the user in the event of an accident when using the service, and waiting time for availability are negative, while access time to private parking is positive. As predicted, usage fees negatively impact the use of sharing services, similar to the results of studies that use discrete choices for other modes of transport. The WTP required to reduce the compensation fee burden by 1% is 159 yen. There is no statistically significant difference in the use of ESS at the 1% level among respondents who have returned their licenses and those who are about to return their licenses within a year compared with the others.

In addition, the analysis results for Questionnaire 1 (right-hand side column in the table), all mean parameters are significant at the 1% level, and the fee and waiting time estimates are positive, whereas the others are negative. WTP for the insurance fee is 206 yen. The model also shows no statistically significant difference at the 1% level regarding willingness to use ESS among respondents who (intend to) return their licenses compared to those who do not. There was a public opinion in Japan that e-scooters were not suitable for the elderly due to their instability. This survey was conducted just before the introduction of ESS in Japan, so it is possible that many respondents doubted the safety of ESS use by the elderly for this reason.

Table 3: Main results of the conditional logit model estimation

	Proportion of cornpensation			Proportion of insurance premium		
	Coeff.		WTP	Coeff.		WTP
Compensation burden/Insurance premiums('	-0.005	***	-159	0.004	***	206
	(0.0002)			(0.0028)		
Time to park(min)	0.106	***	3324	0.140	***	6682
	(0.0059)			(0.0071)		
Waitng time to use(min)	-0.006	***	-188	-0.016	***	-762
	(0.0005)			(0.0010)		
Fee(yen/month)	-0.032	***		-0.021	***	
	(0.0028)			(0.0028)		
ASC for "would not choice"	1.075	***		1.530	***	
	(0.0290)			(0.0456)		
Age	0.001			0.000		
	(0.0090)			(0.0082)		
Gender	0.000			0.001		
	(0.0230)			(0.0232)		
Relicense	0.000			0.000		
	(0.0559)			(0.0232)		
Residual Deviance	60385			58500		
AIC	60403			58518		

*p<0.05, **p<0.01, ***p<0.001

Note: ASC denotes alternative specific constants.

4.3 Main Results with Mixed Logit Model

Table 4 and Table 5 show the results of the ML model without and with the interaction term respectively. Assuming that the coefficients of items (e.g., fees) are normally distributed, Halton sequences are used in the simulations of the random parameter logit model estimation. We used the AIC, BIC (Bayesian information criterion), and 12 log-likelihood as measures of goodness of fit for the ML model.[5]

[5]The BIC (Bayesian Information Criterion, also known as the Schwarz criterion) is a statistical measure used primarily in time-series analyses to assess the goodness of fit between models. It was developed by statistician Gideon Schwarz and is closely related to AIC; the difference between BIC and AIC appears when parameters (independent variables and/or intercepts) are added to increase the goodness of fit of the model. BIC has a larger value (lower evaluation) when the number of parameters is higher. As with AIC, among the various alternative models, the best model is the one with the smallest BIC value. See Kass et al. (1995).

Table 4: Main results of the mixed logit model estimation without interaction term

	Without Interaction Term					
	Proportion of compensation burden			Proportion of insurance premium		
	Coeff.		WTP	Coeff.		WTP
<Non random parameters>						
Compensation burden/insurance premiums(%)	-0.006	***	-150	0.005	***	185
	(0.000)			(0.000)		
Time to park(min)	0.117	***	3166	0.163	***	6380
	(0.000)			(0.008)		
Waiting time to use(min)	-0.007	***	-179	-0.019	***	-747
	(0.000)			(0.001)		
Fee(yen/month)	-0.037	***		-0.025	***	
	(0.003)			(0.004)		
ASC for "would not choice"	1.545	***		2.090	***	
	(0.037)			(0.098)		
<SD>						
Compensation burden/insurance premiums(%)	0.001			0.006	***	
	(0.000)			(0.001)		
Time to park(min)	0.001			0.039	*	
	(0.019)			(0.016)		
Wating time to use(min)	0.001			0.010	***	
	(0.019)			(0.016)		
Fee(yen/month)	0.014			0.049	***	
	(0.000)			(0.004)		
ASC for "would not choice"	1.926	***		2.181	***	
	(0.000)			(0.098)		
AIC	40913			38639		
BIC	40983			38710		
log-Likelihood	-20446			-19310		

*p<0.05,**p<0.01,***p<0.001

Note: ASC denotes alternative specific constants.

Table 5: Main results of the mixed logit model estimation with interaction term

	With Interaction Term			
	Proportion of compensation burden		Proportion of insurance premium	
	Coeff.	WTP	Coeff.	WTP
<Non random parameters>				
Compensation burden/insurance premiums(%)	-0.006 ***	-57	-0.005 ***	-53
	(0.000)		(0.000)	
Time to park(min)	-0.045 ***	-463	-0.072 ***	-743
	(0.010)		(0.010)	
Waiting time to use(min)	-0.014 ***	-141	-0.014 ***	-149
	(0.001)		(0.001)	
Fee(yen/month)	-0.098 ***		-0.096 ***	
	(0.004)		(0.004)	
ASC for "would not choice"				
<SD>				
Compensation burden/insurance premiums(%)	0.006 ***		0.004 ***	
	(0.001)		(0.000)	
Time to park(min)	0.186 ***		0.198 ***	
	(0.007)		(0.008)	
Wating time to use(min)	0.013 ***		0.013 ***	
	(0.001)		(0.001)	
Fee(yen/month)	0.034 ***		0.057 ***	
	(0.005)		(0.004)	
ASC for "would not choice"				
Helmet × compensation burden/insurance premiums	0.041 **	421	0.001	6
	(0.020)		(0.001)	
Helmet × time to park	0.002 *	18	0.090 ***	937
	(0.001)		(0.021)	
Helmet × wating time to use	0.003 *	30	0.005 **	48
	(0.001)		(0.002)	
Helmet × fee	0.015 *	151	0.007	-68
	(0.007)		(0.008)	
AIC	44848		43706	
BIC	44932		43790	
log-Likelihood	-22412		-21841	

*p<0.05,**p<0.01,***p<0.001

Note: ASC denotes alternative specific constants.

As a result of the ML model, all the mean parameter estimates are 1% significant. Compared to the CL model, the AIC value improved, which means that the goodness of fit of the model has improved. In the ML model that considers the diversity of users' preferences, the coefficient of the compensation fee is also negative and significant. Further, the WTP to reduce the compensation fee by one unit is 150 yen. The coefficient of the insurance fee is positive and significant, and the WTP is 185 yen. The sign of the coefficient is also negative in waiting time to use, and the WTP to make a one-unit reduction is 747 yen. The coefficient of waiting time is significantly negative, and the WTP for reducing waiting time by one unit is 179 yen.

The reason for the positive coefficient for only a portion of the insurance premium is that the coefficient for the insurance premiums with interaction terms is positive, while the coefficient for those without interaction terms is negative. This suggests diversity in respondents' preferences. Recent research suggests that WTP for insurance is significantly affected by risk heterogeneity and preference heterogeneity (Cutler et al., 2008). Here, we assume that some users are more interested in the insurance premium, and others are less interested. In other words, users' preferences for the insurance fee and the compensation fee are expected to be diverse.

In the MLM estimation with uniform distribution, all the mean parameter estimates are significant at the 1 % level. Compared with the CL model, the ML model improved the AIC value, which means that the goodness of fit of the model improved. In the ML model, which considers the diversity of user preferences, the compensation fee coefficient is negative and significant, and the WTP to decrease the compensation fee by one unit is 150 yen. The coefficient of the insurance fee is positive and significant, and the WTP is 185 yen. The sign of the coefficient is also negative for waiting time, and the WTP for reducing it by one unit is 747 yen. The coefficient of waiting time is significantly negative and the WTP for a one-unit decrease in waiting time is 179 yen.

The results with the interaction term indicate that all mean parameters are negative and significant at a 1% level, and the interaction term between compensation fees and wearing “helmet” is positive and significant. Therefore, we can see that safety-conscious users are more willing to pay a compensation fee than users who are not as safety-conscious, and the difference in WTP is 421 yen. In addition, all the standard deviation parameters are significant at the 1% level, confirming the diversity of preferences for all attributes. The result for Questionnaire 2 is that the mean parameters are negative and significant at the 1% level. The interaction terms of time to parking lot and wait time with "helmet" are positive and significant at 1%. All standard deviation parameters are also statistically significant at the 1% level. The results show that the impact of wait time and access time to the parking lot, compared to the insurance fee, significantly differs among users with different levels of safety awareness. The differences in WTP for premium burden and time to park for safety-conscious and non-safety-conscious users are 937 and 48 yen, respectively.

In summary, while there are differences among users in their demand for compensation and insurance fees, there are no significant differences in the impact of insurance fees on ESS usage among users with different levels of security awareness in this analysis. Reducing compensation fees positively affects the number of ESS users, whereas reducing the burden of insurance fees negatively affects ESS use. In addition, average users increase their use of ESS more when waiting times are shorter. In all models, "time to park" has a positive coefficient, which may seem counterintuitive. However, the following considerations could explain this phenomenon. Train stations tend to be crowded with people and various forms of traffic, posing risks such as accidents for e-scooter users. This result may indicate that individuals, even if the parks for e-scooters are somewhat distant, prefer riding e-scooters to avoid such crowds and traffic congestion, possibly to minimize associated risks.

5 Discussions

In this section, two analyses are conducted. First, we consider how to promote ESS among the elderly. The proportion of elderly people who choose the "status quo" is compared between the two scenarios ("status quo" means not using an e-scooter). In a scenario that includes the burden ratio of insurance premiums for e-scooters, about 52% of the elderly over 65 years old select "status quo" for at least 7 of the 13 BWS questions. In contrast, approximately 47.3% of respondents below the age of 65 years do so. There are no significant differences between the elderly and the rest of the population in the scenario.

However, in a scenario that includes the burden ratio of repair costs in case of an accident, we observe a difference in the ratio of individuals who choose the “status quo” between the two groups. Specifically, 58% of the elderly over 65 years old choose “status quo” for at least 7 of the 13 BWS questions. In contrast, approximately 44.6% of respondents below the age of 65 years do so. In conclusion, the elderly are willing to lower the compensation risk involved in the event of an accident by paying the insurance premium in advance. In other words, prepayment of premiums can be an important factor in promoting ESS among the elderly.

Second, we use the estimates obtained in Table 3 to estimate the marginal effects of compensation and insurance burden rates on ESS utilization. In the predicted values of the compensation burden rate and ESS utilization (Figure 2), utilization decreased by 5% at a compensation burden rate of 10 %. Utilization also dropped sharply at 100%. The predicted values of the insurance burden rate and ESS utilization (Figure 3) show that the full cost of insurance is not preferred; however, the more the people who are willing to use the ESS, the more willing they are to accept payment for insurance.

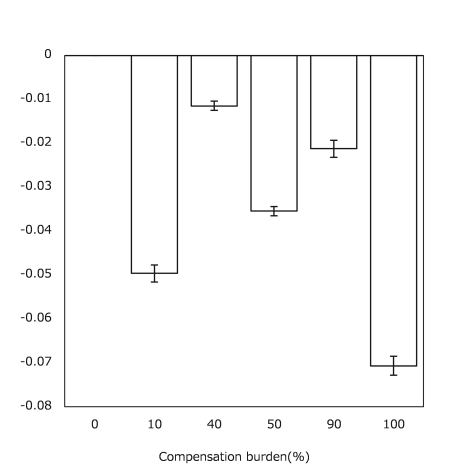

Figure 2: Compensation burden and estimates of utilization

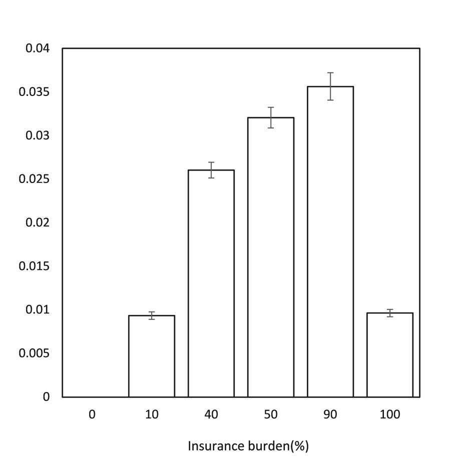

Figure 3: Insurance burden and estimates of utilization

The number of car accidents caused by elderly drivers is increasing every year, prompting the government to encourage the surrender of driver’s licenses. Proliferation of e-scooters as an alternative means of transportation are expected to be a significant factor in the context of elderly license returns. However, currently, e-scooters are not considered an attractive mode of transportation for the elderly. Exploring the factors that would make e-scooters an appealing mode of transport for the elderly is a future research topic.

6 Concluding Remarks

In this study, we analyzed the preferences of the users of ESS in Japan using BWS. The effects of user fees, insurance premiums (or compensation), parking access time, and waiting time were compared using a multi-profile type of BWS. E-scooters are expected to become an important means of transportation for the elderly after they return their driver's licenses. However, we did not show that ESS is an attractive mode of transportation for elderly people. We found that the burden of compensation for accidents discourages users from riding e-scooters. This finding is expected to increase the number of ESS users as they pay premiums to reduce compensation costs. Additionally, those with a low level of safety awareness were less willing to pay the compensation burden than those with a high level of safety awareness. This is probably because of the moral hazard of having a lower level of safety awareness when the burden of compensation is lower. However, adverse selection, in which respondents with a higher level of risk (those who are less safety conscious) are more reluctant to pay premiums, was not present in this study. This may be because the Japanese transportation system requires insurance. Furthermore, the parking spaces for e-scooters should be located some distance from the station.

We examined accident risks in ESS and their countermeasures. The results showed that the number of ESS users will not decrease even if the premium burden increases. Due to the revised Traffic Law, some e-scooters have been classified as "specified small motorized bicycles," to which new traffic rules have been applied since July 2023. Until the end of March 2024, the automobile liability insurance fees for motorized bicycles were applied to specified small motorized bicycles, but new insurance fees for "specified small motorized bicycles" were applied from April 2024. This study provides suggestions for appropriate insurance fees.

ESSs are already widespread in other countries, such as the United Kingdom and Singapore, and many accidents have occurred in some of these usage areas. This may be because sharing-service users do not own e-scooters and if they do not bear the full cost of compensation in the event of an accident, they may behave in ways that increase their risk. Therefore, we examined the impact of safety awareness on willingness to use ESS in terms of compensation rates. The results showed that respondents with low safety awareness (i.e., those who did not wear a helmet while cycling) had lower rates of ESS use (compared to those with high safety awareness) as the burden rate of the compensation fee increased. However, there is no significant difference in the impact of the amount of insurance on ESS use rates for respondents who are more safety conscious than those who are less safety conscious. One reason for this is the relatively low insurance fee. Another reason could be that the purchase of automobile liability insurance is mandatory in Japan.

The positive coefficient of the variable “Time to park” is an unexpected result. However, this result indicates that respondents do not perceive an increase in congestion around the station due to the additional users in the area. In our view, this represents a trade-off between the accessibility of the ESS and the congestion around the stations.

This study has several limitations. The first is the small sample size, that is, the percentage of respondents who returned their licenses or were interested in returning their licenses within one year. As most respondents in our survey were under the age of 80 years and a small number of respondents were over the age of 80 years (a high percentage of whom were returning their licenses), the demand for ESS among those returning their licenses was not significant in our analysis, but this may not be the case in reality. In addition, regarding the respondent profile and the resulting selection bias, this survey was conducted online by a research firm, so there is a possibility of selection bias due to people having access to the Internet and respondents having an interest in the ESS. The second limitation is that this study focused on negative factors in ESS, such as cost and risk; therefore, the results are not available for factors that provide convenience to users. This is one of the reasons why ASC is significantly positive in all models. This is a subject of future research. The third limitation is that SP experiments have some biases. The number of studies combining SP and revealed preference methods has been increasing in recent years (De Corte et al., 2021), because biases may be present in SP survey responses. This study does not adopt this approach. This study attempts to minimize this potential bias by providing detailed scenario information to the survey participants and promoting their understanding. Furthermore, the ESS market in Japan is limited to some urban areas and tourist destinations and is not available in rural areas. In this case, the preference estimated from RP data exhibits a geographical bias, and the data are not a reliable proxy for consumer preference.

Furthermore, our study focuses on the analysis of consumer preferences for ESS. However, we have not conducted an analysis from the perspective of companies providing ESS services. It is important to discuss the future development of ESS from both the consumer and provider sides. In addition, further research is needed to explore whether the use of ESS affects the demand for other modes of transportation. For example, does ESS complement public transport, especially in terms of last-mile problem, or does it replace other modes. Investigating such substitution and complementarity relationships with other modes of transportation remains an open area for future research.

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References

[1] Aarhaug, J., Fearnley, H., Hartveit, KJL., Johnsson, E., Price and competition in emerging shared e-scooter markets. Research in Transportation Economics 98, 101273.

[2] Abouelela, M., Al Haddad, C., Antoniou, C., 2021. Are young users willing to shift from carsharing to scooter–sharing? Transportation Research Part D: Transport and Environment 95, 102821.

[3] Aguinis, H., Gottfredson, R. K., Culpepper, S. A., 2013. Best-practice recommendations for estimating cross-level interaction effects using multilevel modeling. Journal of Management 39(6), 1490–1528.

[4] Axsen, J., Mountain, D.C., Jaccard, M., 2009. Combining stated and revealed choice research to simulate the neighbor effect: the case of hybrid-electric vehicles. Resource and Energy Economics 31, 221–238.

[5] Baek, K., Lee, H., Chung, J-H., Kim, J. 2021. Electric scooter sharing: How do people value it as a last-mile transportation mode? Transportation Research Part D: Transport and Environment 90, 102642.

[6] Beggs, S., Cardell, S., Hausman, J., 1981. Assessing the potential demand for electric cars. Journal of Econometrics 16, 1–19.

[7] Brezovec, P., and Hampl, N., 2021. Electric vehicles ready for breakthrough in MaaS? Consumer adoption of E-car sharing and E-scooter sharing as a part of mobility-as-a-service (MaaS). Energies 14(4), 1088.

[8] Brownstone, D. and Train, K., 1998. Forecasting new product penetration with exible substitution patterns. Journal of Econometrics 89(1-2), 109–129.

[9] Button, K., Frye, H., Reaves, D., 2020. Economic regulation and E-scooter networks in the USA. Research in Transportation Economics 84, 100973.

[10] Calfee, J.E., 1985. Estimating the demand for electric automobiles using disaggregated probabilistic choice analysis. Transportation Research Part B: Methodological 19(4), 287–301.

[11] Cao, Z., Zhang, X., Chua, K., Yu, H., Zhao, J., 2021. E-scooter sharing to serve short-distance transit trips: A Singapore case. Transportation Research Part A: Policy and Practice 147, 177–196.

[12] Cerwick, D. M., Gkritza, K., Shaheed, M. S., Hans, Z., 2014. A comparison of the mixed logit and latent class methods for crash severity analysis. Analytic Methods in Accident Research 3, 11–27.

[13] Cloud, C., Heß, S., Kasinger, J., 2023. Shared e-scooter services and road safety: Evidence from six European countries. European Economic Review 160, 104593.

[14] Cutler, D. M., Finkelstein, A., McGarry, K., 2008. Preference heterogeneity and insurance markets: Explaining a puzzle of insurance. American Economic Review 98(2), 157–162.

[15] De Corte, K., Cairns, J., Grieve, R., 2021. Stated versus revealed preferences: An approach to reduce bias. Health economics, 30(5), 1095-1123.

[16] Eccarius, T., Lu, C.-C., 2020. Adoption intentions for micro-mobility – Insights from electric scooter sharing in Taiwan. Transportation Research Part D: Transport and Environment 84, 102327.

[17] Gaudry, M. J., Jara-Diaz, S. R., de Dios Ortúzar, J., 1989. Value of time sensitivity to model specification. Transportation Research Part B: Methodological, 23(2), 151–158.

[18] Hidrue, M.K., Parsons, G.R., Kempton, W., Gardner, M.P., 2011. Willingness to pay for electric vehicles and their attributes. Resource and Energy Economics 33, 686–705.

[19] Hwang, J.J., 2010. Sustainable transport strategy for promoting zero-emission electric scooters in Taiwan. Renewable and Sustainable Energy Reviews 14(5), 1390–1399.

[20] Ito, N., Takeuchi, K., Managi, S., 2013. Willingness to pay for the infrastructure investments for alternative fuel vehicles. Transportation Research Part D: Transport and Environment 18, 1–8.

[21] Jung, J., Lee, D-J., Yoshida, K., 2022. Comparison between Korean and Japanese consumers' preferences for fuel cell electric vehicles. Transportation Research Part D: Transport and Environment 113, 103511.

[22] Kass, R. E., Wasserman, L., 1995. A reference Bayesian test for nested hypotheses and its relationship to the Schwarz criterion. Journal of the American Statistical Association 90(431), 928–934.

[23] Khan, U., Yamamoto, T., Sato, H., 2020. Consumer preferences for hydrogen fuel cell vehicles in Japan. Transportation Research Part D: Transport and Environment 87, 102542.

[24] Kutela, B., Mwekh'iga, R.J., 2023. A multi-criteria approach to prioritize electric-scooters ordinances. A case of Bloomington City, Indiana. Case Studies on Transport Policy 11, 100959.

[25] Louviere, J.J., Flynn, T.N., Marley, A.A.J., 2015. Best-Worst Scaling: Theory, Methods and Applications. Cambridge University Press.

[26] Luo, H., Zhang, Z., Gkritza, K., Cai, H., 2021. Are shared electric scooters competing with buses? a case study in Indianapolis. Transportation Research Part D: Transport and Environment 97, 102877.

[27] Marley, A. A. J., Pihlens, D., 2012. Models of best–worst choice and ranking among multiattribute options (profiles). Journal of Mathematical Psychology 56(1), 24–34.

[28] May, E., Garrett, R., Ballantyne, A., 2010. Being mobile: electric mobility-scooters and their use by older people. Ageing and Society 30(7), 1219–1237.

[29] McFadden, D., Tye, W. B., Train, K., 1977. An application of diagnostic tests for the independence from irrelevant alternatives property of the multinomial logit model. Transportation Research Record Journal of the Transportation Research Board 637, 39–45.

[30] McQueen, M., Clifton, K.J., 2021. Assessing the perception of E-scooters as a practical and equitable first-mile/last-mile solution. Transportation Research Part A: Policy and Practice 165, 395–418.

[31] Potoglou, D., Kanaroglou, P.S., 2007. Household demand and willingness to pay for clean vehicles. Transportation Research Part D: Transport and Environment 12, 264–274.

[32] Qian, L., Soopramanien, D., 2011. Heterogeneous consumer preferences for alternative fuel cars in China. Transportation Research Part D: Transport and Environment 16, 607–613.

[33] Sanders, R.L., Branion-Calles, M., Nelson, T.A., 2020. To scoot or not to scoot: Findings from a recent survey about the benefits and barriers of using E-scooters for riders and non-riders. Transportation Research Part A: Policy and Practice 139, 217–227.

[34] Szemere, D., Iványi, T., Surman, V., 2024. Exploring electric scooter regulations and user perspectives: A comprehensive study in Hungary. Case Studies on Transport Policy 15, 101135.

[35] Tanaka, M., Ida, T., Murakami, K., Friedman, L.S., 2014. Consumers' willingness to pay for alternative fuel vehicles: A comparative discrete choice analysis between the US and Japan. Transportation Research Part A: Policy and Practice 70, 194–209.

[36] Teixeira, J.F., Diogo, V., Bernát, A., Lukasiewicz, A., Vaiciukynaite, E., Sanna, V.S., 2023. Barriers to bike and e-scooter sharing usage: An analysis of non-users from five European capital cities. Case Studies on Transport Policy 13, 101045.

[37] Train, K.E., 2009. Discrete Choice Methods with Simulation. Cambridge University Press.

[38] Turoń, K., Kubik, A., Folęga, P., Chen, F., 2023. Perception of shared electric scooters: A case study from Poland. Sustainability 15(16), 12596.

[39] Useche, S.A., O'Hern, S., Gonzalez-Marin, A., Gene-Morales, J., Alonso, F., Stephens, A.N., 2022. Unsafety on two wheels, or social prejudice? Proxying behavioral reports on bicycle and e-scooter riding safety—A mixed-methods study. Transportation Research Part F: Traffic Psychology and Behaviour 89, 168–182.

[40] Vanparijs, J., Panis, L. I., Meeusen, R., De Geus, B., 2015. Exposure measurement in bicycle safety analysis: A review of the literature. Accident Analysis and Prevention, 84, 9-19.

[41] Younes, H., Noland, R.B., Andrews, C.J., 2023. Gender split and safety behavior of cyclists and e-scooter users in Asbury Park, NJ. Case Studies on Transport Policy 14, 101073.

[42] Younes, H., Zou, Z., Wu, J., Baiocchi, G., 2020. Comparing the temporal determinants of dockless scooter-share and station-based bike-share in Washington, D.C. Transportation Research Part A: Policy and Practice 134, 308–320.

[43] Ziedan, A., Darling, W., Brakewood, C., Erhardt, G., Watkins, K., 2021. The impacts of shared e-scooters on bus ridership. Transportation Research Part A: Policy and Practice 153, 20–34.

[44] Zhou, J., Zheng, T., Dong, S., Mao, X., Ma, C., 2022. Impact of helmet-wearing policy on e-bike safety riding behavior: a bivariate ordered probit analysis in Ningbo, China. International Journal of Environmental Research and Public Health, 19(5), 2830.

Appendix A

The distribution of the B-W scores for the data used and the causal effect of access time on private parking are shown below. The plan attributes and their attribute values of Questionnaire 1 are shown in Table 6 and Figure 4, ranked by the best-worst score, which is the number of times the plan was selected as the most attractive minus the number of times it was selected as the least attractive. The ranking order for Questionnaire 2 is shown in Table 7 and Figure 5.

The coefficients of the general logit model, including the mixed logit model, indicated odds ratios that could differ from the actual probability of use. Finally, Table 8 and Table 9 shows the causal effect ("conditional effect") of access time to private parking on intention to use (explained variable) in the mixed logit model with interaction terms. The conditional effects are negative in the interquartile range.

Table 6: B-W score and rank of Questionnaire 1

Rank	Best		Worst		B-W score(diff.)	
1	Comp="50"	3687	Fee="10000"	356	Wait time="10"	2095
2	Time to park="5"	3678	Wait time="10"	1376	Time to park="5"	967
3	Wait time="10"	3471	Fee="500"	1944	Fee="500"	878
4	Time to park="1"	3207	Comp="100"	2167	Comp="50"	687
5	Fee="500"	2822	Time to park="3"	2284	Fee="10000"	539
6	Comp="10"	2562	Wait time="30"	2462	Wait time="30"	56
7	Wait time="30"	2518	Time to park="5"	2711	Comp="100"	34
8	Wait time="60"	2461	Fee="5000"	2829	Time to park="1"	-248
9	Fee="5000"	2437	Comp="50"	3000	Fee="5000"	-392
10	Fee="1000"	2296	Comp="10"	3283	Time to park="3"	-719
11	Comp="100"	2201	Fee="1000"	3321	Comp="10"	-721
12	Time to park="3"	1565	Time to park="1"	3455	Fee="1000"	-1025
13	Fee="10000"	895	Wait time="60"	4612	Wait time="60"	-2151

Note: Comp represents Compensation burden and Wait time represents Waiting time to use

Table 7: B-W score and rank of Questionnaire 2

Rank	Best		Worst		B-W score(diff.)	
1	Time to park="5"	5002	Fee="10000"	821	Time to park="5"	2277
2	Fee="500"	3371	Insur="50"	1752	Fee="500"	852
3	Insur="10"	3280	Wait time="30"	2142	Wait time="60"	649
4	Wait time="60"	3232	Fee="1000"	2251	Insur="50"	458
5	Insur="100"	2960	Time to park="1"	2409	Fee="10000"	421
6	Wait time="10"	2849	Fee="500"	2519	Wait time="30"	227
7	Wait time="30"	2369	Wait time="60"	2583	Insur="10"	220
8	Time to park="3"	2249	Time to park="5"	2725	Fee="1000"	-409
9	Insur="50"	2210	Fee="5000"	2859	Insur="100"	-678
10	Fee="5000"	1995	Insur="10"	3060	Fee="5000"	-864
11	Fee="1000"	1842	Time to park="3"	3316	Wait time="10"	-876
12	Fee="10000"	1242	Insur="100"	3638	Time to park="3"	-1067
13	Time to park="1"	1199	Wait time="10"	3725	Time to park="1"	-1210

Note: Insur represents Insurance premium and Wait time represents Waiting time to use

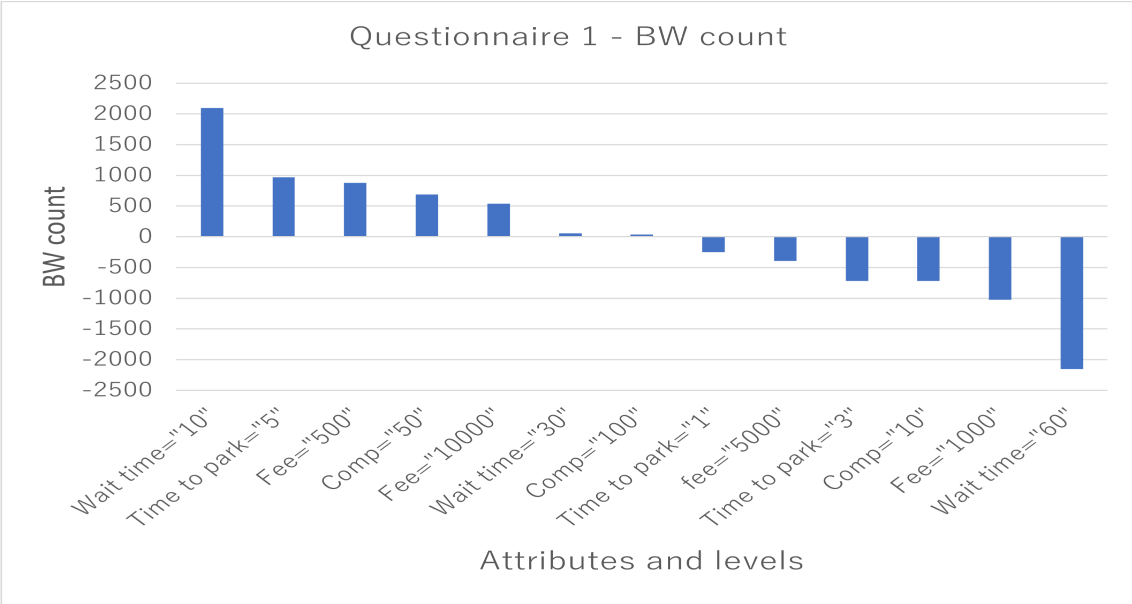

Figure 4: B-W count of Questionnaire 1 (Attribute levels)

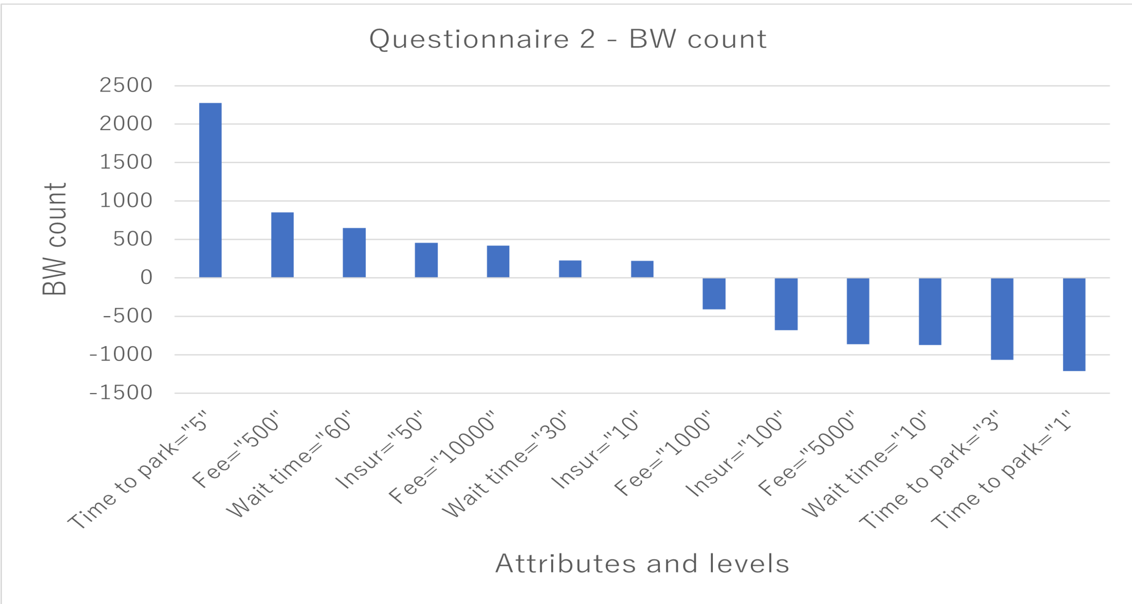

Figure 5: B-W count of Questionnaire 2 (Attribute levels)

Table 8: Conditional individual coefficients (of access time to private parking) for mixed logit with interaction term of Questionnaire 1

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Coef.	-0.13559	-0.1336	-0.13329	-0.12416	-0.09832	-0.09661
SD	0.002904	0.003477	0.003713	0.003729	0.00394	0.005147

Note: Coef. are the conditional expectation of the individual coefficients, and SD are their standard errors

Table 9: Conditional individual coefficients (of access time to private parking) for mixed logit with interaction term of Questionnaire 2

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Coef.	-0.784	-0.454	-0.2859	-0.3051	-0.1771	0.1718
SD	0.1718	0.10431	0.11813	0.12004	0.13443	0.24226

Note: Coef. are the conditional expectation of the individual coefficients, and SD are their standard errors