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Research Article

An Empirical Study on the Segmentation of Potential Users of Shared Parking Spaces considering Individual Heterogeneity

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Shared parking has become the most effective way to utilize existing parking resources. Little attention has been focused on drivers' intention to use shared parking spaces in residential areas considering individual heterogeneity. To fill this gap, this paper explores the influencing factors and mechanism of shared parking use intention (SPUI) and further studies the preferences for the shared parking of different types of drivers. Firstly, based on the extended unified theory of acceptance and use of technology that includes psychological factors, personal attributes, and travel characteristics, the multiple indicator multiple cause (MIMIC) model was employed for parameter estimation and model assessment. Secondly, using MIMIC's output results as input variables, the segmentation method of the latent class model (LCM) was adopted to explore drivers' preferences regarding SPUI. Finally, a quantitative study was carried out through questionnaire data. The empirical results show that: (a) the extended unified theory of acceptance and use of technology has good explanatory power for SPUI. SPUI is directly affected by perceived risk (PR), behavioral habit (BH), social influence (SI), facilitating conditions (FCs), and effort expectancy (EE), while performance expectancy (PE) have no significant effect on SPUI. In addition, some factors of personal attributes and travel characteristics affect SPUI through psychological factors. (b) According to individual heterogeneity, the surveyed driver groups are divided into four segments: sensitive type (36%), conservative type (29.6%), neutral type (24.5%), and approved type (9.9%), respectively. There are significant differences in psychological observation variables such as EE, PE, FC, and SI among the four segments of drivers. According to the influence mechanism of psychological factors and preferences analysis of different types of drivers, the shared parking promotion strategy can be formulated from the aspects of management, operation, and technology.

1. Introduction

With the rapid growth of car ownership, the contradiction between the increasing demand for parking and the limited parking resources has become more and more prominent. Until July 2020, China's parking space gap has reached 80 million [1, 2], which increases search time for parking and creates exhaust emissions and traffic congestions [3–5]. In addition, in the context of COVID-19, travelers are more worried about the safety of public transportation, and the government has adopted a series of antiepidemic measures, such as restricting the passenger capacity of public transportation, which has led to a further decrease in the proportion of citizens taking public transportation and an increase in the proportion of private car trips. Therefore, the contradiction between the supply and demand of parking spaces is further aggravated.

In recent years, the development of the sharing economy has been in full swing and has penetrated into many areas, such as shared cars(Evcard, Gofun), shared accommodation(Airbnb), and ridesharing (Lyft). Parking space has the characteristics of being nonstorable in time and nonmovable in space; besides, the parking demands also vary depending on land properties, so parking demands and spaces are not well matched. Therefore, the concept of shared parking has been proposed; the basic idea of the concept is that the parking space owners sell parking permits for the idle period of their parking space on the network

platform, and drivers with parking demands can purchase parking permits through the network platform [6].

Residents' travel characteristics (often come out early and return late) make the parking spaces in the residential area idle during working hours, which makes the parking spaces in the residential area sharing during the working hours become possible. The number of parking spaces in residential areas accounts for a large proportion of the total number of parking spaces. According to the statistics of the Hong Kong Transport Department (2016), there are 485,000 parking spaces in Hong Kong (70% of the total number of parking spaces are designated for private use). In addition, Yan et al. [7] pointed out that from 2015 to 2019, residential parking resources in Beijing accounted for an average of 53.16% of all parking resources, and nearly 800,000 private parking spaces were idle during working hours. A simulation experiment shows that if 20% of Beijing's existing parking spaces are added to the sharing projects, carbon dioxide emissions can be reduced by 7.3 million tons per year [8]. Therefore, if the idle time of the huge number of parking spaces in residential areas can be fully utilized, the utilization rate of parking spaces can be effectively increased, and traffic congestion and carbon emissions can be further alleviated [9].

Shared parking projects are mainly concentrated in commercial areas in China, while shared parking projects in residential areas are very rare, and the participation is low; the fundamental reason is that drivers' SPUI is not strong [10]. Therefore, it is necessary to explore the drivers' SPUI. In addition, it is worth noting that because of the different sensitivities of drivers to the influencing factors, their performance is different and thus has different effects on the implementation of policy measures [11]. Generally, a segmentation study of travelers is helpful to estimate the differences in their behavior rules and characteristics, to classify travelers with taste heterogeneity, and then to formulate more targeted and effective policy measures [12]. Regarding taste heterogeneity, it has recently received considerable attention in the transportation field [13–15]. To the best of our knowledge, there is a lack of attention to revealing heterogeneity with respect to SPUI although some scholars have studied the SPUI from the perspective of demanders [10, 16], meaning that it would be certainly worthwhile to unveil how the impacts of the variables vary depending on individual heterogeneity as one of the first scientific efforts, adding knowledge to the literature.

This study aims to investigate the intention of drivers to use shared parking spaces in residential areas considering individual heterogeneity. Specifically, it firstly expands the unified theory of the acceptance and use of technology model and uses the extended unified theory of acceptance and use of technology as the theoretical framework. Then, a multiple indicator multiple cause (MIMIC) model is employed for parameter estimation and model assessment to characterize the intention of drivers toward the use of parking space sharing systems. Secondly, based on the results of the MIMIC model, the segmentation method of the latent class model (LCM) was adopted to explore drivers' preferences regarding SPUI, and the selection preferences of

different types of drivers are analyzed according to psychological factors, demographic attributes, and travel characteristics, which will help to clarify the nature of SPUI at a deeper level and to formulate targeted inducement measures based on the driver's heterogeneous characteristics.

In addition, what needs to be elaborated is that exploring the sharing intention of parking space owners is also a critical area of study, since some problems with shared parking schemes, such as overtime, increased noise, and possible traffic congestion, need to be coordinated with parking space owners. However, this is out of the scope of this study, and readers are referred to the study proposed by Wang et al. [17–19], where they explored the influence of demographic attributes, built environment, and other factors of owners on their intention to participate in the shared parking schemes.

The rest of this paper is organized as follows: the next section extensively reviews literature concerning shared parking and research methods; in Section 3, the model framework, the multiple indicator multiple cause model and, the latent class modeling approach are briefly introduced; Section 4 profiles the dataset used in this study, including the survey outline, data collection, selected variables, and its descriptive analysis; in Section 5, the results and analysis are presented, including results of MIMIC and LCM estimation. At last, Section 6 concludes this research by summarizing implications and key findings, discussing limitations of the study, and presenting potential research topics.

2. Literature Review

2.1. Shared Parking. As far as we know, Lalani [20] proposed the concept of shared parking firstly, which also marks the transition from the nature of parking spaces to commodities. Shared parking has become an effective way to improve the utilization of existing parking resources. Litman [21] estimated that shared parking could reduce the need for new spaces by 10–30%. Yan et al. [7] combined prospect theory and logit model to identify the intention of suppliers to participate in shared parking considering uncertain demands. Besides, the matching mechanism of shared parking spaces is an important part of the research related to shared parking. Shao et al. [22] firstly developed a parking space matching model between the supply and demand for residential parking spaces, Iman and Hamid [23] and Kim et al. [24] built matching models based on GIS and other technologies. Xiao et al. [25] proposed a dual auction mechanism for shared parking spaces considering multiple periods. In addition, Zhao et al. [26] developed an intelligent parking management system (IPMS) to simulate the operation of the shared parking system. In addition to the participation behavior and the matching of shared parking, there are also studies based on its pricing. Some scholars have constructed pricing strategies for parking charges based on marginal cost theory and suboptimal pricing theory [27, 28]. Chen and Xie [29] established a dynamic allocation model of shared parking spaces for universities in the central city and conducted an effective evaluation. A competitive auction

mechanism also was presented based on berth allocation rules and transaction payment rules [30].

2.2. Unified Theory of Acceptance and Use of Technology.
Plentiful theoretical models have been developed in behavioral research to analyze and explain the public's acceptance of a certain technology, including rational behavior theory, technology acceptance model, motivation model, planned behavior theory, technology acceptance model, and planned behavior theory [31]. In the study of the acceptance of new technologies, the most widely used models are the technology acceptance model and the unified theory of acceptance and use of technology.

In 2003, Venkatesh et al. [32] proposed a unified model called "the unified theory of acceptance and use of technology." He pointed out that the eight models mentioned above only explained 17%–53% of the differences in users' intention to use information technology, while the unified theory of acceptance and use of technology model performed better than them. Similarly, Chen et al.'s [33] research also supports this conclusion. Four core variables, i.e., performance expectancy (PE), effort expectancy (EE), facilitating conditions (FCs), and social influence (SI), and exogenous variables such as age, gender, income, and education are proposed in the unified theory of acceptance and use of technology.

Some scholars have explored the public's acceptance of various road transportation systems based on the unified theory of acceptance and use of technology [34–38]. Although the unified theory of acceptance and use of technology has a forceful universality in practice, it cannot fully explain the actual behavior in some scenarios [33]; that is, except the above factors, behavioral intention may also be affected by some other hidden factors that have not been discovered. To better explain the intention and behavior, some new variables have been incorporated in plentiful existing studies according to the characteristics of the research object.

2.3. Latent Class Model (LCM).
In recent years, LCM has been applied to traffic segmentation. Teichert et al. [39] recognized the limitations of traditional segmentation techniques, adopted LCM to classify air passengers, and explored the importance of routes and flight segments to airlines' selection behavior; Crouch et al. [40] collected data on people's past vacation experience choices, travel motives, and basic demographic characteristics, established LCM to divide tourists into 5 classes, and explored how tourists choose vacation experiences/activity types. Xiong et al. [41] used the LCM to reveal the significant heterogeneity of Maryland drivers' potential preferences for carpooling, which supports traffic policies and incentive mechanisms related to congestion management strategies (such as HOV/ HOT channel use). In addition, LCM is also widely used in other studies, such as long-distance drivers' route selection behavior [42], bicycle users [43], driving behavior on combined road segments [44], the time spent by tourists at destinations [45], the acceptance of self-driving vehicles [15],

and the satisfaction with public transportation [13]. All of these studies have proved the advantages of potential category model segmentation research. Traveler segmentation studies that consider psychological factors have higher predictive power than individual attribute segmentation studies [46, 47].

2.4. Summary.
Although the related research studies are fruitful, to the best of our knowledge, no previous study has explored the impact of drivers' heterogeneity on the SPUI. In addition, in the above studies on LCM, the explicit variables that determine the classification results are often entered into the LCM estimation without analysis, which will inevitably affect the accuracy of model estimation [48]. Therefore, this study innovatively uses MIMIC's output results as input variables of LCM to analyze the taste heterogeneity of different classes of drivers more accurately. This approach is expected to contribute to the literature by providing first-hand insights into SPUI of different categories of drivers.

3. Methods

3.1. Model Framework.
In order to analyze the influence of psychological factors, personal attributes, and travel characteristics on SPUI, a MIMIC model is constructed to explore the causal relationship between various factors and SPUI. After that, based on the results of the MIMIC model, in order to identify the heterogeneity of preference among different categories of drivers, this study constructs LCM to explore potential driver classes and analyzes the characteristics of different classes. The model framework is shown in Figure 1.

Shared parking provides drivers with more parking options, but it also brings them safety and other concerns; therefore, the SPUI may be influenced by the perceived risks [18]. Besides, Xu [49] pointed out that when travelers have accumulated certain travel experiences in intercity travel choices, travelers tend to form the inertia of adopting a specific behavior under specific selection conditions, and such inertial behavior will enhance the effect of behavior habit (BH) on usage intention (UI). So, we assume that BH will also affect SPUI; therefore, we construct the extended unified theory of the acceptance and use of technology model by incorporating PR and BH variables into the original unified theory of acceptance and use of technology to identify the factors influencing SPUI. The structural equation between the psychological factors can reflect the internal influence relationship between the psychological factors, and the structural equation between the exogenous variables and the psychological factors can reflect the degree of influence of the exogenous variables on the psychological factors [50].

Based on the analysis of the relationship between the influencing factors and SPUI, the difference between the driver's choice intention and preference is further explored. LCM is used to subdivide the driver category, as shown in the LCM framework in Figure 1. In traveler segmentation
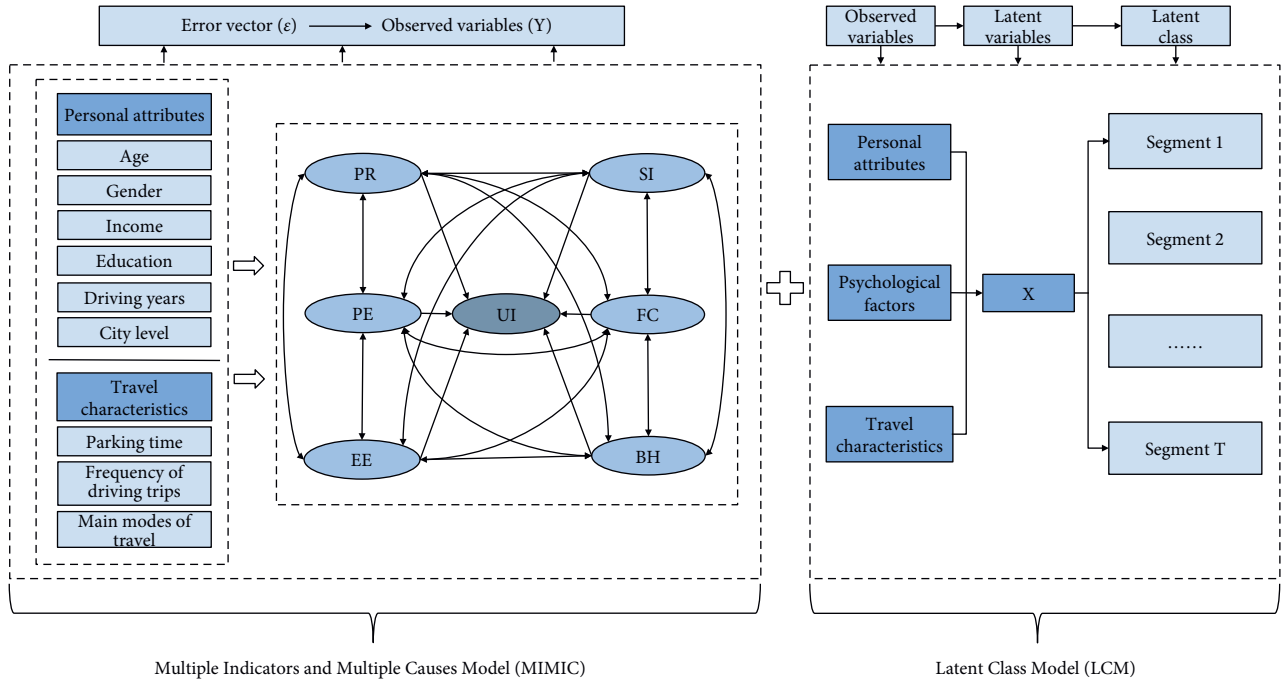
Figure 1: Modeling framework.

studies, demographic factors are usually regarded as basic classification indicators, such as age, gender, occupation, and income [51]. In addition, tourism-related factors [11] and various factor combinations [39] are also used for segmentation research. The driver's choice behavior is closely related to travel characteristics, such as driving frequency and parking time. Therefore, this article comprehensively considers the combination of personal attributes, travel characteristics, and psychological factors for subdivided research. The solution result of the MIMIC model is the influence relationship of various factors on SPUI. Variables that have a significant influence on SPUI are taken as input variables of LCM to obtain the number of types of driver groups and the specific characteristics of each type, such as the distribution and comparison of input variables. Finally, the characteristics of each category are summarized and analyzed.

3.2. Multiple Indicator and Multiple Causes (MIMIC) Model. Compared with the traditional SEM model and other models, the MIMIC model can not only express the exogenous causes and endogenous indicators of latent variables clearly through a strict structural model but also obtain the influence degree of all explanatory variables on latent variables, and this analysis method can make normal statistical relationship test more convenient [52]. Schneider and Enste [53] proposed that the MIMIC model can deal with multiple latent variables and endogenous indicators without strict constraints and assumptions, and allow exogenous causes and endogenous indicators to contain measurement errors. Therefore, its theoretical framework is more flexible than other indirect measurement methods, potentially including all other indirect measurement methods.

Therefore, this study intends to use the MIMIC model to explore the influence of psychological factors and exogenous variables on the SPUI.

The matrix form of MIMIC is shown in the equations as follows:

$$\eta = \Gamma x + \zeta. \tag{1}$$

$$y = \Lambda \eta + \varepsilon, \tag{2}$$

where η is the psychological factor vector; x indicates the exogenous variable vector; y is the observation variable vector; Γ and Λ are the parameter matrixes to be estimated; ζ and ε represent the measurement errors.

We substitute equation (1) into equation (2) to obtain

$$y = \Lambda(\Gamma x + \zeta) + \varepsilon = \Pi x + \nu,$$
$$\Pi = \Lambda \Gamma x, \tag{3}$$
$$\nu = \Lambda \zeta + \varepsilon.$$

Assuming that the measurement errors are independent of each other and subject to normal distribution, then $E(\zeta\varepsilon') = 0$, $E(\zeta^2) = \delta^2$, $E(\zeta\varepsilon') = \Theta^2$. Θ^2 is the lower triangular matrix of ν, so the covariance matrix formula is

$$\sum(\theta) = E(\nu\nu')$$
$$= \delta^2 \Lambda\Lambda' + \Theta^2. \tag{4}$$

The total covariance matrix can be calculated by observing the sample values of the variables, so $\sum = \sum(\theta)$; each parameter can be solved.

In the multiindex part of the MIMIC model, it is equivalent to the confirmatory factor analysis of psychological factors. The multicause part can be expressed as

$$\eta_{li} = \gamma_{l1} X_{\text{gender}_i} + \gamma_{l2} X_{\text{age}_i} + \gamma_{l3} X_{\text{inc}_i}$$
$$+ \gamma_{l4} X_{\text{edu}_i} + \gamma_{l5} X_{\text{year}_i} + \gamma_{l6} X_{\text{city}_i} \tag{5}$$
$$+ \gamma_{l7} X_{\text{awareness}_i} + \gamma_{l8} X_{\text{time}_i} + \gamma_{l9} X_{\text{frequency}_i},$$

where l is the psychological factor, including EE, SI, FC, PE, PR, BH, and UI; γ indicates the parameter to be estimated; i represents the observed individual.

3.3. Latent Class Model (LCM).

LCM is a modeling analysis technique to explore latent variables, which is not only a statistical method but also a statistical methodology [54]. The most important feature of the latent category model is that it can process classification data and use the maximum likelihood method to estimate parameters, which can calculate the appropriate number of categories more accurately. In addition, the classification results are relatively stable and can be generalized in other samples of the same population, which is convenient for practical application [55, 56]. It is an important research method to subdivide travelers' travel behavior differences with distinctive characteristics by using the potential category model [57]. It can overcome the shortcoming of traditional cluster analysis that deterministically assign travelers to a single group while ignoring the possibility of misclassification to the wrong group [58], such as K-means++ and DBSCAN. The LCM analysis process consists of three steps: probability parameterization, model fitting and parameter estimation, and latent classification and result interpretation [59].

(1) Probability parameterization. It is the first step that converts the probability of classifying variables into a parameter model [11]. In this paper, personal attributes, psychological factors, and travel characteristics are taken as three explicit variables A, B, and C, whose conditional probabilities are referred to $\pi_{it}^{\overline{A}x}$, $\pi_{jt}^{\overline{B}x}$, and $\pi_{kt}^{\overline{C}x}$. The sum of conditional probability of all observed variables at each level is 1, and the formula is as follows:

$$\sum_i \pi_{it}^{\overline{A}X} = \sum_j \pi_{jt}^{\overline{B}X} = \sum_k \pi_{kt}^{\overline{C}X} = 1. \tag{6}$$

Assuming that there is a latent variable X with t ($t = 1, 2, 3, \ldots, T$) latent categories can explain the relationship between the three latent variables A, B, and C, the LCM can be expressed as follows [60]:

$$\pi_{ijk}^{ABC} = \sum_{t=1}^{T} \left(\pi_t^X \times \pi_{it}^{\overline{A}X} \times \pi_{jt}^{\overline{B}X} \times \pi_{kt}^{\overline{C}X} \right). \tag{7}$$

(2) Model fitting and parameter estimation. Maximum Likelihood (ML) is mainly used for parameter estimation in potential category models, and the commonly used iterative algorithms include Expectation Maximization (EM), and Newton Rapson (NR). In this paper, the expectation maximization algorithm is used for iterative analysis. The ML estimation function is as follows:

$$\pi_{ijkt}^{ABCX} = \pi_t^X \times \pi_{it}^{\overline{A}X} \times \pi_{jt}^{\overline{B}X} \times \pi_{kt}^{\overline{C}X}. \tag{8}$$

(3) Latent classification and result interpretation. By diving π_{ijkt}^{ABCX} and π_{ijk}^{ABC}, the ML probability of observed variables in different potential categories at each level can be obtained, and the formula is as follows:

$$\pi_{ijkt}^{ABC\overline{X}} = \frac{\pi_{ijkt}^{ABCX}}{\pi_{ijk}^{ABC}}. \tag{9}$$

The posterior probability of each sample belonging to different latent classes is calculated, and the one with the highest value is the class to which the observed value belongs. The formula is as follows:

$$\pi_{tijk}^{\overline{X}ABC} = \frac{\pi_{ijkt}^{ABCX}}{\sum_{t=1}^{T} \pi_{ijkt}^{ABCX}}. \tag{10}$$

4. Data

4.1. Sample.

To ensure the data quality of the questionnaire, we conducted a presurvey in which we asked people with different levels of knowledge about shared parking to fill in the questionnaire and adjusted the questionnaire according to the presurvey results.

The final questionnaire consists of three parts: the first part is the information about parking on the latest trip; the second part is scene simulation; the third part covers the measurement items of the extended unified theory of acceptance and use of technology model variables, including EE, SI, FC, PR, PE, BH, and UI; the fourth part includes the respondents' socioeconomic attributes, parking characteristics, and travel characteristics. This study chiefly used the third and fourth parts of the questionnaire.

This study uses the Likert five-level scale — from "Strongly Disagree (=1)" to "Strongly Agree (=5)" to measure all psychological factors. It is used to rank respondents' recognition of the relevant descriptions given in each questionnaire measurement item for reflecting drivers' psychological feelings about shared parking. The measurement items constituting the questionnaire were adapted from scales validated in previous literature studies and modified by experts to reflect the specific environment and target population of shared parking. The six psychological factors of the theoretical model contain a total of 31 measurement items. Table 1 presents items related to psychological factors.

We carried out the formal survey using an online questionnaire in February 2021. There is no limit to the location distribution of respondents, and individuals with links to the survey and interest in the study are invited to participate. Individuals were considered eligible for inclusion if they met the following criteria: they were Chinese, had a valid driver's license, and had recently parked in an urban area for longer than 30 minutes. After conditional screening, the number of valid questionnaires in this study is

TABLE 1: Construction and measurement items of psychological factors.

Psychological factor	Project	Measurement item	Source
Facilitating Conditions (FCs)	FC1	If the operation of shared parking app is easy to understand, I prefer to choose shared parking space in residential areas	[18, 61]
	FC2	If the transaction of shared parking app is safe and convenient, I prefer to choose shared parking space in residential areas	
	FC3	If relevant institutions establish shared parking credit mechanism, I prefer to use shared parking space in residential areas	
	FC4	Shared parking will certainly get policy support	
	FC5	Existing technology is sufficient to support the normal operation of shared parking	
	FC6	I am willing to increase the walking distance to pay less parking fees	
Social Influence (SI)	SI1	If all my friends and relatives are using the shared parking space in the residential area, I will also use it	[61, 62]
	SI2	The encouragement from relatives and friends around me will make me more willing to choose the shared parking space in the residential area	
	SI3	The encouragement and appeal from the government and media will make me more willing to choose shared parking spaces in residential areas	
	SI4	Choosing to use a shared parking space in a residential area makes me feel technologically advanced	
Effort Expectancy (EE)	EE1	Shared parking spaces in residential areas are easy to find	[32]]
	EE2	I can quickly get used to the shared parking system in my residential area	
	EE3	The shared parking system would be simple to use	
	EE4	I feel completely in control of using the residential parking share system	
Perceived Risk (PR)	PR1	It is difficult to find the reserved shared parking space in the residential area	[18, 63]
	PR2	Choosing to use shared parking spaces in residential areas has a high risk of exposing personal privacy (such as vehicle information and location information)	
	PR3	If you park over time (beyond the scheduled time), it will cause more inconvenience for others to use the parking space	
	PR4	At present, the related equipment and policy mechanism of shared parking are not perfect enough	
	PR5	Parking in a shared parking space in a residential area increases vehicle safety risks	
Performance Expectancy (PE)	PE1	Using a shared parking space in a residential area will reduce my parking expenses	[64–66]
	PE2	Using shared parking spaces in residential areas can reduce the time spent looking for a parking space	
	PE3	Using shared parking spaces in residential areas can improve the efficiency and quality of my study, work, and life	
	PE4	Shared parking is good for the sustainable development of the city	
	PE5	Shared parking can alleviate the problem of "hard parking"	
Behavior Habit (BH)	BH1	Next time when I park my car, I will continue to use the public parking lot	[49]
	BH2	Public parking is my usual choice	
	BH3	I usually do not actively consider choosing new parking options (such as shared parking)	
Usage Intention (UI)	UI1	I would like to try to use shared parking space in residential areas in the future	[33, 38]
	UI2	I would like to give priority to using shared parking spaces in residential areas in the future	
	UI3	I will often use the shared parking space in the residential area	
	UI4	I will strongly recommend my relatives and friends to use shared parking spaces in residential areas in the future	

217. The sample size should be at least 5–10 times the variable in multivariate research using structural equation [50], which means the sample size of formal investigation should be more than 155, so the sample size of formal investigation can meet the research needs.

In an effective sample, the drivers surveyed were evenly distributed in cities of different levels, accounting for about 20% in first-tier, second-tier, and third-tier cities, and 35% in fourth-tier cities. The number of male drivers (63.13%) was higher than that of female drivers (36.87%). The respondents were mainly aged from 18 to 30 years old (61.29%), which accords with the age distribution structure of Chinese drivers, and those older than 30 years old were evenly distributed. 42.86% of the respondents had a college or bachelor's degree, and more than 30% had a master's degree or above. More than half of the respondents earned less than 5,000 yuan, which is consistent with the income characteristics of Chinese residents. Table 2 summarizes the main demographic characteristics of the valid sample.

4.2. Data Analysis

4.2.1. Measurement Model Testing. Firstly, exploratory factor analysis was carried out using SPSS, and KMO and Bartlett's sphere tests were performed on the scale. The

TABLE 2: Demographic characteristics of the participants.

Characteristics	Item	Proportion (%)	Variable naming
Gender	Male	63.13	Gender
	Female	36.87	
Age	18–25	40.09	Old
	26–30	21.2	
	31–40	14.75	
	41–50	11.06	
	51–60	9.68	
	>60	0.46	
Driving experiences	≤1	33.64	Year
	1–3	26.73	
	≥3	39.63	
Education level	High school or below	25.81	Education
	College/undergraduate	42.86	
	Master	26.73	
	Doctor	4.61	
Monthly income	<3000 yuan	31.34	Income
	3000–5000 yuan	23.04	
	5000–7000 yuan	18.43	
	7000–9000 yuan	11.52	
	9000–11000 yuan	3.69	
	>11000 yuan	11.98	
City level	First-tier city	22.58	City
	Second-tier city	22.58	
	Third-tier city	19.82	
	Fourth-tier city	35.02	
Understanding degree of shared parking	Do not understand at all	7.83	Awareness
	Do not understand	24.42	
	General understanding	52.53	
	Better understand	11.98	
	Understand very well	3.23	
Average daytime parking time on weekdays	<2 h	22.12	Time
	2–5 h	23.5	
	5–8 h	30.41	
	>8 h	23.96	
Driving frequency	1–4 times per week	58.53	Frequency
	5–8 times per week	23.96	
	9–12 times per week	9.68	
	>12 times per week	7.83	

results showed that the KMO value was 0.902 (>0.700), and Bartlett's sphericity test value was significant (sig.<0.001), indicating that the questionnaire data met the prerequisite requirements of factor analysis.

Cronbach's α, composite reliability, and average variance extracted were used to evaluate the reliability and validity of the questionnaire. Table 3 shows the reliability and validity of test results. If Cronbach's α is higher than 0.8, the reliability is high; if it is between 0.7 and 0.8, the reliability is acceptable; if it is between 0.6 and 0.7, it is basically acceptable; if it is less than 0.6, the reliability is not good, and the survey scale should be revised [67]. Based on analysis results, only Cronbach's α of BH is 0.784, and Cronbach's α of other psychological factors are all higher than 0.8, indicating that the reliability of the questionnaire is very high.

When the average variance extracted (AVE) value is greater than 0.5, it indicates that the psychological factor has

good convergence validity [68]. In addition, when the outer loading coefficient corresponding to each observation variable is greater than 0.6 and $P < 0.05$, it also indicates that the convergence validity is up to standard. Just as the results in Table 4, the minimum AVE value of the psychological factor is 0.567, and the outer loading coefficient of each measurement item is above 0.66, indicating that the data have strong reliability and internal consistency.

4.2.2. Structural Model Testing. The chi-square degree of freedom ratio ($\chi^2/\mathrm{d}f$), Root Mean Squared Error of Approximation (RMSEA), Goodness-of-Fit Index (GFI), Comparative Fit Index (CFI), and Adjust Goodness-of-Fit Index (AGFI) were selected as evaluation indexes of model fit degree. The MIMIC model was employed for parameter estimation and model assessment to characterize the intentions of drivers toward the use of parking

TABLE 3: Measurement items for all the relevant constructions.

Latent variable	Item no.	Outer loading	Mean	SD	α	AVE
Facilitating Conditions (FCs)	FC1	0.918	3.83	0.793		
	FC2	0.943	3.80	0.811		
	FC3	0.916	3.82	0.787	0.921	0.683
	FC4	0.735	3.68	0.865		
	FC5	0.741	3.47	0.901		
	FC6	0.661	3.76	0.856		
Social Influence (SI)	SI1	0.923	3.65	0.826		
	SI2	0.895	3.60	0.861	0.928	0.765
	SI3	0.900	3.73	0.808		
	SI4	0.775	3.53	0.892		
Effort Expectancy (EE)	EE1	0.693	3.39	3.39		
	EE2	0.854	3.56	0.873	0.876	0.663
	EE3	0.849	3.50	0.918		
	EE4	0.849	3.39	0.886		
Perceived Risk (PR)	PR1	0.843	3.49	0.849		
	PR2	0.748	3.40	0.904		
	PR3	0.914	3.73	0.889	0.915	0.690
	PR4	0.856	3.71	0.842		
	PR5	0.779	3.49	0.942		
Performance Expectancy (PE)	PE1	0.699	3.44	0.925		
	PE2	0.824	3.60	0.797		
	PE3	0.706	3.47	0.926	0.914	0.684
	PE4	0.954	3.79	0.779		
	PE5	0.920	3.76	0.799		
Behavior Habit (BH)	BH1	0.763	3.62	0.822		
	BH2	0.776	3.77	0.775	0.784	0.567
	BH3	0.718	3.42	0.881		
Usage Intention (UI)	UI1	0.866	3.71	0.774		
	UI2	0.922	3.45	0.793	0.940	0.815
	UI3	0.938	3.43	0.800		
	UI4	0.885	3.39	0.815		

TABLE 4: Test results of goodness of fit.

Index	$\chi^2/\mathrm{d}f$	RMSEA	GFI	CFI	AGFI
Actual value	1.537	0.064	0.801	0.950	0.737
Standard value	<3	<0.3	>0.8	>0.9	>0.8

space sharing systems based on AMOS software. Then, we found that the theoretical model and empirical data cannot be entirely fitting. Under the premise of not affecting the completeness of the theoretical model, the model was revised, and the path that had no significant impact was deleted. The calculation results of the test index of the final model fit are shown in Table 4. Except that the AGFI is slightly less than the standard value, other models are proposed. All the compliance indicators meet the requirements.

5. Result Analysis

5.1. Analysis of MIMIC Estimation Results. From the calibration results of the MIMIC model, we can see the relationship between personal attributes, travel characteristics and psychological factors, as well as the influence relationship between the psychological factors.

5.1.1. Analysis of the Influence Relationship between Psychological factors. The path relationship between the psychological factors in the shared parking use intention model is shown in Figure 2. The values on the path in the figure are standardized coefficients. In the figure, * means $P < 0.05$, ** means $P < 0.01$, and ***means $P < 0.001$.

The impact of each psychological factor on UI is ranked from the highest to lowest as follows: FC ($\beta = 0.677$, t-value $= 4.025$, $P < 0.001$), SI ($\beta = 0.452$, t value $= 1.958$, $P < 0.05$), EE ($\beta = 0.443$, t value $= 3.306$, $P < 0.001$), BH ($\beta = 0.229$, t value $= 2.052$, $P < 0.05$), PR ($\beta = -0.214$, t value $= -0.232$, $P < 0.05$), except PE ($\beta = 0.170$, t value $= 1.100$, $P = 0.271 > 0.05$), other psychological factors all have a significant impact on UI, with a confidence interval of 95% (corresponding to $P < 0.05$), the proportion of variance in UI that can be explained by FC, SI, EE, PR, BH is 59.6% ($R^2 = 0.596$). Marcoulides [69] pointed out the following evaluation criteria: R^2 lower

than 0.19 indicates unacceptable explanatory power; 0.19–0.33 indicates weak explanatory power; 0.33–0.67 indicates moderate explanatory power; higher than 0.67 indicates good explanatory power. Besides, the evaluation standard proposed by Cohen et al. [70] pointed out that when R^2 is greater than 0.4, the model is considered to have good explanatory power. According to the evaluation criteria proposed by Marcoulides and Cohen, in addition, the results of Chen's [33] study ($R^2 = 0.48$) also illustrate the validity of our result. So, it can be inferred that the theoretical model we constructed has a good explanatory power for the use intention of shared parking.

5.1.2. Analysis of the Influence Relationship of Exogenous Variables on Psychological factors. A summary of the impact of exogenous factors including population socioeconomic attributes, parking characteristics, and travel characteristics on FC, SI, PE, BH, EE, and PR is shown in Table 5.

Exogenous factors do not directly affect UI but indirectly affect UI by affecting FC, SI, PE, BH, EE, and PR. It can be seen from Table 5 that those exogenous variables do not have a significant impact on every psychological factor. Gender and the city level have no significant impact on all psychological factors, indicating that gender and the city level of the respondent do not affect their SPUI.

Age has a significant positive effect on EE ($P < 0.05$), indicating that within a certain range, older people have to work harder to accept and adapt to the shared parking system. On the contrary, young people have strong confidence in the control of new things, which may be related to the limited network information and physiological factors accepted by the elderly, while modern young people receive more extensive information from the outside world and have more active thinking. Driving experiences have a significant positive impact on PR ($P < 0.05$), indicating that the older the driving experiences, the more sensitive they are to the potential risks of shared parking; income has a significant negative impact on both FC ($P < 0.01$) and SI ($P < 0.05$); this shows that the higher the income, the less sensitive the attitudes of the external conditions and the surrounding people will be and will not be easily influenced by the outside world, this may be because people with higher incomes will look at new things more rationally; parking time has a significant positive effect on PE ($P < 0.001$), FC ($P < 0.001$), BH ($P < 0.05$), SI ($P < 0.01$), and EE ($P < 0.01$); driving frequency has a significant negative impact on PR ($P < 0.05$), PE ($P < 0.05$), FC ($P < 0.05$), and SI ($P < 0.05$), indicating that the higher frequency of driving.

5.2. Analysis of LCM Segmentation Results. In this study, based on the results of the MIMIC model, 11 factors were selected initially to subdivide the driver category. These factors are age, income, driving experiences, education level, parking time, frequency of driving, the degree of confidence in the control of shared parking systems (EE4), the influence of walking distance (PC6), the influence of government and news media (SI3), the attractiveness of preferential fees (PE1), and the influence of parking choice habit (BH3). After

calculation, the P value of BH in LCM is greater than 0.05, so the null hypothesis cannot be rejected. This variable cannot be effectively explained by the potential category, so BH is excluded from the explicit variables.

Because the number of classes C is initially unknown, we need to specify the value of C beforehand. According to literature [71], CAIC (Consistent Akaike Information Criterion) and BIC (Bayesian Information Criterion) indicators of LCM are used to determine category C. The smaller the CAIC and BIC values are, the higher the model fit degree is. Therefore, it is assumed that the samples can be divided into 1–10 classes. Then, LatentGOLD 5.0 software is used for LCM fitting and parameter estimation to obtain the CAIC and BIC values under a different number of classes. It can be seen from Figure 3 that when the number of classes is 4, CAIC and BIC have the smallest values, so the sample can be divided into four classes.

Respondents are modeled based on potential category analysis, and model parameters are estimated. The results are shown in Table 6. From the results, the probabilities of the four potential classes are 0.3602, 0.2964, 0.2449, and 0.0988, respectively. Finally, the classification accuracy of the model is $\lambda = 0.95$, which shows that the classification accuracy is high, and the classification results are reasonable [72].

The different observation factors of the latent class are analyzed, as shown in Figures 4–13. It is can be seen that the five observed psychological factors (EE4, SI3, FC6, and PE1) are also different in the latent classes, as shown in Figures 4–7, which shows their different psychological characteristics. There are significant differences among the observed factors age, driving experience, education level, income, parking time, and travel frequency in the latent classes, as shown in Figures 8–13.

According to the results of Figures 4–13 and Table 6, we characterized the segments as follows:

Segment 1 (36% of the respondents) is mainly composed of people with relatively more positive psychological characteristics. This type of driver makes up the largest proportion. They are more likely to accept "long distance in exchange for less parking fees" than segments 2 and 3, and they are more optimistic about the potential economic benefits of shared parking, but they are more susceptible to the influence of the government and the media than segments 2 and 3, so we call them "sensitive type." The age and income distribution of the members of this class are relatively even. 61.1% of the respondents have more than three years of driving experience, more than 98% of the respondents have a bachelor's degree or above, and more than 40% of respondents parked for more than 8h during working hours.

Segment 2 (29.6% of the respondents) is mainly composed of people with relatively more conservative attitudes, which we call the "conservative type." Their degree of influence by the government and media is the least among the four segments, and their degree of confidence in the control of the shared parking system is basically the same as that of segment 3 but lower than that of segments 1 and 4; besides, they have no great expectation of reduced parking fees compared with other segments. The age distribution of this
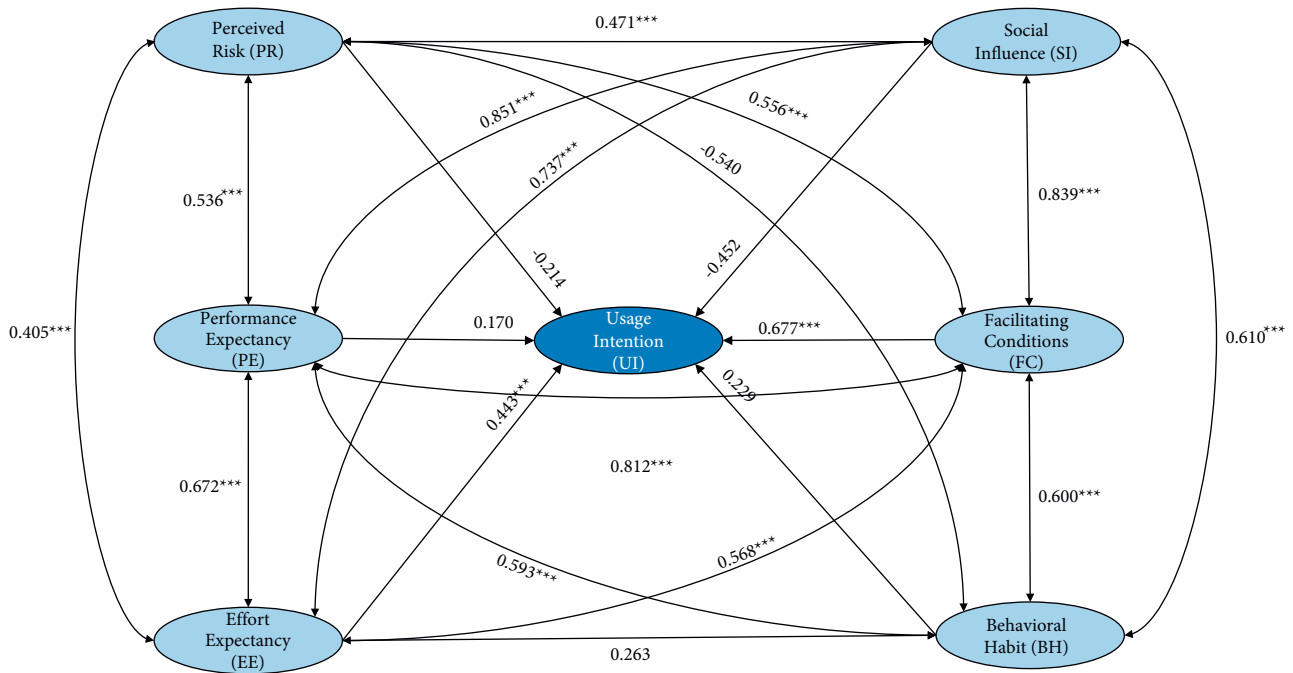
Figure 2: Analysis results of the structural model. Solid line indicates that there is a significant influence relationship; dashed line indicates that there is no significant influence relationship.

Table 5: Results of ANOVA.

Variable	Frequency	Parking time	City level	Income	Education	Driving experiences	Age	Male
PR	**−0.614**[*]	0.395	−0.133	−0.247	0.067	**0.494**[*]	−0.22	0.067
PE	**−0.287**[*]	**0.844**[***]	−0.069	−0.048	0.221	0.000	0.131	0.148
FC	**−0.279**[*]	**0.734**[***]	−0.206	**−0.384**[**]	0.222	0.037	0.212	0.155
BH	−0.376	**0.539**[*]	−0.010	−0.384	0.112	0.198	0.000	0.296
SI	**−0.462**[*]	**0.701**[**]	−0.246	**−0.358**[*]	0.045	0.162	0.236	0.017
EE	−0.064	**0.578**[**]	−0.246	0.088	**0.449**[*]	0.156	**0.540**[*]	0.191

Note. If the P value is greater than 0.05, the moderating effect is not significant; if the P value is lower than 0.05, the moderating effect is significant. [***]$P < 0.001$, [**]$P < 0.01$, and [*]$P < 0.05$.
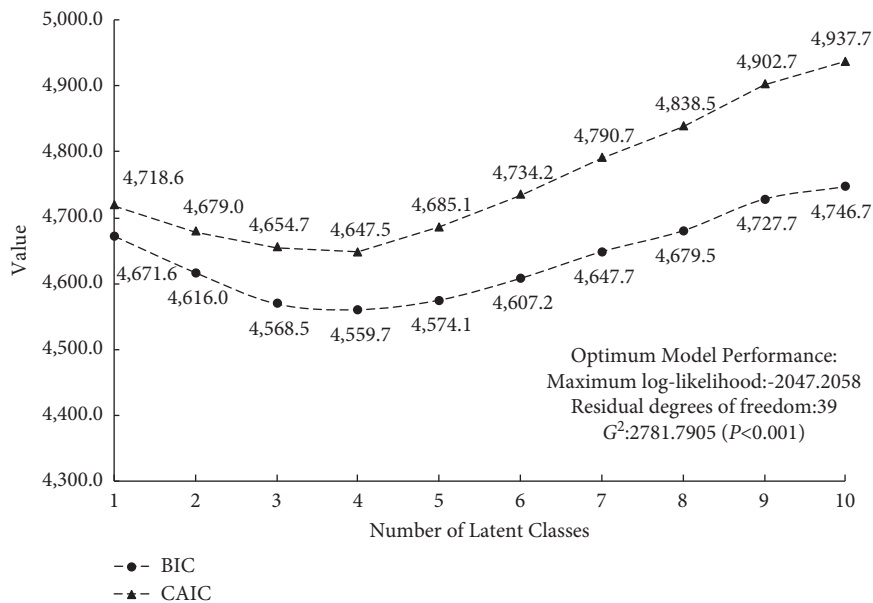
Figure 3: Optimum number of classes in the latent class model.

TABLE 6: Parameter estimation results of LCM (four latent classes: C1, C2, C3, and C4).

| Variable	Observed Variable	Level	Description	Conditional Probability of Latent Class			
				C1	C2	C3	C4
Psychological factors	EE4	1	Strongly disagree	0.0178	0.0431	0.0436	0.0000
		2	Disagree	0.0716	0.1176	0.1182	0.0000
		3	Generally agree	0.4425	0.4913	0.4916	0.0013
		4	Agree	0.4538	0.3407	0.3395	0.1842
		5	Strongly agree	0.0144	0.0073	0.0072	0.8145
		Mean	3.3753	3.1514	3.1487	4.8132	
	SI3	1	Strongly disagree	0.0071	0.0393	0.0334	0.0000
		2	Disagree	0.0080	0.0232	0.0210	0.0000
		3	Generally agree	0.2697	0.4055	0.3929	0.0000
		4	Agree	0.6377	0.5003	0.5176	0.0291
		5	Strongly agree	0.0775	0.0317	0.0350	0.9709
		Mean	3.7704	3.4619	3.4999	4.9708	
	FC6	1	Strongly disagree	0.0074	0.0436	0.0278	0.0000
		2	Disagree	0.0165	0.0495	0.0378	0.0000
		3	Generally agree	0.2713	0.4134	0.3792	0.0043
		4	Agree	0.5673	0.4393	0.4838	0.1746
		5	Strongly agree	0.1375	0.0541	0.0715	0.8211
		Mean	3.8110	3.4108	3.5335	4.8168	
	PE1	1	Strongly disagree	0.0332	0.0758	0.0423	0.0000
		2	Disagree	0.0604	0.0959	0.0694	0.0000
		3	Generally agree	0.4032	0.4469	0.4189	0.0048
		4	Agree	0.4714	0.3643	0.4423	0.2479
		5	Strongly agree	0.0319	0.0172	0.0270	0.7474
		Mean	3.4083	3.1512	3.3423	4.7426	
Personal attributes	Age	1	18–25	0.0038	0.0001	0.0544	0.0020
		2	26–30	0.2752	0.0300	0.7637	0.1862
		3	31–40	0.2916	0.0883	0.1547	0.2528
		4	41–50	0.2408	0.2024	0.0244	0.2675
		5	51–60	0.1309	0.3056	0.0025	0.1864
		6	>60	0.0576	0.3735	0.0002	0.1051
		Mean	3.3929	4.9038	2.1576	3.7654	
	Driving experience	1	≤1	0.1490	0.2572	0.6764	0.1818
		2	1–3	0.2403	0.2760	0.2155	0.2550
		3	≥3	0.6107	0.4668	0.1081	0.5632
		Mean	2.4617	2.2096	1.4317	2.3813	
Personal attributes	Education level	1	High school or below	0.0166	0.7945	0.0178	0.5355
		2	College/Undergraduate	0.4631	0.2038	0.4749	0.4517
		3	Master	0.4319	0.0017	0.4241	0.0127
		4	Doctor	0.0884	0.0000	0.0832	0.0001
		Mean	2.5922	1.2073	2.5727	1.4774	
	Income	1	<3000 yuan	0.0769	0.3299	0.6277	0.2719
		2	3000–5000 yuan	0.1602	0.3281	0.2777	0.3124
		3	5000–7000 yuan	0.2118	0.2069	0.0779	0.2276
		4	7000–9000 yuan	0.1814	0.0846	0.0142	0.1074
		5	9000–11000 yuan	0.0968	0.0215	0.0016	0.0316
		6	>11000 yuan	0.2729	0.0289	0.0010	0.0491
		Mean	3.8797	2.2265	1.4871	2.4617	
Travel characteristics	Parking time	1	<2 h	0.0752	0.2609	0.3218	0.1858
		2	2–5 h	0.1258	0.2199	0.2324	0.1945
		3	5–8 h	0.3764	0.3316	0.3003	0.3640
		4	>8h	0.4226	0.1876	0.1456	0.2557
		Mean	3.1463	2.4460	2.2696	2.6896	
	Frequency of driving	1	1–4 times per week	0.6159	0.3487	0.9920	0.5204
		2	5–8 times per week	0.2888	0.3405	0.0080	0.3238
		3	9–12 times per week	0.0665	0.1633	0.0000	0.0989
		4	>12 times per week	0.0288	0.1475	0.0000	0.0569
		Mean	1.5082	2.1096	1.0080	1.6924	
Probability of latent class				0.3602	0.2961	0.2449	0.0988
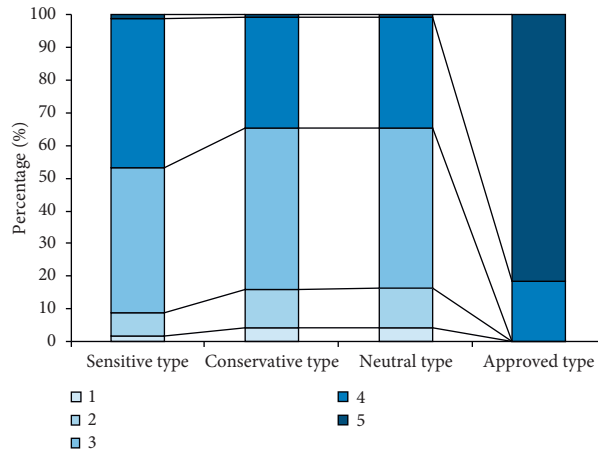
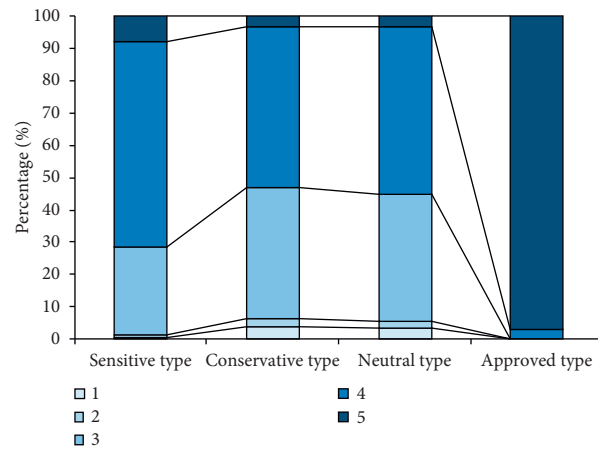FIGURE 4: EE of drivers in the four segments.
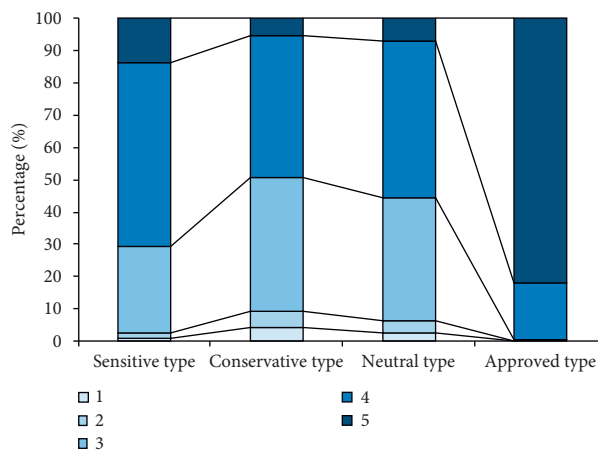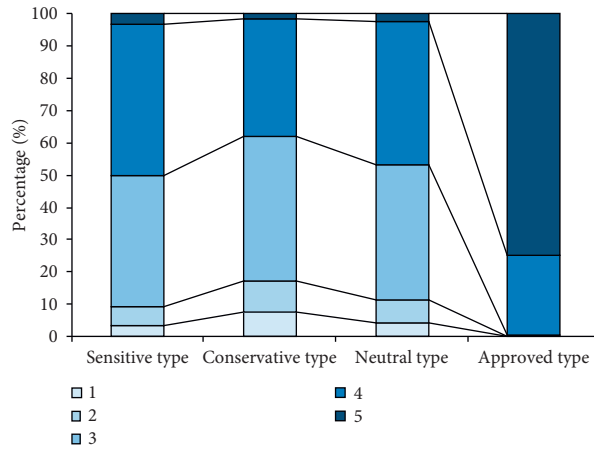

FIGURE 5: SI of drivers in the four segments.

FIGURE 6: FC of drivers in the four segments.

segment is relatively uniform, and the average education level is the lowest, while the average driving frequency is the highest; among the four segments, their monthly income is concentrated below 7000 yuan (86.5%), but the parking time is lower than segments 1 and 4. Therefore, it can be inferred that the randomness of their trips may be strong.

Segment 3 (24.5% of the respondents) has the least confidence in the control of new things, and their response

FIGURE 7: PE of drivers in the four segments.
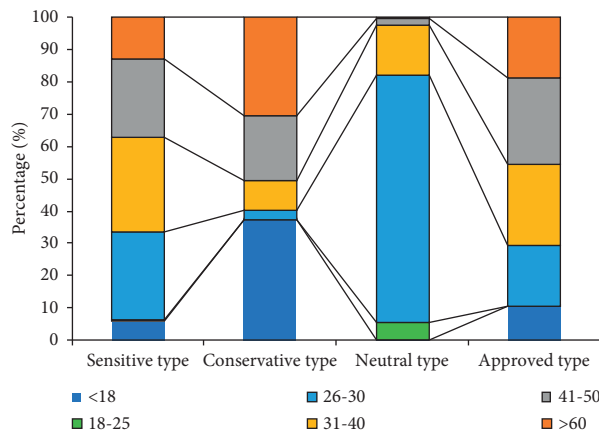
FIGURE 8: Age of drivers in the four segments.
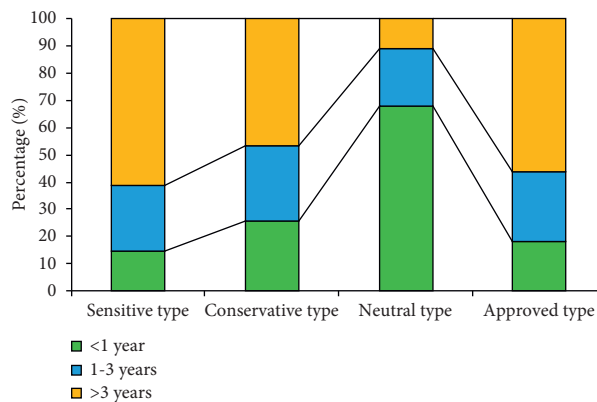
FIGURE 9: Driving experience of drivers in the four segments.

to the government and the media is basically the same as segment 2. The expectation for reduced parking fees is comparable to segment 1, lower than segment 4 but higher than segment 2, which is why we call it the "neutral type." Members of this segment are more often people younger than 25 years of age (76.4%) and more often have driving experience within 1 year (67.6%), which is also consistent with the distribution of age. Their average educational background is slightly lower than that of segment 1 but much higher than that of segments 2 and 4, and their monthly income is less than 5,000 yuan (90.5%), so it can be inferred that this group may be college students or newly
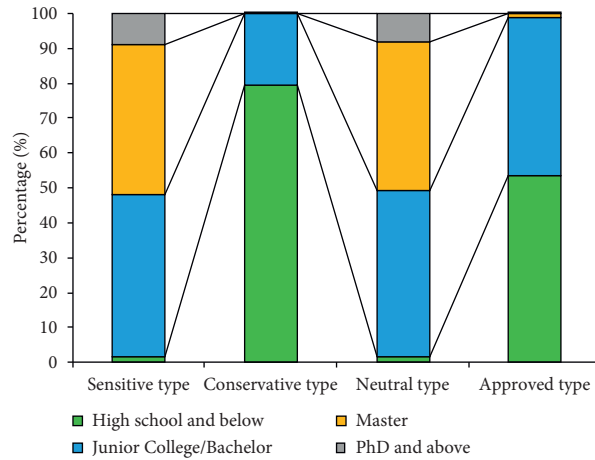
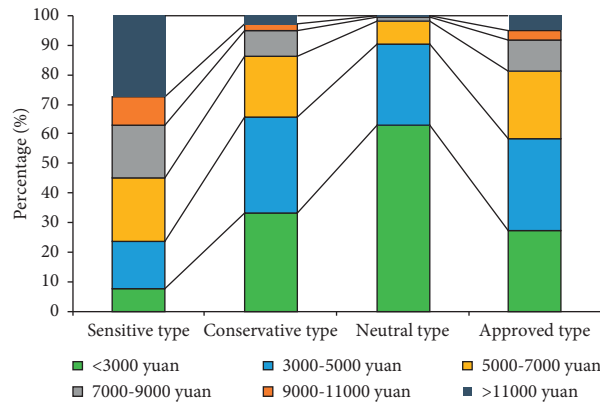FIGURE 10: Education level of drivers in the four segments.

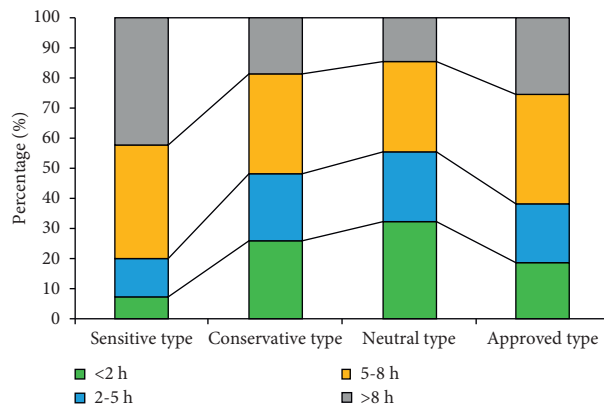FIGURE 11: Income of drivers in the four segments.

FIGURE 12: Parking time of drivers in the four segments.

graduated workers. In addition, they also have the lowest amount of parking time and the lowest frequency of driving trips, which reinforced our above hypothesis.

Segment 4 (9.9% of the respondents) has the highest score among all psychological factors. This type of driver has the smallest percentage. People in this segment are generally confident in their ability to control new things and are also

willing to respond to the call of the government and the media. 82% of the drivers in this group tend to "replace long distances for lower costs," which also reflects that they are very appreciative of shared parking projects, so we call it the "approved type." In this segment, their ages are evenly distributed, their educational backgrounds are concentrated in undergraduates and below (98%), and their monthly
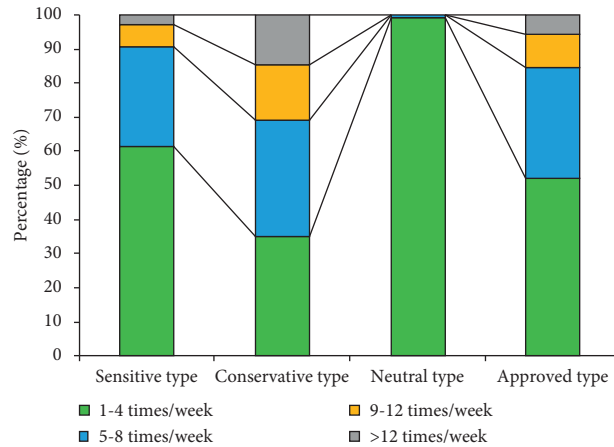
FIGURE 13: Driving frequency of drivers in the four segments.

income is concentrated below 9000 yuan. In addition, their driving frequency and parking time are both higher than segment 1 and lower than segment 2.

6. Conclusions and Discussion

In this paper, we use the output of the MIMIC model as the input variables of LCM to explore the SPUI of drivers considering individual heterogeneity. The results showed that the surveyed driver groups can be divided into four segments: sensitive type (36%), conservative type (29.6%), neutral type (24.5%), and approved type (9.9%). In exploring those characteristics, we can better understand "the respective natures of the four segments." This study contributes to the literature by providing first-hand insights into SPUI of different categories of drivers.

Firstly, the multiple indicator multiple cause model was used to explore the relationship between psychological factors, personal attributes, travel characteristics, and SPUI. The research shows the following: (1) The extended theoretical model has good explanatory power for SPUI, and SPUI is directly affected by perceived risk (PR), behavioral habit (BH), social influence (SI), facilitating conditions (FC), and effort expectancy (EE), while performance expectancy (PE) have no significant effect on SPUI. Among them, FC has the largest effect and PR has the smallest effect on SPUI. (2) Personal attribute variables including age, education level, monthly income, driving experience and driving frequency, and parking time in travel characteristics all have a significant influence on psychological variables.

Secondly, based on the analysis results of MIMIC, this paper uses LCM to explore the SPUI of different types of drivers from a microperspective. According to individual attributes, travel characteristics, and psychological factors, the potential classes of drivers are analyzed and simulated. Ten observation variables are used including age, education level, monthly income, driving experience, driving frequency, parking time, confidence in the control of shared parking systems (EE), response to the government and media (SI), perceived cost effectiveness (PE), and "long distance in exchange for less parking fees" tendency (FC).

Finally, the surveyed driver groups are divided into four segments: sensitive type (36%), conservative type (29.6%), neutral type (24.5%), and approved type (9.9%). The results show that for different types of drivers, their SPUI is closely related to personal attributes, travel characteristics, and psychological factors. Therefore, in order to attract drivers to choose shared parking, it is recommended that managers or operators can start with psychological factors, such as effort expectations, facilitating conditions, performance expectancy, and social influence.

More targeted measures can be implemented for different categories of drivers:

(1) For the first segment (sensitive type), they are more optimistic about the potential economic benefits of shared parking, which may be due to their higher average educational level and stronger acceptance of emerging things, and are exposed to a wider range of online information, so they are more susceptible to government and media influence than segment 2 and segment 3. It is not difficult for shared parking operators to attract users from this largest proportion of the drivers through various promotional methods, such as providing incentives for demanders and suppliers. At the same time, government-level countermeasures are very important to substantially promote dominoreaction. The government can introduce policies and regulations to encourage the development of shared parking, thereby stimulating the development of the shared parking industry.

(2) For the second segment (conservative type), their attitude toward shared parking is more conservative, less susceptible to the influence of the government and the media, and more rational than other segments, but their confidence in the control of the shared parking system is less than that of segments 1 and 4. The perceived potential economic benefit is the smallest among the four segments. Therefore, saving more parking fees may be the most important point to attract them. Reasonable parking fees are

determined, and the negative impact of shared parking fees is reduced on them. For example, those who use shared berths flexibly or who have little parking demand can charge parking fees according to the parking time or the number of use times. For those who use shared parking spaces for a long time and have stable demand, a monthly or yearly fee with preferential rates can be adopted.

(3) For the third segment (neutral type), they have the least confidence in the control of the shared parking system. Therefore, creating a convenient, simple, and fully functional shared parking operating system may be the most important measure to attract them. However, since most of the available commercial maps cannot provide guidance in residential areas, it is important to display the turn-by-turn navigation function and detailed maps of the vacant parking spaces. In addition, some studies advocate the application of ergonomic principles in system design to make it more humane [73]. Finally, well-designed instruction manuals and training courses may help develop users' sense of self efficacy and ability to use technology [74]. These measures may help to improve users' technical compliance.

(4) For the fourth segment (approval type), they are very optimistic about the economic benefits of using shared parking. 82% of drivers have a strong intention to save parking fees even if the walking distance is increased. This group may have been exposed to the actual shared parking projects or in areas with high parking pressure. Therefore, the potential target areas of shared parking projects can be explored according to their spatial distribution characteristics.

However, this study inevitably has limitations that need to be resolved. Firstly, this study only considered the impact of latent variables and individual socioeconomic characteristics on the SPUI in residential areas and did not consider the impact of variables such as parking fees and walking distance, which is crucial for operators to determine reasonable prices. Secondly, this study explores the SPUI rather than the actual user behavior. In the future, the research can be extended to the investigation of the factors affecting actual use behavior. Thirdly, it is more valuable to jointly analyze the factors that affect the participation of suppliers and demanders in shared parking programs. This may promote better cooperation and matching between the two sides.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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