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Parking Choice Analysis of Automated Vehicle Users: Comparing Nested Logit and Random Forest Approaches

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Abstract

Parking shortages and high costs in Chinese central business districts (CBDs) remain major urban challenges. Emerging automated vehicles (AVs) are expected to diversify parking options and mitigate these problems. However, AV users' parking preferences and their influencing factors within existing urban zoning frameworks remain unclear. This study examines Nanjing as a representative case, proposing six distinct AV parking modes. Using survey data from 4644 responses collected from 1634 potential users, we employed nested logit models and random forest algorithms to analyze parking choice behavior. Results indicate that diversified AV parking modes would significantly reduce CBD parking demand. Users with medium- to long-term needs prefer home-parking, while short-term users favor CBD proximity. Key influencing factors include parking service satisfaction, duration, congestion time, AV punctuality, and individual characteristics, with satisfaction attributes showing the greatest impact across all modes. Comparative analysis reveals that random forest algorithms provide superior predictive accuracy for parking mode importance, while nested logit models better explain causal relationships between choices and influencing factors. This study establishes a dual analytical framework combining interpretability and predictive accuracy for urban AV parking research, providing valuable insights for transportation management and future metropolitan studies.

Keywords: behavior analysis; nested logit model; machine learning model; automated vehicles; parking choices

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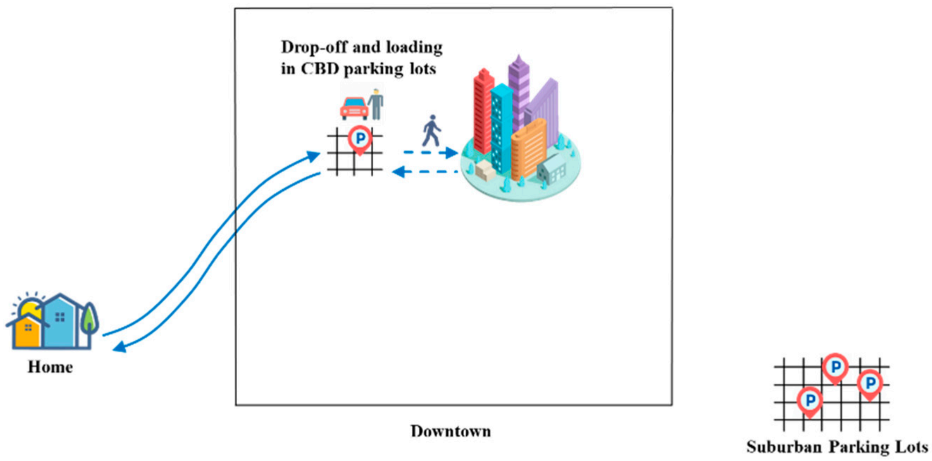
1. Introduction

Parking issues in central business districts (CBDs) remain a persistent challenge for metropolises worldwide, especially in developing countries. In recent years, this challenge has been exacerbated by the rapid increase in vehicle ownership in China. The primary parking issues in the context of human-driving are as follows: First, parking spaces remain insufficient. In large metropolises in China, the parking space-to-vehicle ratio ranges from 0.4:1 to 0.7:1, which is much lower than the 1.3:1 ratio common in developed countries [1]. Therefore, finding proper parking spaces during peak hours is often a huge challenge. Second, parking costs have increased. Because existing parking facilities in big cities cannot meet the increasing demand for parking, this imbalance between supply and demand has driven up parking costs. For example, daily parking costs in urban areas in China can reach as high as 300 CNY [2]. Third, walking issues remain a problem after parking.

93% of commuters expressed concerns about the distance they have to walk after parking as a decisive factor in choosing a parking location [3], especially people with disabilities.

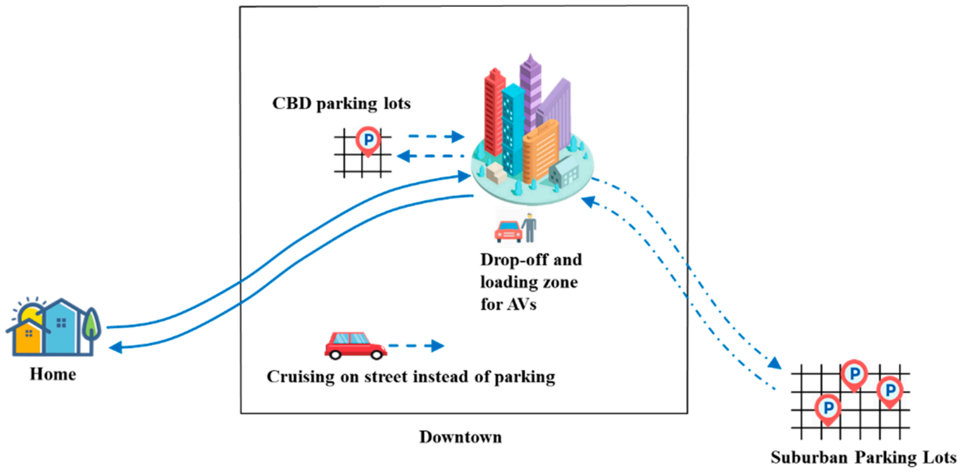
These parking issues primarily occur with human-driven vehicles (HVs). However, the emergence of automated vehicles (AVs) is expected to change this dilemma. The development of the AV industry has received much attention in China in recent years. Regions such as Shanghai, Nanjing, Suzhou, and Shenzhen have successively established industrial demonstration zones for AVs and proposed the concept of "vehicle-road-cloud integration" as a consensus for industry development. Compared with traditional human-driven vehicles (HVs), automated vehicles (AVs) possess the potential to fundamentally change traditional parking modes and parking planning strategies [4,5].

In this paper, we focus on Level 5 (L5) electric automated vehicles, which represent fully autonomous vehicles, with particular attention to parking scenarios when users travel to the central business district (CBD). Figure 1a,b, respectively, illustrate the contrasting parking patterns between HVs and AVs when traveling to the urban central business district. In traditional human-driven vehicle scenarios, when users drive to the destination in the CBD, they need to park their cars first and then walk to target buildings. Consequently, users typically seek parking locations as close as possible to their destinations within CBD parking areas. Research indicates that parking choice decisions are primarily influenced by available parking space, parking fees, and proximity to destinations [6]. Automated driving technology fundamentally transforms this parking paradigm. AVs can be instructed to transport users to CBD destinations and subsequently navigate autonomously to designated parking locations based on user preferences and instructions. This technological capability enables diverse parking strategies: users may prioritize safety by directing vehicles to return home for parking, adopt cost-optimization approaches by selecting suburban parking lots with lower fees despite greater distances, choose convenience by parking within CBD areas, or implement dynamic cruising strategies on city roads during working hours as an alternative to parking [7]. Therefore, the introduction of AVs addresses traditional CBD parking constraints by expanding available options beyond proximate parking spaces. This diversification enables users to optimize parking decisions according to multiple criteria—including cost, safety, convenience, and time—rather than being limited by the proximity imperative that characterizes human-driven vehicle parking. Consequently, automated vehicle technology offers systematic solutions to urban parking challenges by providing flexible, personalized parking alternatives that can better accommodate varied user preferences and requirements.



(**a**)

Figure 1. *Cont.*



(**b**)

Figure 1. (**a**) Parking modes of human-driven vehicles (HVs). (**b**) Parking modes of automated vehicles (AVs).

In terms of solving current parking problems through AVs, a series of studies have been conducted mainly focusing on two areas: parking management methods [7–9] and user parking behavior [10]. The previous literature on parking management has mainly conceptualized AV parking methods from various perspectives, including cost savings and congestion reduction. These methods have produced remarkable results, but the personal parking preferences and choices of AV users have been overlooked in most cases. Indeed, an effective functional parking management model should prioritize users' willingness, preferences, and requirements. Because of the great flexibility inherent in AVs, which allows them to be adapted to different parking environments, user personalities, and parking needs, it is necessary to understand in detail the choice preferences of AV users before proceeding with urban parking design and management. On the other hand, studies of AV parking behavior have so far mainly focused on users' willingness to move, parking choices, and related environmental impacts. However, the city's unique natural, historical, and parking zoning characteristics also influence AV parking modes, a phenomenon that has rarely been addressed in the previous literature. Implementation of AVs is a gradual process that includes stages of acceptance and subsequent familiarity [11,12]. During this process, planners and operators should incorporate an inherent urban parking zoning system, local parking behavior characteristics, and socioeconomic attributes into urban parking studies. This approach will ensure that AV parking strategies better reflect current urban realities and user needs.

This study is based on Nanjing, a city with a history of more than 2500 years and nearly 500 years as the historical capital. In this city, Zhongshan Mountain, Qinhuai River, and the Yangtze River form a complex topography that forms the typical "mountain–water–city" layout. Numerous historical relics, complex topography, and road networks combine to define the city's existing parking zoning system. The current Nanjing Vehicle Parking Management Regulations [13] categorizes parking zones into four types: Core area, Level 1 area, Level 2 area, and Level 3 area. To ensure compatibility with the existing parking zoning regulation when the parking mode for AVs is introduced, the existing four types of parking zoning systems are used as the basis for adding AV-specific parking modes, namely cruising and home-parking. Therefore, a total of six parking modes are considered in this paper: cruising, home-parking, core area parking, level 1 area parking, level 2 area parking, and level 3 area parking. In this context of urban parking zones, we do not yet know the choice behavior of AV users in the six parking modes. Moreover, previous studies of AV parking behavior have been analyzed mainly using conventional discrete choice models. Consequently, there is a dearth of research on AV parking behavior using machine-learning models, and the question of whether machine-learning models yield anomalous results remains unanswered. In this study, we propose an AV parking model based on the common zoning system for urban parking, using discrete choice models and a machine-learning model. Prior research on automated vehicle parking behavior has predominantly focused on parking behavior attributes and individual socioeconomic characteristics, with limited consideration given to urban parking service attributes. These often-overlooked attributes include satisfaction degree with urban traffic safety (SSD), satisfaction degree with parking conditions across the entire city (PSD), and satisfaction degree with parking conditions in the CBD area (CSD). Consequently, this study incorporates the consideration of urban parking service attributes into its analysis.

Given the current unavailability of fully automated vehicles in the commercial market, a stated preference (SP) survey is used to collect data on six options for parking modes in CBD areas. The data collected will be used in the second phase to develop parking choice models, including the nested logit (NL) model and the random forest model. These models are used to analyze the parking decisions and preferences of AV users for four types of parking duration. Specifically, this study addresses three key research questions:

(i) What are the parking choice preference characteristics of AV users within existing urban parking zoning frameworks?
(ii) Which factors significantly influence AV users' travel choice behavior, and what are the interrelationships among these influencing factors?
(iii) What are the similarities and differences between results generated by discrete choice models and machine learning models?

The findings will contribute to the design of parking systems tailored to the diverse needs of different user groups within the original context of urban parking zoning. Since our study is conducted in existing urban parking zoning systems, it will inform the development of ecologically sustainable parking management strategies for AVs. In addition, it also provides a theoretical basis and practical guidelines for long-term parking planning and parking management for AVs.

The rest of this article is organized as follows. Section 2 provides an overview of previous research on parking management and behavior. This is followed by Section 3, which explains the experimental design and data collection. Section 4 introduces the methodology for model development. Section 5 describes sample results, model parameter estimates, and comparative analysis of discrete choice models and machine learning models. Finally, Section 6 summarizes key results and future research.

2. Literature Review

The acceptance and future development of automated driving have attracted growing attention in recent years [12,14–16]. Researchers from an increasing number of countries have begun to explore AV parking choices and management. Some researchers have examined the AV parking modes in which automated vehicles were arranged to park in more costs-effective suburban locations far from travelers' destinations, and the impact of adjusting parking costs to influence such decisions was also explored [9]. This article achieved valuable research results on AV parking, but it mainly focused on parking choices distant from destinations, without considering other potential parking strategies. Subsequently, the feasibility of implementing an AV parking method in a designated area with multiple parking facilities was investigated [5]. The proposed solutions included the implementation of costs-optimizing structures designed to distribute overall parking demand among available parking spaces. A control theory was employed to address parking allocation;

however, the behavioral heterogeneity of users was not discussed. Other follow-up studies have simulated scenarios in which AVs were assigned to cruise when parking is required. These studies have designed measures such as dynamic pricing and congestion charges to alleviate traffic congestion caused by prolonged cruising [7,8]. However, Amirgholy et al. [17] believed that parking fees represent a more practical alternative to congestion pricing, as they avoid the social resistance that congestion charges often provoke. They developed a spatiotemporal parking pricing strategy and a new parking supply design, proposing a measure that leverages parking fees to incentivize travelers to adjust their departure times. This approach is presented as a pragmatic substitute for conventional dynamic congestion pricing. Overall, research on AV parking management has made significant progress, but the in-depth exploration of individual preferences and users' demand characteristics still needs further study. Moreover, current studies often fail to propose context-specific AV parking designs tailored to the specific natural, historical, and existing characteristics of individual cities.

Understanding parking preferences and choices among AV users is a critical foundation for AV parking systems planning and design. Only with a full understanding of users' parking preferences and demands can the design and planning of parking facilities be managed usefully and efficiently [18]. Previous research has extensively discussed the parking preferences and demand of human-driven vehicles and identified parking costs [6,19–21] and parking durations [20,22] as the most critical factors influencing parking decisions for human-driven vehicles. Research on parking choices for AVs remains relatively limited. Existing research on autonomous vehicles mainly focused on shared autonomous vehicles (SAVs) and privately owned autonomous vehicles (PAVs). As for SAVs, the factors affecting users' willingness to accept SAVs and their parking behavior have been analyzed in detail [23], including travel time, parking costs, and so on. For PAVs, research on the users' parking behavior has investigated several factors, such as trip purpose, parking distance, parking duration, and parking costs [24]. Most of these studies have employed discrete choice models as the primary analytical framework. Additionally, some studies have incorporated unique perspectives, such as measuring willingness-to-relocate (WTR) to quantify the time travelers were willing to spend relocating their PAVs [10], considering time windows and vehicle retrieval frequency [25], and examining the energy consumption of PAV parking [26]. These contributions have provided beneficial references to AV parking behaviors and user preferences. However, it is noteworthy that existing studies have largely ignored the impact of urban-specific parking zoning on AV parking behavior and have not examined the effects of varying parking durations on specific parking choices. In addition, the application of machine learning models as analytical tools in AV parking behavior research remains unexplored. Unlike discrete choice models which rely on predetermined assumptions, machine learning can uncover complex, nonlinear relationships within data as an advanced branch of artificial intelligence [27,28]. In this paper, we attempt to use machine learning models to analyze the parking preference of AV users in six parking modes.

3. Stated Choice Experiment

3.1. Survey Overview

This study focuses on the parking choices of AVs in scenarios within the CBD of Nanjing, China. It primarily relies on real-world data, including parking costs, energy consumption costs, and zoning maps of Nanjing, to extend the findings to other major Chinese cities in the future. This research focuses specifically on fully automated electric vehicles. For advance clarity, both urban roads and suburban roads in China are toll-free. Moreover, this study assumes that when AVs are widely adopted in the future, the costs of autonomous driving services will be integrated into monthly subscription plans, following the current practices of Tesla [29].

The six parking modes were introduced in the introduction, and the parking zoning system in Nanjing is depicted in Figure 2. For the stated preference (SP) parking experiment, three primary attributes were mainly considered: four parking duration levels (1 h, 3 h, 6 h, and 8 h), two vehicle arrival punctuality conditions (on-time and delayed arrival), and four congestion duration scenarios (0 min, 5 min, 10 min, and 15 min). Six distinct parking modes were presented as choice alternatives in the survey questionnaire: cruising as a parking substitute, returning home for parking, parking in the core area, level 1 area, level 2 area, and level 3 area.

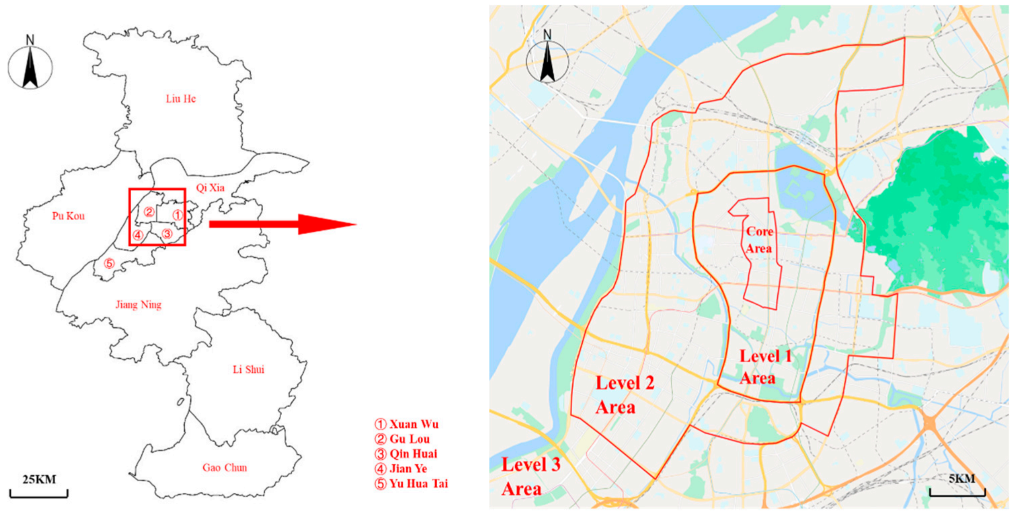


Figure 2. Distribution of parking zoning system in Nanjing.

For the four parking modes in the core area, level 1 area, level 2 area, and level 3 area, parking fees were set according to the standards defined in the Nanjing Regulations on Vehicle Parking Service Charges [30] which are about 8 CNY/h, 6 CNY/h, 4 CNY/h, and 2 CNY/h, respectively. In contrast, the cruising mode eliminates the need for parking space search, while the home-parking option assumes direct access to private residential parking facilities. Consequently, both cruising and home parking modes incur zero parking fees, as they do not require commercial parking space utilization. To facilitate the calculation of energy consumption costs during parking periods, we integrated energy consumption expenses with parking fees, expressing the combined cost as an average hourly rate. This unified metric represents the total cost per unit time, comprising both parking fees and energy consumption expenses. This methodological approach serves to mitigate potential multicollinearity issues in subsequent discrete choice modeling analyses.

Parking durations are closely related to travel purposes, and this study considers two primary purposes: commuting and non-commuting. For commuting trips, the parking durations are set at 8 h. For non-commuting trips, parking durations are categorized into three levels: 1 h (short-term parking), 3 h (medium-term parking), and 6 h (long-term parking). Thus, the parking duration analyzed in this study includes four levels: 1 h, 3 h, 6 h, and 8 h. Considering that the increased empty vehicle miles traveled (VMT) during cruising and home-parking could potentially exacerbate road congestion, we introduced two attributes: arrival punctuality and congestion duration. The punctuality of arrivals refers to whether AVs can pick up users on time after leaving the parking facility, which depends on several factors, including traffic congestion and the vehicle's departure time. In this study, punctuality is classified into two categories: on-time and delayed. Additionally, traffic congestion during the journey from the parking facility to the user's location is considered, as it may impact vehicle arrival time. Congestion time is included as an attribute for analysis. Based on domestic traffic congestion levels [31], congestion times vary significantly throughout the day, with the most common delays ranging from 0 to 20 min. Therefore, this study defines congestion time at four levels: 0 min, 5 min, 10 min, and 15 min.

Previous studies [32] have shown that user satisfaction significantly influences parking location choices. Therefore, three key satisfaction factors are considered in this study: satisfaction degree with the parking conditions in the CBD area (CSD), satisfaction degree with the parking conditions across the entire city (PSD), and satisfaction degree with urban traffic safety (SSD), to represent parking service level. Additionally, individual socioeconomic characteristics, such as gender, age, monthly per capita household income, driver's license ownership, educational level, and occupation, are also included in the analysis, as shown in Table 1.

Table 1. The list of influencing factors corresponding to the three types of attributes.

Factor Type	Factor Symbol	Factor Definition
Parking service attributes	SSD	Satisfaction degree with urban traffic safety
	PSD	Satisfaction degree with the parking conditions across the entire city
	CSD	Satisfaction degree with the parking conditions in the CBD area
Socioeconomic attributes	GEN	Gender
	AGE	Age
	FI	Monthly household income per capita
	DL	driver's license ownership
	EDU	Education
	CA	Career or occupation
	EXP	Experience with auto-pilot vehicles
Parking behavior attributes	P_PF1	Hourly costs for cruising
	P_PF2	Hourly costs of home-parking
	P_PF3	Hourly parking costs if parking in the core area
	P_PF4	Hourly parking costs if parking in the level 1 area
	P_PF5	Hourly parking costs if parking in the level 2 area
	P_PF6	Hourly parking costs if parking in the level 3 area
	CT	Congestion time
	PA	Punctuality of arrival
	PD	Parking durations

3.2. Parking Choice Experiment Design

A survey was conducted using the SoJump platform [33]. First, we invited two researchers with expertise in empirical studies to conduct an expert review and three respondents to participate in cognitive interviews. Based on their feedback, ambiguous words were revised, and irrelevant questions that did not match the survey objectives were removed. The final version of the survey consisted of four sections and 25 items.

The first section contained general introductory information and educational materials. Before the beginning of the survey, we explained the background and motivation of the study, assuring respondents that their personal information would remain confidential and not be used for commercial purposes. We then introduced the concept of automated vehicles (AVs), highlighting their recent developments and applications, to provide respondents with a clear and intuitive understanding of AVs. We also provided respondents with an introduction to automated parking systems [34] and a short video on auto-pilot driving [35]. These materials were designed to help respondents fully understand the study's background and strive to minimize any potential misunderstandings among participants, thereby improving response rates and data quality. The second section focused on travel background characteristics. A stated preference (SP) survey was conducted to collect data on respondents' current travel behavior. The survey included questions about driver's license ownership, the most commonly used travel mode for daily commuting, and other related factors. The third section investigated respondents' parking mode choices for AVs. This section used a stated preference (SP) approach with 16 scenarios designed through orthogonal experimental design. Here an example question from scenario 1 is shown in Figure 3. The fourth section collected respondents' socioeconomic attributes. This section included questions on gender, age, educational background, and other related factors.

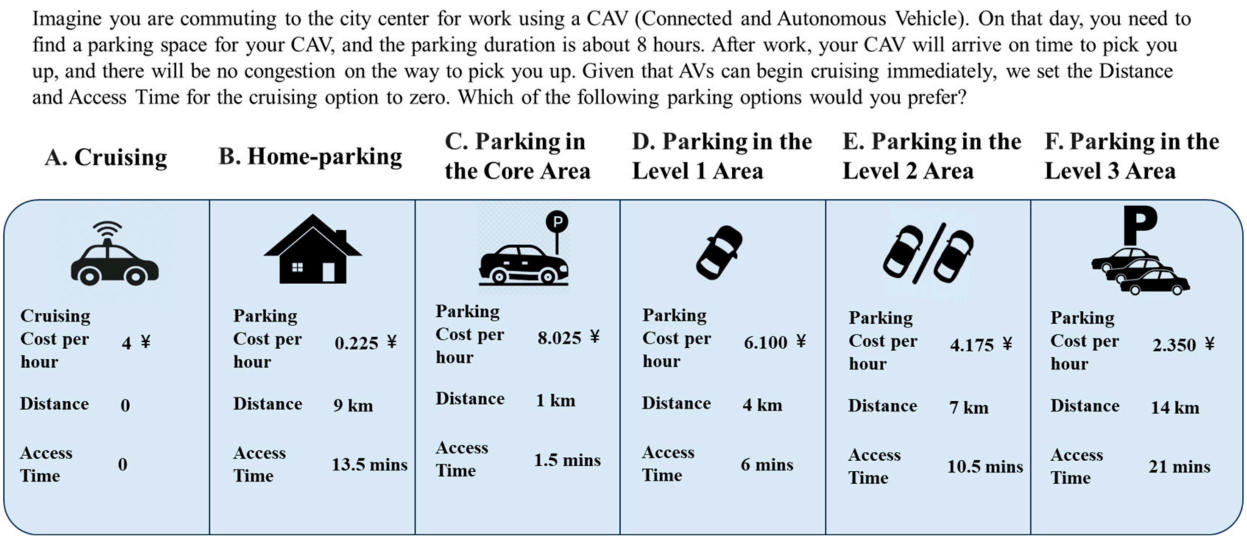


Figure 3. Example of choice sets presented to the respondent.

3.3. Sample and Sample Characteristics

The survey was conducted in Nanjing, Jiangsu Province, from 21 June to 17 July. A combination of online surveys and field surveys was used to collect data. The field surveys were conducted at the Xinjiekou CBD parking lots, while online surveys were distributed via internet platforms. A total of 1634 questionnaires were collected. After data cleaning, 1161 valid questionnaires were retained, yielding an effective response rate of 71%. From these valid responses, 4644 observations were obtained for analysis and model estimation. Strict screening criteria were used in data cleaning, including a reliability check and a consistency check.

The sample size met the minimum requirements for random sampling as calculated using the formula proposed by Krejcie and Morgan [36]. At the same time, the sample size also met the minimum requirements for orthogonal experiments as defined by [37].

According to the latest census data [38], 51.05% of the population is male and 48.95% is female. In this survey, 51.85% of the respondents were male and 48.15% were female, indicating that the gender distribution is close to the actual demographic structure. The Nanjing Statistics Bureau classifies annual household income per capita into four categories: low-income households (below 38,000 CNY), middle-income households (38,000–120,000 CNY), upper-middle-income households (120,000–240,000 CNY), and high-income households (above 240,000 CNY) [39]. Among respondents, the proportions of these income groups were 6.20%, 49.10%, 27.13%, and 17.57%, respectively, with the majority belonging to the middle-income group. Moreover, the survey revealed that 84.24% of respondents held a valid driver's license, while 15.76% did not. Table 2 summarizes the sociodemographic characteristics of the respondents.

Table 2. Summary of demographic-related information (n = 1161).

Variable	Category	N	%
Gender	Male	602	51.85%
	Female	559	48.15%
Age	18–30	473	40.74%
	30–50	475	40.82%
	>50	213	18.35%
Education	High school graduate or lower	66	5.69%
	Bachelor's degree or Associate's degree	628	54.09%
	Graduate or professional degree	467	40.22%
Occupation	Undergraduate students and graduate students	334	28.77%
	Corporate employees	722	62.19%
	Freelancers and nonprofit organizations	64	5.51%
	Others (e.g., retirees and unemployed individuals)	41	3.53%
Annual household income per capita (CNY)	<36,000	72	6.20%
	36,000–120,000	570	49.10%
	120,000–240,000	315	27.13%
	>240,000	204	17.57%
Driver's license ownership	Yes	978	84.24%
	No	183	15.76%

4. Model Design

4.1. Discrete Choice Model: Nested Logit Model

4.1.1. The Choice of Discrete Choice Model

Discrete choice models have been widely applied in studies of travel behavior selection [40–43]. This study adopts the nested logit model to construct decision-making structures tailored to the research objectives [44,45].

The NL model is selected for several reasons. First, they group similar alternatives into nests, allowing for higher correlation among choices within the same nest while maintaining independence across nests. This structure aligns well with users' parking mode selection behavior. Second, they effectively capture hierarchical decision-making processes. For example, in this study, users initially decide whether they "need to find parking" or "do not need to find parking," which are represented as categories A and categories B, respectively. Subsequently, within the selected category, they choose specific parking options. The NL model can mitigate the limitations of the multinomial logit (MNL) model, particularly its restrictive assumption of the independence of irrelevant alternatives (IIA) [46]. The two-layer nested logit model is illustrated in Figure 4.

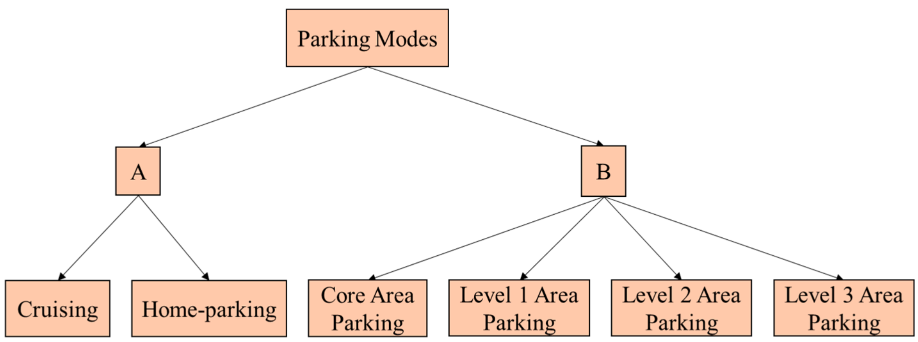


Figure 4. Model structure of the nested logit model.

4.1.2. Parameter Estimation of Nested Logit Model

This study employs the Biogeme 3.2.14 to estimate parameters using sample data. The model assumes that individuals choose alternatives that maximize their utility. The nested logit model consists of two layers of choices. The upper layer contains J alternative nests, and each nest j includes K_j options. The utility derived by individual i from selecting option k within nest j is expressed as:

$$U_{jk} = {x'}_{jk}\beta + {z'}_{j}\gamma_j + \varepsilon_{jk}(j = 1, \ldots, J; k = 1, \ldots, K) \quad (1)$$

where U_{jk} represents the total utility of option k within nest j, which includes both the systematic utility and the random error term ε_{jk}. $x'_{jk}\beta$ measures the utility contribution of the attributes of option k. $z'_j\gamma_j$ represents the utility contribution at the nest level, which is a key component of the nested logit model, reflecting the differences between nests.

In the corresponding nested logit model, the choice probability for option k within branch j is given by:

$$p_{jk} = p_j \times p_{k|j} = \frac{\exp({z'}_j\gamma + \tau_j I_j)}{\sum_{m=1}^{J}\exp({z'}_m\gamma + \tau_m I_m)} \times \frac{\exp\left({x'}_{jk}\beta_j/\tau_j\right)}{\sum_{l=1}^{K_j}\exp\left({x'}_{jl}\beta_j/\tau_j\right)} \quad (2)$$

In the nested logit model, several key probabilities and parameters are defined as follows: P_j represents the probability of selecting nest j. $P_{k|j}$ is the conditional probability of selecting option k given the choice of nest j. γ means the coefficient vector for the option level, representing the effects of option-specific attributes on utility. β_j represents the coefficient vector for the nest level, representing the effects of nest-specific attributes on utility. τ_j is the scale parameter for nest j, reflecting the degree of similarity among options within the same nest. I_j is the inclusive value for nest j, which captures the aggregate attractiveness of all options within the nest.

The log-likelihood function is defined as the sum of the logarithms of the probabilities for all observed choices in the dataset. It can be expressed as:

$$LL = \sum_{n=1}^{N}\sum_{j=1}^{J}\sum_{k=1}^{K_j} y_{njk} \cdot \ln\left(P_{jk}\right) \quad (3)$$

where $y_{njk} = 1$ indicates that decision-maker n selected option k within nest j; otherwise, $y_{njk} = 0$.

This study employs robust t-values and robust p-values to assess the significance of the regression coefficients in the model [47]. Adjusted Rho-square is used to measure the goodness-of-fit of the model [48].

4.2. Random Forest Algorithm

In recent years, machine learning (ML) techniques have been increasingly applied in travel analysis [49–53]. An existing study [54] has suggested that ML methods can either replace discrete choice models (DCMs) or achieve higher predictive accuracy compared to DCMs. The random forest (RF) method, a prominent ML method, was formally introduced by Breiman [55] and is based on the principles of ensemble learning. RF integrates multiple independent decision tree models using bootstrap sampling and combines their predictions through majority voting (for classification tasks) or averaging (for regression tasks). This approach enhances the generalization ability of the model and improves predictive performance for both classification and regression tasks.

The primary reasons for selecting the random forest model are as follows: First, RF has been demonstrated to be one of the most accurate classifiers for handling high-dimensional data and is widely used in travel behavior prediction [56]. Second, by introducing randomness, RF effectively reduces the variance of individual models, thereby improving the overall generalization ability. Furthermore, RF captures nonlinear relationships between features and target variables, enabling the evaluation of feature importance. This characteristic addresses the strict multicollinearity requirements of discrete choice models. Based on these advantages, the RF model is employed for simulation and computation in this study. The implementation of the random forest classifier was performed using the RandomForestClassifier module from the Python scikit-learn library. This framework was utilized to conduct classification analysis and prediction based on sample data.

5. Model Results

5.1. Parking Choice Behavior Characteristics

Building upon the experimental setup and methodology detailed in the preceding two chapters, we conducted a feature analysis based on attributes of parking service and parking behavior from the survey data. As presented in Table 3, dissatisfaction with downtown parking conditions (27.31%) was higher than satisfaction (23.86%), while satisfaction with overall downtown parking conditions (27.48%) was higher than dissatisfaction (22.57%). Thus, we can conclude that parking problems in the CBD are more severe than parking problems in the city as a whole, which is consistent with real observations [2]. Furthermore, most respondents (69.76%) indicated that they were satisfied with traffic safety in the past six months, while only 7.84% were dissatisfied.

Table 3. Summary of parking service information (n = 1161).

Variable	Category	Frequency (n = 1161)	Percentage
satisfaction degree with the parking conditions in the CBD area (CSD)	Very dissatisfied	99	8.53%
	Somewhat dissatisfied	218	18.78%
	Neutral	567	48.84%
	Somewhat satisfied	206	17.74%
	Very satisfied	71	6.12%
satisfaction degree with the parking conditions across the entire city (PSD)	Very dissatisfied	70	6.03%
	Somewhat dissatisfied	192	16.54%
	Neutral	580	49.96%
	Somewhat satisfied	252	21.71%
	Very satisfied	67	5.77%
satisfaction degree with urban traffic safety (SSD)	Very dissatisfied	20	1.72%
	Somewhat dissatisfied	71	6.12%
	Neutral	260	22.39%
	Somewhat satisfied	604	52.02%
	Very satisfied	206	17.74%

As shown in Figure 5, we can also conclude that parking at home will be the most preferred option (37.47%) when users drive to the CBD with AVs, followed by parking in the core area (23.51%), level 1 parking (14.04%) and cruising (12.92%). Level 3 and level 2 parking will be chosen the least, at 6.37% and 5.68%, respectively. Specifically, the survey results reveal user preferences for six parking options at four different parking durations, as shown in Figure 6:

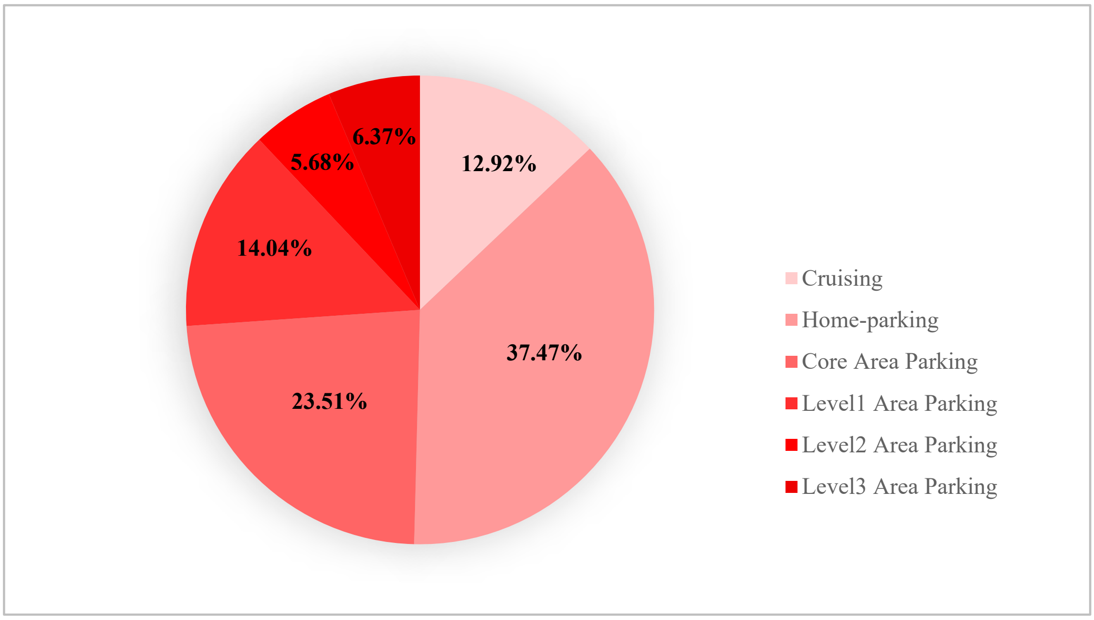


Figure 5. Parking choices of AV users in Nanjing.

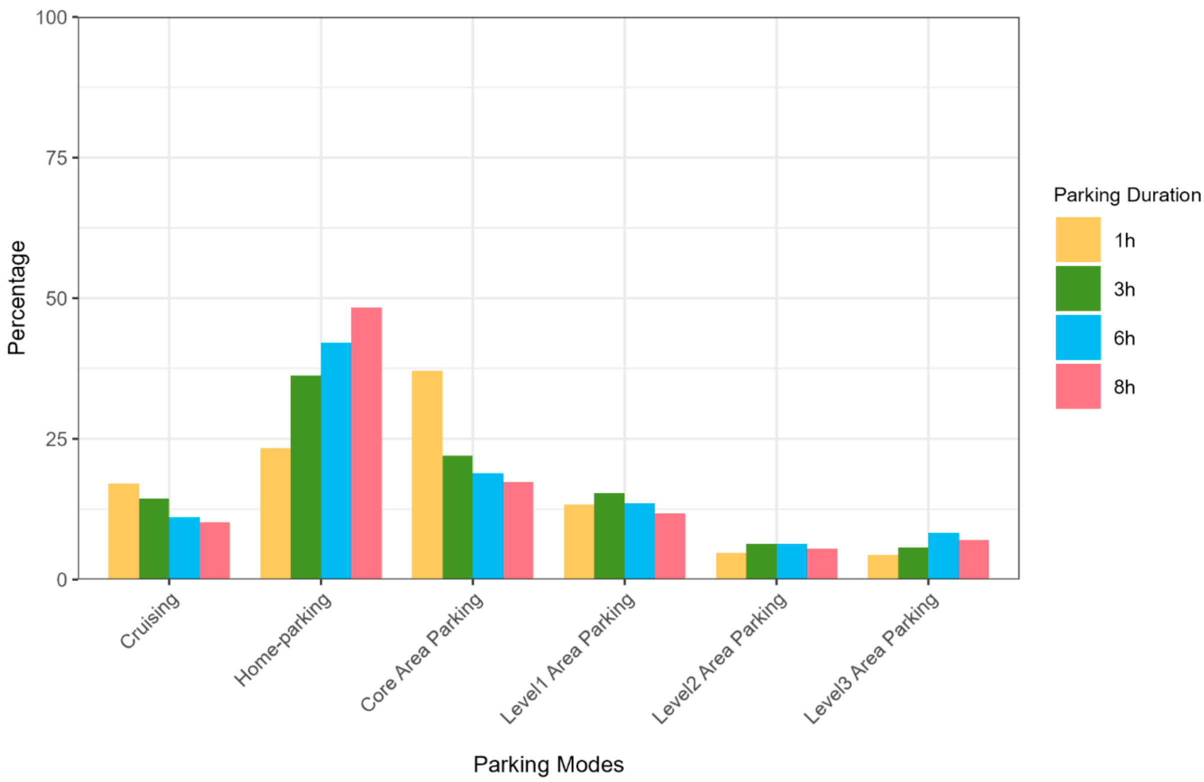


Figure 6. Parking choices of AV users in Nanjing under different parking durations.

When AV users drive to the CBD for work and need to park for 8 h, parking at home will be the most preferred option (37.49%), followed by parking in the core area (23.84%), level 1 parking (13.48%) and cruising (13.16%). In this context, level 3 parking (6.33%) and level 2 parking (5.71%) will be chosen the least.

For the 1 h parking duration, parking in the core area will be the most frequently chosen option (37.12%), followed by parking at home (23.34%), cruising (17.05%), and level 1 parking (13.35%). Level 2 parking (4.74%) and level 3 parking (4.39%) will receive the fewest selections.

For the 3 h parking duration, home-parking will be the most popular choice (36.26%), followed by core area parking (22.05%), level 1 parking (15.33%), and cruising (14.38%). Level 2 (6.29%) and level 3 (5.68%) parking will be the least preferred.

For parking duration of 6 h, home-parking will remain the most preferred option (42.03%), followed by core area parking (18.86%), level 1 parking (13.52%), and cruising (11.02%). Level 3 parking (8.27%) and level 2 parking (6.29%) will receive the lowest selection percentages.

5.2. Results Analysis of Discrete Choice Model

Before analyzing the results of the discrete choice model, it is essential to assess whether there is multicollinearity between variables. We eliminated variables with high multicollinearity by generating a heat map using Python 3.9.19. Then the nested logit model was estimated in an iterative manner using the Biogeme library of Python 3.9.19, and the running results with a good degree of fit were obtained, as shown in Table 4.

Table 4. Estimation results of nested logit model.

Variable	Value	Rob. *t*-Test	Rob. *p*-Value
Cruising			
Parking Duration_cruising	1.080	11.400	0.000
Parking Costs_cruising	−0.123	2.820	0.005
Age_cruising	0.147	3.990	0.000
Gender_cruising	0.171	5.300	0.000
CSD_cruising	1.630	6.030	0.000
PSD_cruising	1.750	5.970	0.000
SSD_cruising	0.951	3.060	0.002
Home-parking			
Parking Duration_home-parking	1.190	15.700	0.000
Age_home-parking	0.214	5.810	0.000
Driver Licence_home-parking	0.095	2.300	0.022
Gender_home-parking	0.159	5.000	0.000
CSD_home-parking	1.840	7.000	0.000
PSD_home-parking	1.210	4.250	0.000
SSD_home-parking	1.220	3.900	0.000
Core area parking			
Parking Duration_core	−0.506	2.010	0.045
Parking Costs_core	−1.190	29.400	0.000
CSD_core	1.540	9.500	0.000
PSD_core	1.910	10.700	0.000
Level 1 area parking			
Parking Duration_Level 1 area	0.106	2.010	0.045
Punctuality of arrival_Level 1 area	0.211	9.370	0.000
Experiences with Auto-pilot_Level 1 area	0.157	6.550	0.000
Career_Level 1 area	0.072	2.100	0.036
PSD_Level 1 area	2.270	10.800	0.000
CSD_Level 1 area	1.520	7.760	0.000
Level 2 area parking			
Parking Duration_Level 2 area	0.499	7.300	0.000
Punctuality of arrival_Level 2 area	0.059	2.230	0.026
Career_Level 2 area	0.233	4.690	0.000
PSD_Level 2 area	0.861	3.300	0.001

Table 4. *Cont.*

Variable	Value	Rob. *t*-Test	Rob. *p*-Value
Level 3 area parking			
Parking Duration_Level 3 area	0.577	9.040	0.000
Congestion Time_Level 3 area	−0.114	3.050	0.002
Career_Level 3 area	0.151	3.570	0.000
Experiences with Auto-pilot_Level 3 area	0.133	4.800	0.000
Gender_Level 3 area	0.160	5.720	0.000
PSD_Level 3 area	1.930	8.780	0.000
SSD_Level 3 area	0.223	29.300	0.000
Null log-likelihood	−9320.931		
Final log-likelihood	−7044.643		
Adjusted Rho-square	0.242		

To ensure model interpretability, we evaluated the discrete choice models based on the adjusted Rho-squared. The adjusted Rho-square for the nested logit model was 0.242, indicating that the nested logical model has a strong fit. Consequently, we can analyze the factors affecting users' parking mode choices based on the nested logit model.

As illustrated in Table 4, the results of the nested logit model indicate that the attributes of parking services, parking behavior, and individual socioeconomic status exert a significant influence on the selection of parking mode. Among these three categories, the influence of parking service attributes is the most substantial. Specifically, satisfaction with parking conditions in the CBD area (CSD), satisfaction with parking conditions in the city (PSD), and satisfaction with traffic safety in the city (SSD) emerged as crucial factors influencing parking mode selection. It is worth noting that PSD has been found to exert a significant positive influence on the selection of all six parking modes, with coefficients of 1.75, 1.21, 1.91, 2.27, 0.861, and 1.93, respectively. Consequently, it can be concluded that an enhancement in satisfaction with parking conditions within the city has a favorable impact on the selection of parking modes.

Parking behavior attributes (including parking duration, parking costs, punctuality of arrival, congestion time, etc.) also significantly influence the choice of parking modes. Notably, in Table 4, parking duration significantly influences all parking modes, and the difference in the coefficients illustrates the different effects of parking duration on the probability of choosing different modes. The effects of parking duration on home-parking, cruising, and level 1, level 2, and level 3 area parking modes are all positive, suggesting that longer parking durations increase the likelihood of choosing these modes. The largest effect is observed for home-parking (value = +1.190), indicating a stronger preference for home-parking as the parking duration increases, followed by cruising and level 3 area parking modes. On the other hand, the coefficient of the effect of parking duration on the core area parking is −0.506, indicating that an increase in parking duration reduces the likelihood of choosing to park in the core area, which may be due to the limited availability and higher cost of parking in the core area. In addition, we find that punctuality of arrival has a significant impact on users' choice of parking options in level 1 and level 2 area parking modes, with an impact coefficient of 0.211 and 0.059, respectively, suggesting that the arrival of AVs at the designated time significantly increases the likelihood that users will choose to park at level 1 and level 2 areas. An increase in congestion time has been shown to reduce the probability that users will choose to park in the level 3 area (value = −0.114). Thus, it can be concluded that a reduction in congestion time tends to render the level 3 area parking more appealing.

Socioeconomic characteristics (e.g., age, gender, occupation, driver's license ownership, and experience with auto-pilot vehicles) also had a significant impact on the choice of different parking modes, although their impact coefficients were lower compared to those of parking services and parking behavior characteristics. Specifically, the factor age exhibited a positive and significant influence on both cruising and home parking, with a higher impact coefficient for home parking (value = +0.214), suggesting that senior users are more inclined to opt for home parking. Furthermore, the gender factor exhibited a substantial impact on the selection of cruising, parking at home, and parking in a tertiary area, with coefficients of 0.171, 0.160, and 0.159, respectively. These findings suggest that the male group is more inclined to opt for cruising, parking in a tertiary area, and home-parking compared to the female group. Furthermore, the analysis revealed a substantial positive impact of autopilot experiences on parking mode selection, particularly at Levels 1 and 3. This finding suggests that autopilot experiences may serve as a crucial factor in influencing users' parking decisions.

Of the six parking modes, parking in the core area is least affected by factors. The main determinants of parking in the core area, in order of importance, are PSD, CSD, parking costs, and parking duration. In contrast, Level 3 area parking mode is influenced by the greatest number of significant factors, including PSD, SSD, parking duration, gender, occupation, experiences with autopilot, and congestion time.

5.3. Results of the Random Forest Algorithm

To further capture the complex relationships among variables, in addition to the discrete choice models, we also employed a random forest model to analyze the samples. In this study, the random forest model used a total of 4644 samples, of which 70% (3251 samples) were assigned to the training set and 30% (1393 samples) were assigned to the test set. The performance of the random forest algorithm is affected not only by the quality of the data and feature characteristics, but also, more importantly, by hyperparameters such as the number of trees, the number of features considered at each split, the depth of the trees, and the minimum number of samples needed to split a node [57]. A grid search approach was used to identify the best parameter combination, which was then used to train the final model. The optimized parameters include max_features set to log2, n_estimators set to 200, max_depth set to 20, and min_samples_split set to 5.

To evaluate the performance of the model on the test set, we used multiple metrics, including accuracy, precision, recall, F1 score, and Cohen's Kappa [58]. As shown in Table 5, the six parking choice models meet the required standards for precision, recall, F1 score, training accuracy, and Cohen's Kappa. These results indicate that the model shows strong performance. The calculated precision confirms that the model has high predictive accuracy. Cohen's Kappa further highlights the high consistency between the predicted and actual values [58].

Table 5. Evaluation index of random forest model.

	Precision	Recall	F1-Score	Accuracy	Cohen's Kappa
Cruising	0.96	0.90	0.93	0.96	0.86
Home-parking	0.96	0.96	0.96	0.96	0.92
Core area	0.96	0.95	0.96	0.96	0.90
Level 1 area	0.96	0.97	0.97	0.98	0.93
Level 2 area	0.92	0.89	0.90	0.98	0.80
Level 3 area	0.95	0.94	0.95	0.99	0.89

The feature importance calculated by the random forest algorithm for the six parking modes is displayed in Figure 7. In this figure, darker bar colors represent the higher importance of a feature, indicating the extent to which the model relies on each feature when making decisions. Higher feature importance indicates a greater impact on the model's predictions. Clear patterns and variations in feature importance are observed across the six parking modes.

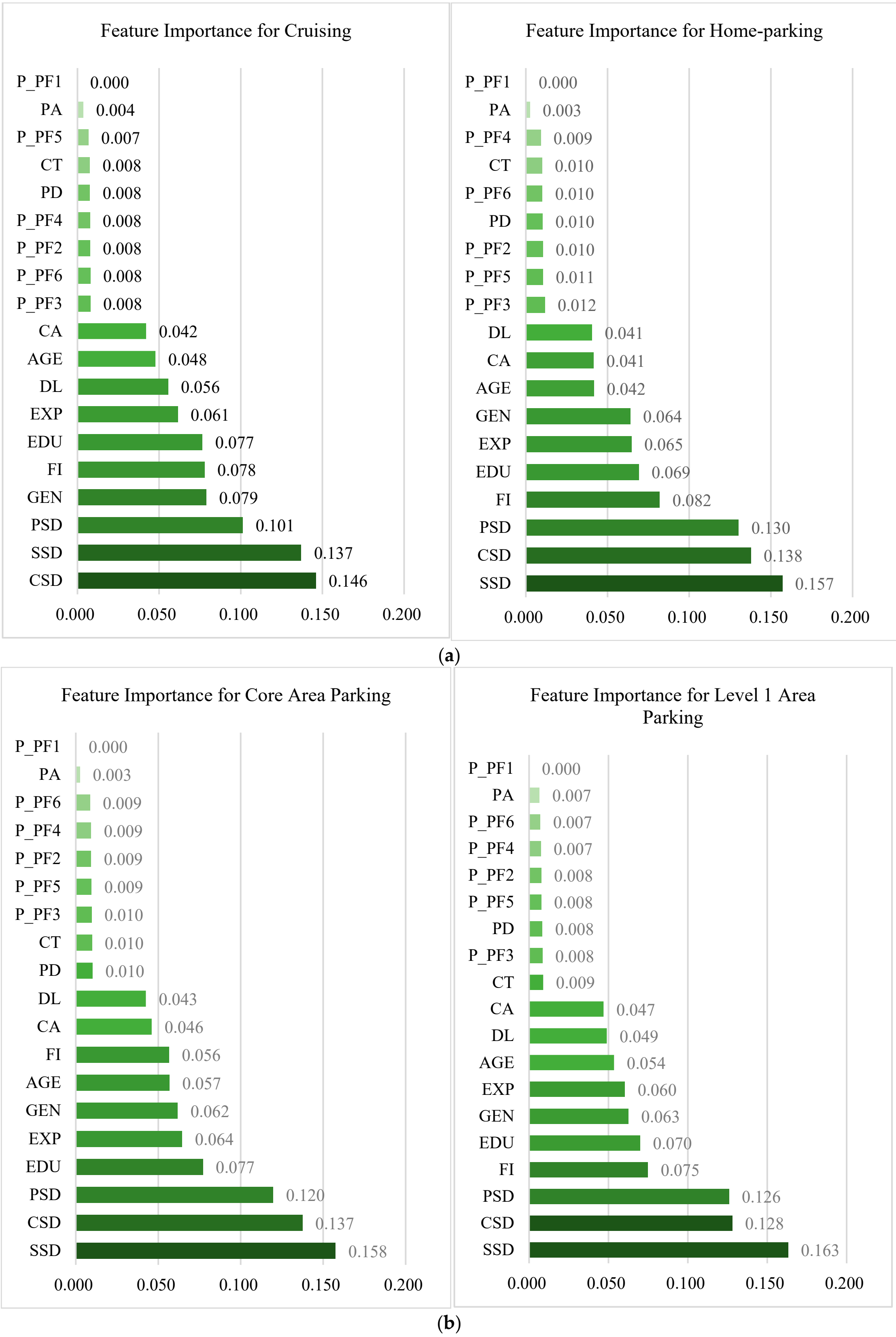
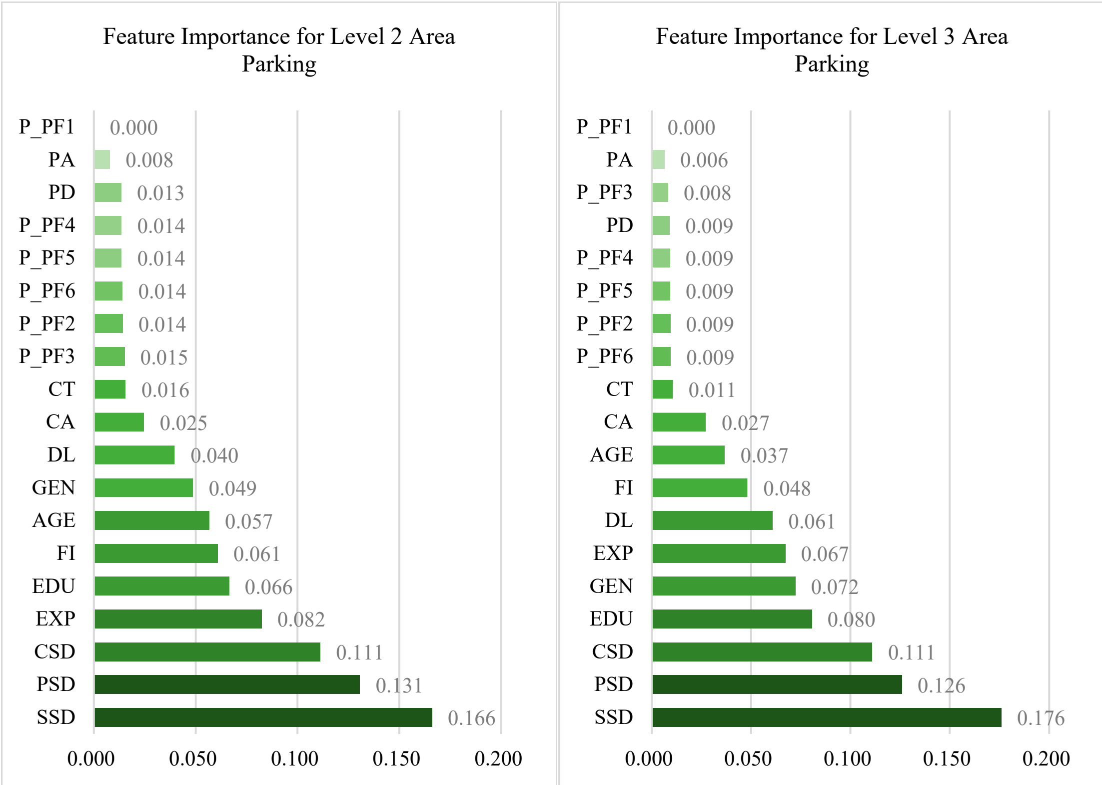


Figure 7. *Cont.*



(**c**)

Figure 7. (**a**). The feature importance for cruising and home-parking. (**b**). The feature importance for core area parking and level 1 area parking. (**c**). The feature importance for level 2 area parking and level 3 area parking. **Notes: Parking service attributes:** SSD: satisfaction degree with urban traffic safety; PSD: satisfaction degree with the parking conditions across the entire city; CSD: satisfaction degree with the parking conditions in the CBD area. **Socioeconomic attributes:** GEN: Gender; AGE: Age; FI: Monthly household income per capita; DL: driver's license ownership; EDU: Education; CA: Career or occupation; EXP: Experience with auto-pilot vehicles. **Parking behavior attributes:** P_PF1: Hourly costs for cruising; P_PF2: Hourly costs of home-parking; P_PF3: Hourly parking costs if parking in the core area; P_PF4: Hourly parking costs if parking in the level 1 area; P_PF5: Hourly parking costs if parking in the level 2 area; P_PF6: Hourly parking costs if parking in the level 3 area; CT: Congestion time; PA: Punctuality of arrival; PD: Parking durations.

The results indicate that parking service attributes, namely SSD, CSD, and PSD, are consistently the most significant features in the six parking modes, as their contributions to the model's predictive outcomes exceed 0.100. These three attributes represent satisfaction with urban traffic safety, parking conditions in the CBD, and parking conditions across the entire city, respectively. The high importance of these attributes underscores their crucial roles in model prediction and classification decisions.

In addition, socioeconomic attributes such as FI (Monthly household income per capita), EDU (education), EXP (experience with auto-pilot vehicles), GEN (gender), AGE (age), CA (occupation), and DL (driver's license ownership) are of moderate significance. Their contributions to the model's predictive outcomes for the six parking modes range from 0.04 to 0.08, with slight variations in specific values. A representative factor is FI (monthly household income per capita), which has a significance of 0.048 in level 3 area parking but increases to 0.082 in home-parking. This suggests that household income influences parking choices differently across various parking modes. It has less influence on the choice of level 3 area parking, but more on home-parking. We further speculate that economic factors may significantly influence parking choices. Meanwhile, gender has the greatest impact on cruising (0.079) but the least on level 2 area parking (0.049), reflecting the diversity in parking preferences across different gender groups.

In contrast, parking behavior attributes related to parking duration (PD), congestion time (CT), punctuality of arrivals (PA), and parking costs (P_PF2, P_PF3, P_PF4, P_PF5, P_PF6) generally show low importance, typically around 0.01. Notably, the costs of cruising (P_PF1) have almost no impact on all tasks, suggesting minimal contribution to predicting parking choices. A reasonable explanation is that the driving fees of electric automated vehicles are relatively low, especially compared to the parking costs of other modes, which diminishes their influence on users' parking mode choices.

6. Discussion

6.1. Parking Choice Preferences of AV Users

Based on the aforementioned research findings, we observed that across all parking durations—both short-term (1 h) and long-term (3, 6, 8 h)— the "home-parking" and "the core area parking" were the two most frequently chosen parking modes among the six available options. Conversely, "the level 2 area parking" and "the level 3 area parking", located farther from the destination (Central Business District), were consistently the least preferred choices. More specifically, user groups requiring 8 h, 6 h, and 3 h parking durations showed the strongest preference for "home-parking", followed by "the core area parking" and "the level 1 area parking". In contrast, users with a 1 h parking requirement predominantly favored the core area parking, with home-parking and cruising as their subsequent preferences.

Prior research on autonomous vehicle parking preferences is relatively scarce. Among the limited existing studies, Garus et al. [26] solely considered four parking modes: cruising, garage parking, sending the AV home, and on-street parking, without differentiating by parking duration. Their study found that sending the AV home was the most popular choice due to its convenience. This finding aligns with our conclusion that users with 8 h, 6 h, and 3 h parking durations are most inclined to select the home-parking option.

Furthermore, a specific observation of users who chose cruising instead of parking in our study revealed a decreasing trend in cruising preference as parking duration increased. This conclusion is also consistent with previous research [26], where they attributed the unpopularity of cruising primarily to environmental concerns.

6.2. Factors Influencing AV Parking Choice

Through the analysis employing both traditional statistical modeling and machine learning approaches, we identified parking service attributes as the primary influencing factors on user parking mode choice. These attributes include satisfaction degree with urban traffic safety (SSD), satisfaction degree with parking conditions across the entire city (PSD), and satisfaction degree with parking conditions in the CBD area (CSD). Previous studies [23,26] have rarely considered the impact of parking service attributes, primarily focusing on factors such as parking behavior attributes and individual socioeconomic characteristics. Our findings reveal that PSD exerts a significant positive influence on the selection of all six parking modes. This underscores the critical importance of improving overall city-wide parking condition satisfaction for AV users. Simultaneously, we found that parking behavior attributes and socioeconomic attributes also significantly affect parking mode choices. This aligns with the conclusions drawn by Jia et al. [10] and Ye et al. [23], whose research similarly acknowledged the impact of travel attributes (e.g., parking duration, travel time, and trip purpose) and individual socioeconomic characteristics on parking behavior decisions.

6.3. Policy Implications

Our analysis indicates that "the core area parking" remains a highly popular parking option, especially for short-term users. The key influencing factors for this mode include parking satisfaction, parking fees, and parking duration. Therefore, we recommend implementing a progressive pricing model in the core area that varies with parking duration. An initially lower price for the first hour of parking could attract short-term users, followed by a substantial increase in fees for extended durations. This strategy aims to enhance parking space turnover, meet the genuine needs of short-term users for quick errands, and incentivize long-term parkers to choose alternative options. Such a refined pricing mechanism would not only cater to the diverse needs of different user groups but also facilitate the efficient allocation of urban transportation resources.

Furthermore, our findings show that "the level 1 area parking" is also a frequently chosen option, ranking just below "home-parking" and "the core area parking". Its primary influencing factors include parking satisfaction, the punctuality of AVs for picking up passengers, and parking duration. Therefore, by focusing on improving parking service satisfaction and pickup punctuality, we can develop the level 1 area into the buffer parking area for the Central Business District, capable of accommodating a larger volume of parking demand.

While "cruising" and "home-parking" may appear to be less costly for individual users than parking in the city center, and "home-parking" allows for the full utilization of a user's home parking space, both strategies inevitably lead to an increase in vehicle miles traveled (VMT). From an environmental perspective, this increase in VMT translates to higher electricity consumption and elevated emissions. Simultaneously, the added VMT may also exacerbate traffic congestion. Although individual users might save on parking fees through these two modes, from a system-wide perspective, they significantly increase societal costs, including energy waste, heightened emissions, and road congestion. Therefore, future traffic authorities must implement policy interventions targeting these two parking modes. For instance, a VMT fee could be imposed on Autonomous Vehicles (AVs) when their empty cruising time or empty travel time for returning home exceeds a certain threshold (e.g., 10 min). This measure aims to reduce excessive empty VMT. Concurrently, traffic authorities could also offer incentives such as public parking discounts or short-distance parking incentives. Such measures would reduce the necessity for AVs to undertake long-distance return trips, thereby aligning individual cost minimization with broader societal sustainable development goals.

6.4. Comparative Analysis of Discrete Choice and Random Forest Models

The results of the two models have both similarities and differences. The similarity is that the primary factor in the results of both models is the parking service attributes. However, the second-tier and third-tier influences differ between the two methods. In the discrete choice model, parking behavior attributes had a greater influence than socioeconomic attributes. In contrast, in the random forest model, socioeconomic attributes had a greater influence than attributes of parking behavior. These differences reflect the different emphases of the variable attributes of the models. The discrete choice model is primarily based on economic theory, which assumes that users' choices follow the principles of random utility theory and that the relationships among variables are linear [59]. In the nested logit model, a clear hierarchical structure was predefined, with the decision to seek parking as a branching decision. This assumption imposed strong constraints on correlations between options and clarified the logical relationships between parking behavior attributes (e.g., parking duration and costs) and parking decisions. Consequently, the nested logit model effectively emphasized the effects of parking-related variables but struggled to capture the nonlinear relationships and indirect associations that arose from personal socioeconomic attributes. In contrast, the random forest model automatically learned the relationships among variables from the data without relying on assumptions about previous distributions or predefined utility functions and decision rules. Instead, it identified the variables that most effectively reduced prediction error by splitting feature nodes [55]. Thus, the random forest model relies heavily on the characteristics of the data itself and captures complex nonlinear relationships and interactions. In this way, the complex nonlinear relationships introduced by socioeconomic characteristics are represented more effectively in the random forest model.

The second difference is that the machine learning model reveals a greater variety of significant factors compared to discrete choice models. This result aligns with previous research [60], which can be attributed to the random forest model's weaker distributional assumptions, superior capacity to capture nonlinear relationships and interaction effects, and its robustness in handling complex data structures. In addition, the random forest model's insensitivity to multicollinearity allows it to retain more variables. However, it is important to note that the significant factors identified by the random forest model may only reflect correlations between data rather than causal relationships, while the discrete choice model more effectively explains the causality underlying parking choices. The third difference between the two models is their operational differences. The discrete choice model required more complex design and modeling processes, longer computation times, and higher performance demands on computer systems. In contrast, the random forest model offered higher computational speeds and lower computational power requirements.

7. Conclusions and Limitations

With the continued advancement of automated vehicle technologies, the choice of parking modes in urban areas has become an unavoidable situation in the future. AVs with autonomous remote travel capabilities will enable users to select optimal parking locations that best meet their needs. This study used Nanjing, a representative city in China, as a case study to design a stated preference (SP) experiment that collected data on parking preferences among potential AV users. The analysis focused on users' parking behavior under four parking duration scenarios and six parking mode options, using discrete choice models and machine-learning models. This study examined the factors influencing parking mode options and categorized factors into three groups: parking service attributes, individual socioeconomic attributes, and parking behavior attributes. The similarities and differences between the two modeling approaches were then compared.

This study shows that the introduction of AV technology is expected to significantly change users' parking behavior. The emergence of multiple parking modes enabled by AVs will provide alternatives to the parking problems downtown. Multiple parking modes for AVs will be expected to significantly reduce parking demands in CBD areas and redefine the parking preferences of users in these areas. The results reveal distinct user preferences for AV parking when traveling to urban centers. Home-parking emerges as the most preferred option, selected by 37.47% of respondents. Peripheral parking zones (level 1, level 2, or level 3 areas) collectively attract 26.09% of users, whereas parking in CBD areas is chosen by only 23.51% of participants. The cruising mode, wherein vehicles continue operating rather than parking, demonstrates the lowest preference rate at 12.92%. Parking preferences vary significantly by duration. Medium- to long-term users (3, 6, and 8 h) prefer home-parking, while short-term users (1 h) favor central business district proximity.

Among all factors, parking service attributes, which include satisfaction with parking conditions in the CBD area (CSD), satisfaction with parking conditions citywide (PSD), and satisfaction with city traffic safety (SSD), have the greatest influence on users' parking choices. This finding is consistent with the results reported by Niu et al. [32], who emphasized that higher satisfaction was an important factor for repeated parking choices in shared parking situations. The importance of parking service characteristics underscores that user experience is the most important determinant of users' parking decisions. Attributes of parking behavior, including parking duration, parking costs per hour, punctuality of arrival, and congestion time, also influence parking choices. These results are consistent with previous related studies [23], which also highlight the importance of parking behavior attributes in parking decisions. Regional differences in parking preferences are also observed: AV users who want to park in the core area will prioritize parking costs, those who choose to cruise or park at home will focus on parking duration, and users who park in peripheral areas (level 1 area, level 2 area, and level 3 area) will consider parking duration, vehicle arrival punctuality, and congestion time. Socioeconomic attributes, such as age, gender, driver's license ownership, autopilot experience, and occupation, reflect the diversity of user needs and the heterogeneity of individual preferences. Similar conclusions were also drawn in previous research [26].

A comparison of the discrete choice model and the random forest model shows that their results are roughly similar. Due to differences in the underlying principles, the relative importance of influencing factors varies between the two approaches. Random forest models, unaffected by multicollinearity, are better suited for predicting parking behavior and assessing the relative importance of different factors in complex scenarios. In contrast, discrete choice models are more effective for interpreting causal relationships.

Although this study provides valuable insights into the parking choices of AV users, it also has several limitations. First, the data collection and analysis are restricted to Nanjing, China, and future research could extend this work by conducting comparative analyses across different regions and countries. In addition, a more comprehensive sensitivity analysis of price variations across regions would further enrich the findings. Our SP experiment primarily considers four parking duration scenarios corresponding to commuting and non-commuting trips; future studies may incorporate travel purposes into the analysis for greater depth. Moreover, due to space constraints, this study does not provide a detailed examination of the specific impacts and mechanisms of cruising and home-parking on traffic congestion and emissions. Future research could address these issues through experimental analysis or simulation-based modeling. Finally, given the flexibility of behavioral choice models in capturing diverse scenarios, subsequent studies may build upon this foundation to undertake broader and more in-depth investigations.

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