

Article

Influence of Driver Factors on On-Street Parking Choice: Evidence from a Hybrid SP–RP Survey with Binary Logistic Analysis

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Abstract

This study investigates the influence of driver-related factors on on-street parking choice by integrating stated preference (SP) and revealed preference (RP) survey methods. A hybrid SP–RP survey was designed to simulate realistic parking scenarios, and 423 valid questionnaires were collected online and offline. Key factors affecting parking choice were identified through descriptive analysis, including user acceptance of differentiated pricing and satisfaction with existing policies. The Kaiser–Meyer–Olkin (KMO = 0.904) and Bartlett’s test ($p < 0.001$) confirmed data suitability for factor analysis. A binary logistic regression model was developed to quantify variable effects under different travel purposes. Key findings include the following: monthly parking fee had the strongest effect (OR = 6.691, $p = 0.010$) on parking choice for shopping/entertainment trips; model prediction accuracy ranged from 80.87% to 83.56% across travel purposes; and goodness-of-fit metrics were strong (McFadden $R^2 = 0.630$, Nagelkerke $R^2 = 0.772$). The results provide empirical evidence on parking choice determinants and support the design of demand-responsive parking policies through dynamic and differentiated pricing strategies.

Keywords: on-street parking choice; driver-related factors; hybrid SP–RP survey; binary logistic regression



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1. Introduction

With the continuous progress of the automobile manufacturing industry and the steady growth of the national economy, the number of automobiles in China is also increasing year by year. According to statistics [1], as of the end of June 2025, the total number of motor vehicles in China has exceeded 460 million, of which the total number of cars exceeds 359 million.

With the increasing number of cars and the limited urban space, the supply–demand contradiction of parking spaces is becoming increasingly prominent.

However, in many cities, parking problems are not solely caused by insufficient supply but rather by improper pricing strategies for parking fees [2]. The current parking fee system is mostly based on the economic situation [3] and parking demand of administrative regions [4,5] but ignores the characteristics of parking time and location, lacking

scientific theoretical support. This leads to parking fees not fully utilizing their price lever adjustment function and hence being unable to effectively guide the traffic flow of the city. Therefore, it is crucial to study and implement differentiated charging methods based on the characteristics of parking time and space demand. By comprehensively considering the spatio-temporal characteristics of parking, we can more accurately reflect the true value of parking, guide drivers to choose parking locations and times more reasonably, alleviate parking pressure in cities, and promote the healthy development of urban transportation.

On-street parking and cruising behavior is an implicit behavior pattern of drivers in the process of choosing to park. When making parking decisions, drivers will consider many factors, including but not limited to parking fees, convenience of parking location, surrounding traffic conditions, etc. [6,7]. Sometimes, in search of an ideal parking space, drivers may drive slowly on the road at lower speeds, which often creates congestion and creates a mobility bottleneck. Inci [5] investigated the economic influence of pricing on on-street parking and pointed out that reasonable parking pricing can attract more drivers to choose on-street parking and make better use of on-street parking resources. In order to study and understand this behavior in depth, Albert et al. used the stated preference (SP) survey method to conduct extensive research on travel groups to explore the impact of congestion charging and parking charging on residents' travel choice behavior. His research results show that when faced with a choice, travelers are more inclined to pay parking fees rather than congestion fees [8]. Tian conducted an in-depth study on the impact of randomly distributed parking spaces on drivers' micro-parking behavior on the roadside. In his study, he considered multiple measures, including vehicle cruising, travel costs, walking costs, and delay costs, to analyze how these factors affect the time a driver chooses to stop and the arrival time [9]. Hensher, David A., and King conducted a survey on eight parking lots in the Sydney CBD area and found that increasing parking fees will encourage travelers to choose to use public transportation and will have a significant impact on the way drivers choose to park [10]. Guo and Zhan used the B-Logit method to model the survey data of 840 households in New York. The results showed that drivers with family parking spaces tend to use cars, while drivers without family parking spaces choose other travel modes [11]. Jakob [2] uses macro modeling methods to study the short-term impact of different parking policies on urban transportation and parking systems, with a particular focus on two major strategies: parking pricing and parking occupancy rate. The paper takes the central area of Zurich, Switzerland as a case study to demonstrate the application of the model and the actual effects of policies. Qian et al. [12] found in their research that differences in lifestyle and the level of environmental awareness will have a significant impact on the choice of travel mode. As residents' awareness of environmental protection gradually increases, they are more inclined to choose public transportation, and accordingly, the frequency of private car travel will gradually decrease. Hensher [13] and others used discrete choice models to study travel choice behavior. Their studies all found that income level has a significant impact on the choice of travel mode. This study provides an important basis for understanding the differences in travel decisions of different income groups.

When discussing travelers' parking choice behavior, although scholars made extensive use of parking data and conducted multi-angle, multi-objective research, they failed to fully take into account the time and space needs of travelers when making parking choices as well as the influencing factors behind these needs.

Roadside parking and cruising are one of the main causes of traffic congestion [14]. Relevant research has pointed out that when the utilization rate of parking spaces is maintained at 85%, the parking spaces reach a state of supply–demand balance, and the parking fee price at this time is considered relatively reasonable [15]. Fosgerau et al. considered

the travel conditions during peak hours in the morning and evening and proposed a strategy of dynamically charging based on parking hours. They applied the queuing theory to calculate the optimal charging rate and suggested eliminating queuing time by distinguishing different time periods. Specifically, in the first time period (when parking demand is low), the parking fee is zero to reduce queuing phenomena; in the second period (when there is a high demand for parking), parking fees are charged to alleviate the problem of parking congestion [16]. Qin et al. [17] conducted several on-street parking surveys in Beijing's business districts and built a parking location choice model and decision rules for the cruising process.

When exploring the parking choice behavior of travelers, scholars have extensively used parking data and conducted multi-angle and multi-objective research based on the personal attributes of travelers, such as gender and age, as well as travel attributes, such as parking costs and parking time. Unfortunately, they failed to fully consider the time and space demand characteristics of travelers in parking choices, as well as the influencing factors behind these demands.

Based on the state of the art, the contributions of this study are as follows:

- 1, Establish a hybrid SP-RP survey to investigate and analyze people's choice for on-street parking.
- 2, Based on the questionnaire survey data of on-street parking, this study investigates their on-street parking choice behavior.
- 3, Establish a binomial logit model to model and analyze on-road parking choice behavior.

2. Survey Design

Parking choice behavior is usually influenced by multiple factors, and on-road parking choices have differentiated characteristics due to different travel purposes, destination areas, and travelers' satisfaction with on-road toll policies. Therefore, this chapter uses questionnaire surveys to obtain characteristic data of travelers when making on-road parking choices.

2.1. Survey Content

In order to effectively grasp the characteristics of travelers in their daily parking process as well as their specific behavior under the differentiated on-road parking fee model, especially the need to deeply understand how various influencing factors affect parking choice behavior, this study extensively collected various influencing factors related to parking choice behavior, combined with the unique characteristics exhibited by parking choice behavior under the differentiated fee model, and divided the survey content into the following four main categories: user attribute, travel feature information, parking fee satisfaction, and parking choice model scenarios.

2.2. Survey Manner

The survey of non-aggregated models mainly includes two forms: actual survey (RP) and intention survey (SP). The RP survey focuses on selective behavior that has already occurred, that is, the actual selection results and selection conditions of the respondents in a certain state. This survey method can collect data on behavior that has already occurred or can be observed; therefore, the traffic behavior model established based on this method has high reliability.

The SP survey focuses on the choice intention under hypothetical conditions. By setting the future selection status and attribute values of the selection scheme, this method can

flexibly adjust the selection conditions as needed. This is particularly useful in analyzing options that do not yet exist or have a small number in reality.

Considering the research focus on parking choice behavior in this article, the user attributes and parking feature data of travelers are based on past actual events. This part of the data belongs to RP data, covering key information such as parking purpose, parking duration, and parking costs. However, due to the fact that differentiated on-road parking fee models have not been widely implemented, it is necessary to rely on hypothetical scenarios and combine their own actual situations to speculate on the parking choices of respondents in this environment. Therefore, this part of the data will use SP data to predict the differences in parking choices in this mode.

2.3. The Design of the Questionnaire Scales

The questionnaire consists of three sections:

Basic Information of User attribute: User attributes generally include basic information such as age, gender, income, occupation, and education level. Based on the research focus of this paper, user attributes also include attributes closely related to user travel and parking behavior, such as the respondent's driving experience, frequency of use, and monthly parking fees.

Parking Characteristics of Users: The personal attribute information of travelers, such as the internal driving force of their parking choice behavior, reflects the reasons behind their decisions. The characteristic information of parking lots, as an external manifestation, reveals the parking choice behavior of travelers' patterns in actual environments. This parking lot's feature information includes factors that travelers consider when parking, travel purposes, parking locations, transportation methods used, typical parking hours, and the availability of public transportation.

Willingness to Differentiate Charge: The survey on satisfaction with parking fees is mainly divided into two categories. Firstly, the satisfaction evaluation of the existing on-road parking fee policy aims to understand the views and opinions of travelers on the current on-road parking fee policy in order to reveal the public's public opinion tendency. Secondly, the survey focuses on the acceptance level of differentiated on-road parking fees. By collecting the opinions and suggestions of travelers on the differentiated charging model as well as the target areas they expect to implement differentiated charging, important references are provided for future policy adjustments.

2.4. Sample Size

Determining sample size is a crucial step in a questionnaire survey. When determining the sample size, the basic principle is to strive to minimize costs while ensuring a certain level of accuracy; or, under certain budget conditions, pursue the highest accuracy. This principle helps to ensure the quality of investigations while also considering the rational utilization of resources.

When the overall size of the survey object is quite large or infinitely large ($N > 10,000$), its impact on the sample size is minimal.

The research object of this questionnaire is drivers in Xi'an city, so the minimum sample size for this survey can be determined using the sample calculation formula for the large population in Equation (1).

$$n = \frac{z_{(1-\alpha/2)}^2 p(1-p)}{e^2} = 384.16 \rightarrow 384 \quad (1)$$

where $z_{(1-\alpha/2)}$ is z-score, which is related to the chosen confidence level. (for $\alpha = 0.05$, $z = 1.96$). p as the expected proportion (for $p = 0.5$). e as the margin of error. ($e = 0.05$ for ± 5 percentage points.)

This study successfully collected 423 valid questionnaires responses through a combination of offline and online methods, which meets the minimum sample size requirement of 384.

3. Survey Analysis

Parking choice behavior is typically influenced by multiple factors. On-street parking choices, in particular, exhibit variations due to differences in travel purposes, the area of the destination, and travelers' satisfaction with on-street parking pricing policies. Therefore, this section employs a questionnaire survey to collect data on the characteristics of travelers' on-street parking choices in Xi'an, China.

3.1. Analysis on Survey Agent

User attribute information is a comprehensive collection that encompasses various social and economic attributes of drivers. These attributes include the driver's gender, age, driving experience, and educational background, as shown in Table 1.

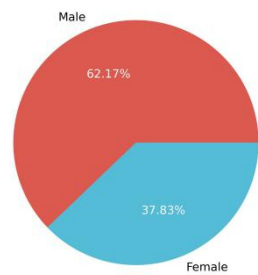
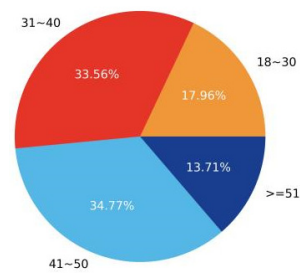
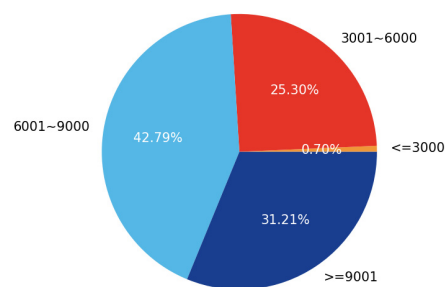
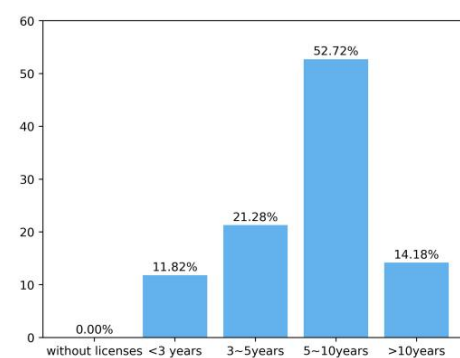
Table 1. Drivers' personal attribute information settings.

Feature Variable	Setting
Sex	Male
	Female
Age	18~30
	31~40
	41~50
	>50
Salary per month	<3000 yuan
	3001~6000 yuan
	6001~9000 yuan
	>9000 yuan
Driving experience	<3 years
	3~5 years
	5~10 years
	>10 years
Profession	Full-time students
	Public institutions
	Enterprise
	Independent entrepreneurship
	Agricultural, forestry, animal husbandry, and fishery workers
Education	Junior high school and below
	High school and vocational school
	Undergraduate and associate degree
	Master's degree or above
Driving frequency	6~7 days
	4~5 days
	2~3 days
	0~1 day

Table 1. *Cont.*

Feature Variable	Setting
Parking fee per month	<100 yuan
	100~300 yuan
	300~500 yuan
	>500 yuan

The distribution of user attributes among travelers in the questionnaire survey is shown in Figures 1–8.

**Figure 1.** Drivers' gender distribution.**Figure 2.** Drivers' age distribution.**Figure 3.** Drivers' monthly salary distribution.**Figure 4.** Drivers' driving experience distribution.

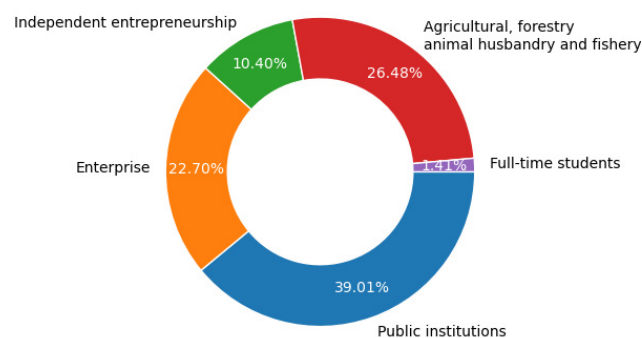


Figure 5. Drivers' profession distribution.

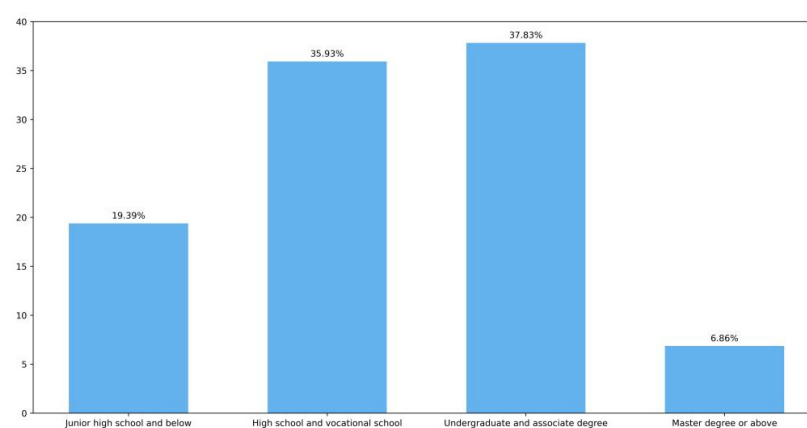


Figure 6. Drivers' education experience distribution.

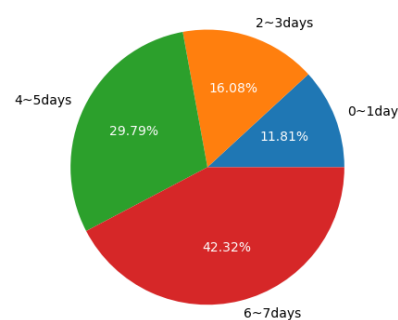


Figure 7. Drivers' using vehicles frequency distribution.

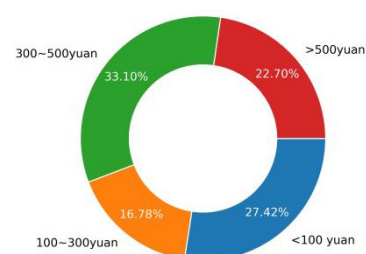


Figure 8. Drivers' monthly parking fee distribution.

The results of the questionnaire survey reveal that in Xi'an, male drivers dominate, but female drivers also make up a certain proportion of about 38%. From the perspective of age distribution, drivers are mainly concentrated between the ages of 18 and 50, with the highest number of drivers aged 41 to 50, indicating that middle-aged people are the main group for parking needs. In terms of driving experience, most drivers have less than 10 years of driving experience. In addition, the majority of drivers have a high school

education or above, while drivers with a graduate degree or above also make up a certain proportion, close to 7%. This is mainly because Xi'an, as a new first tier city, generally has a higher level of education among its drivers.

3.2. Parking Characteristics Analysis

The personal attribute information of travelers, as the internal driving force of their parking choice behavior, reflects the reasons behind their decisions. The characteristic information of parking lots, as an external manifestation, reveals the patterns of parking choice behavior of travelers in actual environments. These parking lot features include considerations for travelers when parking, travel purposes, parking locations, transportation methods used, typical parking hours, and the availability of public transportation. This detailed parking feature information, their settings, and classifications can be found in Table 2.

Table 2. Parking feature information setting.

Feature Variable	Setting Situations
Parking Considerations	Parking duration, number of available parking spaces, parking time points, time spent searching for parking spaces, distance to destination, parking safety, travel purpose, parking lot type, weather conditions, parking prices
Travel purpose	Working, dining, entertainment, seeking medical treatment, returning home, picking up and dropping off children
Parking location	Roadside parking spaces, off road parking lots, and random parking
Transportation mode	Private cars, public transportation
General parking time	0–2 h, 2–4 h, 4–8 h, >8 h
Highest tolerable parking fee	3 yuan, 5 yuan, 10 yuan, >20 yuan
Longest tolerable walking time	<5 min, 5~10 min, 10~15 min, >15 min
Longest tolerant time it takes to find a parking spot	<5 min, 5~10 min, 10~15 min, >15 min
Public transportation situation at the departure location	With options for public transportation, without options for public transportation
Public transportation situation at the destination	With options for public transportation, without options for public transportation
Reason for not selecting public transportation	Public transportation is incomplete, time-consuming, or inconvenient
Reason for not selecting a parking lot	High price, not convenient enough, far from the destination, few parking spaces, no parking lot, long search time for parking spaces, and high difficulty in parking operations

3.2.1. Analysis of Factors Influencing Parking Lot Selection

Parking decision-making is a complex process involving multiple factors, and travelers often need to weigh various factors when making choices. In order to deeply explore the choice behavior of travelers, this survey adopted an importance ranking method, designed multiple choice questions with at least three choices, and ranked them according to their importance. Through this approach, it is possible to gain a more comprehensive understanding of the factors that travelers consider when choosing a parking lot. Based on the survey results, further multiple response analysis was conducted to determine the top three factors that travelers value most when choosing a parking lot. The analysis result is shown in Table 3.

Table 3. Multiple response analysis of parking choice factors—first ranking.

First Ranking Consideration Factors	N	Response Percentage	The Percentage of Cases
Parking prices	196	46.3%	46.3%
Time to find parking position	95	22.5%	22.5%
Parking time point	43	10.2%	10.2%
Parking duration	44	10.4%	10.4%
Number of empty parking positions	35	8.3%	8.3%
Distance to destination	7	1.7%	1.7%
Travel purpose	1	0.2%	0.2%
Parking safety	2	0.5%	0.5%
Total	423	100%	100%

According to Table 3, the multiple response analysis of first ranking parking lot selection factors shows that among the primary factors that travelers consider when choosing a parking lot, parking price ranks first, accounting for about half, followed by parking time, accounting for 22.5% of cases, and parking time, accounting for 10.4%.

Table 4 shows that about 25% of travelers consider the time point of parking as the second factor when choosing a parking lot, and the number of available parking spaces also accounts for a large proportion of the second factor, at around 20%. The time required to find a parking space accounts for 19.9%.

Table 4. Multiple response analysis of parking choice factors—second ranking.

Second Ranking Consideration Factors	N	Response Percentage	The Percentage of Cases
Parking prices	5	1.2%	1.2%
Time to find parking position	84	19.9%	19.9%
Parking time point	108	25.5%	25.5%
Parking duration	67	15.8%	15.8%
Number of empty parking positions	85	20.1%	20.1%
Distance to destination	41	9.7%	9.7%
Travel purpose	10	2.4%	2.4%
Parking safety	16	3.8%	3.8%
Weather conditions	3	0.7%	0.7%
Type of parking lots	4	0.9%	0.9%
Total	243	100%	100%

The third ranking factor to consider when choosing a parking lot is the length of parking time (shown in Table 5), which is approximately 21.5%; next are the available parking spaces and the distance to the destination, which are 21.3% and 18.2%, respectively.

Table 5. Multiple response analysis of parking choice factors—third ranking.

No.3 Consideration Factors	N	Response Percentage	The Percentage of Cases
Parking prices	7	1.7%	1.7%
Time to find parking position	5	1.2%	1.2%
Parking time point	39	9.2%	9.2%
Parking duration	91	21.5%	21.5%
Number of empty parking positions	90	21.3%	21.3%
Distance to destination	77	18.2%	18.2%
Travel purpose	46	10.9%	10.9%
Parking safety	41	9.7%	9.7%
Weather conditions	16	3.8%	3.8%
Type of parking lots	11	2.6%	2.6%
Total	243	100%	100%

The analysis of the factors influencing the choice of parking lots for travelers in the previous text is mainly based on a simple qualitative description of statistical data. In order to further analyze the selection differences among various influencing factors, this article adopts the assignment scoring method to more accurately evaluate the results of the sorting analysis. The steps of calculation are as follows:

Step 1: Ranking of importance of selection factors

Travelers have screened out all factors that affect parking lot selection decisions based on their subjective perceptions and ranked them in order of their importance. Among them, number 1 represents the first important influencing factor, number 2 represents the second important influencing factor, and so on. When designing the questionnaire, travelers are required to select at least three items and sort them. However, the statistical results show that the number of choices exceeding three is relatively small. In order to eliminate the potential interference caused by differences in the number of choices, this article has decided to only conduct a ranking analysis on the first three items.

Step 2: Descending assignment

Assign values to the first three factors in descending order. The first influencing factor is assigned a value of 3, the second influencing factor is assigned a value of 2, the third influencing factor is assigned a value of 1, and all other choices are assigned a value of 0.

Step 3: Final scoring

In order to analyze the importance of each influencing factor more deeply, the total score of each factor and the total number of drivers who chose that factor were calculated, and the results were sorted in a descending order of scores. In the analysis process, the list comparison method was used to present the differences between various factors more intuitively.

It should be noted that since the sorting of multiple questions during the questionnaire input is performed in the form of strings, it is necessary to convert these data variables before conducting analysis. At the same time, it is necessary to convert the sorting order into corresponding numerical values to ensure the accuracy and reliability of the analysis.

Taking parking fees as an example, a total of 196 people considered parking prices as the primary factor, while five and seven people listed them as the second and third factors, respectively. However, 215 people did not choose parking prices as their consideration factor or placed them in a lower position. Based on these data, the total assigned score for

parking prices can be calculated. Table 6 shows a summary of the descending assigned values for the factors considered in parking selection. Based on the ranking results of the respondents, drivers generally believe that parking price, parking time, and parking time are the most critical factors, ranking among the top three factors considered. In contrast, the impact of weather conditions and parking lot types is slightly weaker.

Table 6. Descending assignment of parking selection factors.

Parking Lots Selection Factors	No.1 Factors	No.2 Factors	No.3 Factors	Other Factors
	3	2	1	0
Parking prices	196	5	7	215
Time to find parking position	95	84	5	239
Parking time point	43	108	39	233
Parking duration	44	67	91	221
Number of empty parking positions	35	85	90	213
Distance to destination	7	41	77	298
Travel purpose	1	10	46	366
Parking safety	2	16	41	364
Weather conditions	0	3	16	404
Type of parking lots	0	4	11	408

Based on the total score of each selection factor listed in Table 7 and the total number of people of 423, the statistics clearly identify the differences in the importance of each influencing factor in driver parking lot selection. Among them, parking price is the most important influencing factor for drivers, with a total of 208 people choosing it. The total score after descending assignment reached 605 points, with an average score of 1.43 points. Following closely behind was the time to find a parking spot, with a total of 184 people choosing this factor, with an average score of 1.08 points. The third influencing factor is the parking time point, with an average score of 0.92 points after descending assignment. These data intuitively demonstrate the degree to which drivers attach importance to different factors in the parking lot selection process; the average score of each selection factor can be further calculated.

Table 7. Ranking of factors for parking lot selection.

Parking Lots Selection Factors	Total Score	Selected Person	Average Score
Parking prices	605	208	1.43
Time to find parking position	458	184	1.08
Parking time point	384	190	0.91
Parking duration	357	202	0.84
Number of empty parking positions	365	210	0.86
Distance to destination	180	125	0.43
Travel purpose	69	57	0.16
Parking safety	79	59	0.19
Weather conditions	22	19	0.05
Type of parking lots	19	15	0.04

3.2.2. Analysis of the Longest Tolerable Time for Finding a Parking Spot Under Different Travel Purposes

From the distribution Figure 9, it is evident that when the purpose of travel is entertainment and dining, drivers spend most of their time searching for parking spaces within 5 min. However, for commuting purposes such as going to work, going home, and picking up and dropping off children, the time spent searching for a parking spot is relatively long, mainly concentrated within the range of 5 to 10 min.

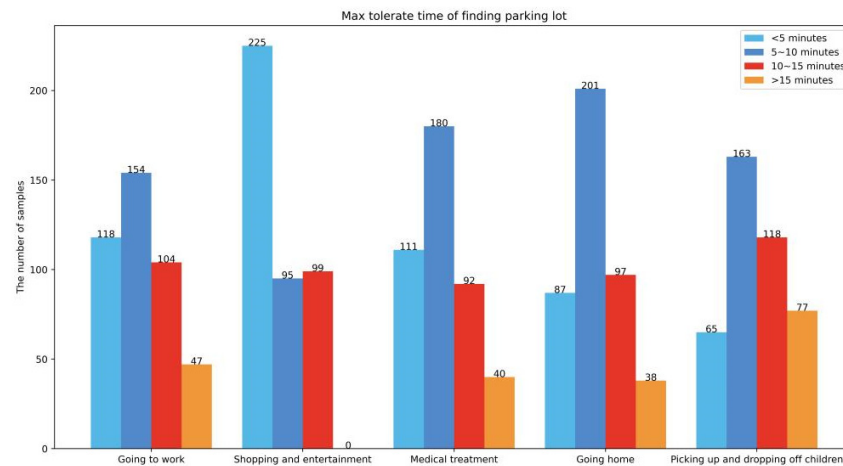


Figure 9. Time distribution of searching for parking space for different travel purposes.

3.2.3. Analysis of Parking Time Under Different Travel Purposes

According to Figure 10, the distribution of parking time for drivers with different travel purposes can be observed. It can be clearly seen that the parking time for commuting (such as work and home) is relatively similar, with most parking times exceeding 4 h. For non commuting purposes such as shopping, dining, entertainment, and medical treatment, the parking time is mainly concentrated between 4 and 8 h. In addition, the parking time for picking up and dropping off children for travel is relatively short, mainly concentrated in the range of 0 to 2 h.

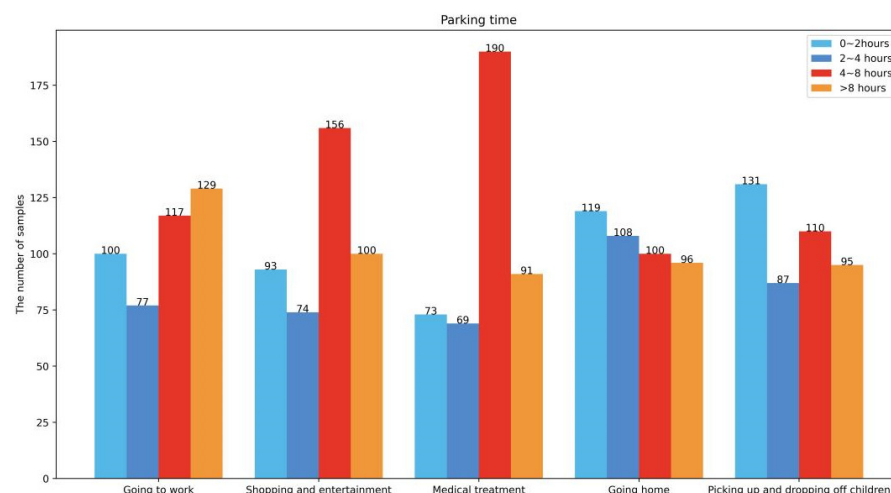


Figure 10. Time distribution of parking for different travel purposes.

3.2.4. Analysis of the Maximum Parking Fee That Can Be Tolerated Under Different Travel Purposes

Figure 11 shows the distribution of maximum parking rates that drivers can tolerate. From the graph, it can be seen that the maximum parking rate that drivers can tolerate

for travel purposes such as going to work, going home, and picking up and dropping off children is mainly concentrated in the option of 3 yuan/hour. For drivers who travel for shopping, dining, entertainment, and medical purposes, their maximum parking rates are more concentrated in the range of 5–10 yuan/hour.

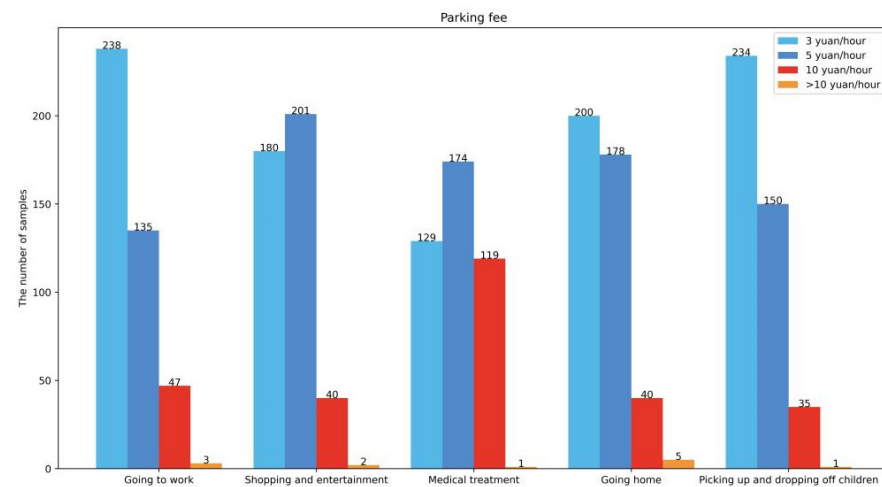


Figure 11. Distribution of maximum tolerant parking fee under different travel purposes.

3.2.5. Analysis of the Longest Walking Time That Can Be Tolerated Under Different Travel Purposes

The distribution of the longest walking time that drivers can tolerate is shown in Figure 12. From Figure 12, we can observe that under various travel purposes, the median of the longest walking time that drivers can tolerate is in the second level, which is within the range of 5 to 10 min.

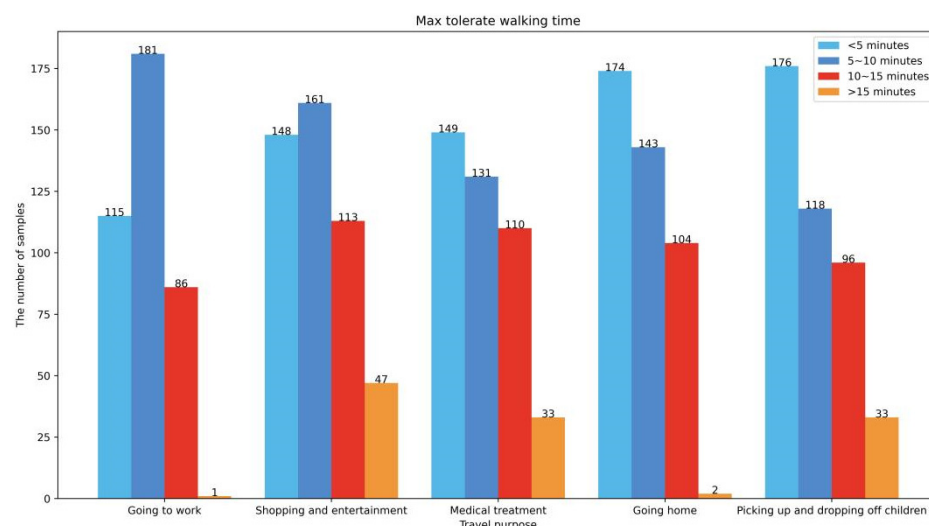


Figure 12. Distribution of maximum walking time that drivers can tolerate under different travel purposes.

4. Analysis on On-Street Parking Selection Behavior

4.1. Analysis Method

In order to analyze the influencing factors of on-road parking choice behavior of travelers with different travel purposes and provide theoretical support for regulating on-road parking demand, this section examines on-road parking choice behavior and models and analyzes their choice behavior through a binomial logit model using the data from the

questionnaire survey and the spatio-temporal characteristics of on-road parking, combined with the parking feature data of the respondents.

4.1.1. Logistic Model

Logistic regression [18], also known as logistic regression analysis, is a generalized linear regression analysis model, and its general expression is as follows:

$$p = \frac{1}{1 + \exp(-z)}, -\infty < z < \infty \quad (2)$$

$$1 - p = \frac{\exp(-z)}{1 + \exp(-z)}, -\infty < z < \infty \quad (3)$$

According to Equations (2) and (3), we have Equations (4) and (5).

$$\frac{p}{1 - p} = \frac{1 + \exp(z)}{1 + \exp(-z)} = \exp(z) \quad (4)$$

$$z = \ln\left(\frac{p}{1 - p}\right) \quad (5)$$

where Equation (5) is the logarithmic form of Equation (4).

4.1.2. Binomial Logistic Model

The Binomial Logistic (BL) model is the most common discrete choice model, commonly used to analyze and predict the process of decision-makers selecting one option from two choices [19].

We let $Y \sim B(m, p)$. p represent the probability of $Y = 1$, also represented as $\pi(Y = 1)$ here. m means that there are m independent variables $X_1, X_2, \dots, X_m$ in this model. The corresponding BL regression model is shown in Equation (6):

$$\pi(Y = 1) = \frac{\exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_m X_m)}{1 + \exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_m X_m)} \quad (6)$$

where β_0 is the intercept and β_i is the partial regression coefficient of X_i when $i = 1, 2, \dots, m$.

Let $z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_m X_m$, we have Equation (7):

$$L = \ln\left(\frac{p}{1 - p}\right) = z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_m X_m \quad (7)$$

The above equation is the logarithmic form of the Logistic function, i.e., the logit function, where $\frac{p}{1-p}$ is called the occurrence ratio of events (odds), also known as the ratio of the probability of an event occurring to not occurring.

4.1.3. Parameter Estimation of Binomial Logistic Model

Assuming y is a binary variable, $x_1, x_2, \dots, x_m$ are variables related to y that can be accurately measured. Corresponding observation values are $(x_{i,1}, x_{i,2}, \dots, x_{i,m}; y_i)$, $i = 1, 2, \dots, n$; thus, the corresponding logit model is shown as Equation (8):

$$f(p_i) = \frac{\exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_m X_m)}{1 + \exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_m X_m)} \quad (8)$$

The probability function of y_i is Equation (9):

$$P(y_i) = f(p_i)^{y_i} [1 - f(p_i)]^{1-y_i}, y_i \in \{0, 1\} \quad (9)$$

We can obtain the likelihood function of $y_1, y_2, \dots, y_n$, Equation (10):

$$l = \prod_{i=1}^n P(y_i) = \prod_{i=1}^n f(p_i)^{y_i} [1 - f(p_i)]^{1-y_i} \quad (10)$$

Therefore, its natural logarithmic log function is Equations (11) and (12):

$$L = \ln l = \sum_{i=1}^n \{y_i f(p_i) + (1 - y_i)[1 - f(p_i)]\} \quad (11)$$

$$L = \ln l = \sum_{i=1}^n \left[y_i (\beta_0 + \beta_1 x_{i,1} + \beta_2 x_{i,2} + \dots + \beta_m x_{i,m}) - \ln \left(1 + e^{\beta_0 + \beta_1 x_{i,1} + \beta_2 x_{i,2} + \dots + \beta_m x_{i,m}} \right) \right] \quad (12)$$

Therefore, we can obtain $\hat{\beta}_0, \hat{\beta}_1, \dots, \hat{\beta}_m$, the maximum likelihood estimate of $\beta_0, \beta_1, \dots, \beta_m$, through iterative calculation.

4.1.4. Regression Coefficient of Binomial Logistic Model

The coefficients of the variables included in the logistic model should be significant; therefore, significance testing [20] should be conducted on the regression coefficients included in the model before analyzing the results.

The original hypothesis H_0 and alternative hypothesis H_1 for testing the significance of regression coefficients of variables are shown in Equation (13):

$$H_0 : \beta_i = 0 (i = 1, 2, \dots, k) \quad H_1 : \beta_i \neq 0 (i = 1, 2, \dots, k) \quad (13)$$

Use the following statistical measures to test the significance of regression coefficients, as shown in Equation (14):

$$Wald_i = \frac{\hat{\beta}_i}{Var(\hat{\beta}_i)} \sim \chi^2(k) \quad (14)$$

If $P(H_0) < \alpha$, and the probability of the original hypothesis is less than the pre-determined level of significance, we reject the original hypothesis H_0 and assume that the regression coefficient of the variable is not entirely zero. Accept the alternative hypothesis H_1 and assume that the regression coefficient of the variable plays a role in predicting changes in the dependent variable.

4.1.5. Significance Test of Binomial Logistic Model

In the goodness-of-fit test of a model, which is the significance test of the model, a classification table is usually used to characterize the fitting effect, as shown in the following Table 8:

Table 8. Classification table.

z		Prediction Value		
		0	1	Correct Classification Ratio
Observation value	0	N_{00}	N_{01}	f_0
	1	N_{10}	N_{11}	f_1
	Total			f

The boundary value is $p = 0.500$.

Where N_{ij} ($i = 0, 1; j = 0, 1$), the number of samples with real observation value is i , while that of prediction value is j . The calculations of f_0 , f_1 , and f are shown as Equations (15)–(17):

$$f_0 = \frac{N_{00}}{N_{00} + N_{01}} \quad (15)$$

$$f_1 = \frac{N_{11}}{N_{10} + N_{11}} \quad (16)$$

$$f = \frac{N_{00} + N_{11}}{N_{00} + N_{01} + N_{10} + N_{11}} \quad (17)$$

We can also obtain the statistical measure of the goodness of fit by the following Equation (18):

$$\sum_{i=1}^n \frac{w_i(y_i - p_i)^2}{\hat{\pi}_i(1 - p_i)} \quad (18)$$

Among them, n is the total number of samples, w_i is the weight of the i^{th} sample, and y_i is the observation value for i^{th} sample of the binary dependent variable. p_i is the logistic regression prediction probability for the i^{th} sample.

Additionally, we applied another three significant test methods: Hosmer–Lemeshow goodness-of-fit, Cox & Snell goodness-of-fit, and Nagelkerke goodness-of-fit to test our proposed model.

1. Hosmer–Lemeshow test

Hosmer–Lemeshow test [21] groups all observation units based on the predicted probability of the model and then calculates the Pearson chi-square based on the measured and expected values of each dependent variable. The goodness-of-fit statistic calculation is shown in Equations (19) and (20):

$$\chi^2(HL) = \sum_{k=1}^g \frac{(O_{1,k} - E_{1,k})^2}{E_{1,k}\zeta_k} \sim \chi^2(g - 2) \quad (19)$$

$$H_0 : O_{1,k} = E_{1,k} \quad (20)$$

In the formula, g is the number of groups, $O_{1,k}$ represents the actual observation frequency of the k^{th} group event ($Y = 1$). $E_{1,k}$ represents the expected frequency of the k^{th} group event ($Y = 1$), and ζ_k represents the average probability of the k^{th} group event ($Y = 1$) occurring.

The original assumption of the model is that H_0 is the same as the observation and expectation; if $P(H_0) < \alpha$, we refuse the null hypothesis, which assumes that the observed values of the model are different from the expected values, indicating poor fitting performance.

2. Cox & Snell R^2 [22]

The calculation of goodness of fit is shown as Equation (21):

$$R_{CS}^2 = 1 - \frac{l(0)}{l(\hat{\beta})} \quad (21)$$

In the formula, $l(0)$ is the likelihood ratio of the initial model, which is the likelihood ratio when the model only contains a constant term. $l(\hat{\beta})$ is the likelihood ratio of the current model. N is the size of samples. R_{CS}^2 denotes the obtained goodness of fit.

3. Nagelkerke R^2

The value of Cox & Snell R^2 cannot be equal to 1, because $l(0) \neq 0$. Thus, we use Nagelkerke to modify goodness of fit obtained by Cox & Snell R^2 , and we obtained Nagelkerke R^2 [23].

In this work, we use R_N^2 to denote Nagelkerke R^2 . The calculation of R_N^2 is shown as Equation (22):

$$R_N^2 = \frac{R_{CS}^2}{\max(R_{CS}^2)} \quad (22)$$

where $\max(R_{CS}^2) = 1 - (l(0))^{\frac{2}{n}}$, this statistic represents the proportion of the dependent variable's variance that is explained by the regression equation.

4.1.6. Virtual Independent Variable

In regression analysis, the independent variables are usually numerical variables, which have a linear explanatory effect on the dependent variable. However, in logistic regression, the independent variables are mostly categorical variables, including nominal and ordered variables, which cannot be directly used as explanatory variables in the regression equation. They need to be first transformed into dummy variables.

The main purpose of using categorical variables in regression analysis is to study the differences in the impact of each categorical variable on the dependent variable. By using a binary variable of 0/1, each categorical variable is recorded, with 1 indicating belonging to the same category and 0 indicating not belonging to the same category. For categorical variables of category N, once the reference category is determined, only N – 1 dummy variables need to be set. The coefficient in the obtained logistic regression equation represents the difference in the average contribution of each category to the dependent variable relative to the reference category.

4.2. Model Parameters

The research on parking choice behavior in this article is based on the survey plan design and data in Section 2. The influencing factors of parking choice behavior are divided into three categories: personal socio-economic attributes, parking characteristics, and factors affecting parking behavior under sharing modes. The detailed definitions and expressions are shown in Tables 9–11 below.

Table 9. User attribute factor.

Variable	Symbol	Definition	The Meaning of Number in the Model
Sex	X_1	Sex	1 represents male, 2 represents female
Age	X_2	Age	Numbers 1–5 represent five age categories
Salary	X_3	Payment per month	Numbers 1–5 represent five categories of monthly income level classification
Drivage	X_4	Driving experience	Number 1–4 represent four categories of driving experience
Job	X_5	Profession	Number 1–4 represent four types of professions
Education	X_6	Education experience	Numbers 1–4 represent four types of education experience
Frequency	X_7	Using vehicles frequency	Numbers 1–4 represent the 4 types of using car frequency
Parkfee	X_8	Monthly parking fee	Numbers 1–4 represent four types of monthly parking fees

Table 10. Factors Affecting Parking Conditions.

Variable	Symbol	Definition	The Meaning of Number in the Model
Attitude	X_9	Attitude towards differentiated on-road toll collection	Numbers 1–4 represent four types of attitudes towards differentiated on-road toll collection
Satisfaction	X_{10}	Satisfaction with existing charging policies	Numbers 1–4 represent four types of satisfactions with existing charging policies

Table 11. Parking characteristic factors.

Variable	Symbol	Definition	The Meaning of Number in the Model
Purpose	X_{11}	Travel purpose	Numbers 1–5 represent five categories of travel purposes
Public_transportation	X_{12}	Public transportation conditions	1 denotes that public transportation is available, 0 denotes public transportation is unavailable,
Parktime	X_{13}	Normal parking time	Numbers 1–4 to represent four types of normal parking time
Maxfee	X_{14}	Maximum tolerable parking fee	Numbers 1–4 represent four types of maximum tolerable parking fee
Maxwalktime	X_{15}	Maximum tolerable walking time	Numbers 1–4 represent four types of maximum tolerable walking time
Maxsearchtime	X_{16}	The longest tolerable time for finding a parking spot	Numbers 1–4 represent four types of longest tolerable time for finding a parking spot

4.3. Independent Variable Factor Analysis

The research on parking choice behavior has a large number of independent variables. In order to avoid the errors caused by the linear relationship between the independent variables in the Logit selection model, factor analysis of the independent variables is first necessary.

Factor analysis is a multivariate statistical analysis method that starts with studying the internal dependencies of variables and then categorizing the variables with complex relationships into a few comprehensive factors.

The KMO test and Bartlett test results for a total of 16 variables, including user attributes, parking characteristics, and parking status, of the respondents are shown in Table 12. The KMO measure of the independent variable is 0.904, which is greater than 0.5, and the significance of Bartlett's sphericity test is less than 0.05, rejecting the null hypothesis that the correlation matrix is not the identity matrix. Therefore, this group of variables is suitable for factor analysis.

Table 12. KMO and Bartlett test analysis.

Sampling Sufficient KMO Values		0.904
Bartlett's sphericity test	Approximate chi-square	2245.352
	Degree of Freedom df	120
	Significance sig	0.000

Table 13 shows the process of extracting common factors, indicating the contribution of each variable to the common factors. Extracting common factor variance refers to the estimated variance of each variable explained by the factor in the factor solution. A smaller value indicates that the variable is not suitable as a factor and can be filtered out in the analysis. It can be seen that six variables have a contribution rate of over 70%, while the

proportion of other common factors extracted is less than 70%, indicating that they cannot explain other variables well.

Table 13. Common factor variance.

Variable	Initial Common Factor Variance	Extract Common Factor Variance
Sex	1.000	0.495
Age	1.000	0.726
Salary	1.000	0.391
Drivage	1.000	0.717
Job	1.000	0.701
Education	1.000	0.609
Frequency	1.000	0.766
Parkfee	1.000	0.754
Attitude	1.000	0.478
Satisfaction	1.000	0.271
Purpose	1.000	0.665
Public_transportation	1.000	0.674
Parktime	1.000	0.575
Maxfee	1.000	0.762
Maxwalktime	1.000	0.539
Maxsearchtime	1.000	0.633

In order to better analyze the contributions of variables to the result, we arranged the calculated principal component contribution in descending order and numbered variables sequentially from 1 to 16. The principal component results are shown in Table 14, which lists all principal components and ranks them according to the size of their eigenvalues. According to the table, the eigenvalues of the first principal component are 5.137, with a variance contribution rate of 32.107%. There is a total of five components with eigenvalues greater than 1, and the cumulative variance contribution rate of the first five factors is 60.981%, indicating that the first five factors cannot explain the remaining variables well.

Although factor analysis is useful for understanding the underlying structure of the data, as noted by a reviewer, it is not a direct tool for diagnosing multicollinearity in regression models. To ensure the reliability of the subsequent binomial logit models, we calculated the Variance Inflation Factor (VIF) for all independent variables to formally assess multicollinearity. The VIF measures how much the variance of an estimated regression coefficient is increased due to collinearity with other predictors. A common rule of thumb is that a VIF value above 10 indicates severe multicollinearity [24].

We performed VIF diagnostics on all continuous variables and categorical variables (after being converted into dummy variables). The results (shown in Table 15) indicated that all VIF values were well below the threshold of 10, with the maximum VIF being 3.69. This clearly demonstrates that no severe multicollinearity exists among the independent variables selected for our final logit models, and that the model estimates are stable and reliable.

Table 14. Total variance analysis table.

Variable Order	Total Variance	Variance Percentage	Accumulated Percentage
1	5.137	32.107	32.107
2	1.275	7.971	40.079
3	1.185	7.409	47.488
4	1.132	7.078	54.566
5	1.027	6.416	60.981
6	0.936	5.853	66.384
7	0.918	5.740	72.575
8	0.862	5.387	77.962
9	0.850	5.314	83.275
10	0.662	4.140	87.415
11	0.487	3.044	90.460
12	0.386	2.412	92.871
13	0.348	2.172	95.043
14	0.289	1.809	96.852
15	0.255	1.596	98.448
16	0.248	1.552	100.00

Table 15. Variance Inflation Factor.

Variable	Variance Inflation Factor	Variable	Variance Inflation Factor
Sex	2.02	Attitude	2.09
Age	1.38	Satisfaction	3.69
Salary	2.56	Purpose	1.50
Drivage	1.39	Public_transportation	1.48
Job	1.43	Parktime	1.74
Education	1.64	Maxfee	1.31
Frequency	1.31	Maxwalktime	1.86
Parkfee	1.33	Maxsearchtime	1.58

4.4. Analysis on Logit Model

According to the descriptive analysis in Section 2, it can be concluded that there are significant differences in the parking characteristics of the respondents with different travel purposes. Based on this, this section establishes a parking choice behavior model under differentiated on-road parking fee models for different travel purposes.

4.4.1. Model Relevant Parameter Examine

According to the analysis results in Section 2, it can be seen that there are significant differences in the parking choice characteristics of travelers with different travel purposes. Therefore, correlation tests should be conducted on the parameter variables under different travel purposes to determine the significant correlation variables of on-road parking choice behavior under different travel purposes. The corresponding Table 16 for travel purposes is shown below.

Table 16. The sample size of different purposes.

Travel Purpose	Sample Number
Going to work	127
Shopping and entertainment	85
Medical treatment	62
Going home	87
Picking up and dropping off children	62

Taking shopping, dining, and entertainment as an example, Spearman analysis was conducted using SPSS 26.0 software to examine the significant correlation variables and their coefficients of parking choice behavior under the purpose of shopping, dining, and entertainment travel. The results are shown in Table 17.

Table 17. Different variables' correlation coefficient and significance.

Variable	Correlation Coefficient	Significance (Double Tailed)
Age	0.527	0.000 ***
Salary	−0.405	0.000 ***
Job	0.669	0.000 ***
Education	−0.577	0.000 ***
Frequency	0.662	0.000 ***
Parkfee	−0.775	0.000 ***
Parktime	−0.631	0.000 ***
Satisfaction	−0.523	0.000 ***

*** represent significant levels of 5%.

According to the rank correlation test results in the table above, when $\alpha = 0.01$, significant variables related to whether to choose on-road parking spaces for shopping, dining, and entertainment purposes include age, monthly income, occupation, education level, weekly driving days, monthly parking fee, daily parking time, and satisfaction with existing charging policies.

Among them, age, occupation, and weekly driving days are positively correlated, that is, the larger the independent variable value, the easier it is to choose on-road parking spaces; the larger the value for monthly salary, education level, monthly parking fees, daily parking hours, and satisfaction with existing charging policies, the less likely it is to choose on-road parking spaces. For example, the higher the monthly parking fee, the less likely it is to choose on-road parking spaces.

Similarly, the coefficients and significant variables of the rank correlation coefficient test for other travel purposes can be obtained, as Table 18.

Table 18. Spearman rank correlation coefficient test for significant variables under different travel purposes.

Travel Purpose	Significant Correlated Variables
Going to work	Age, Salary, Education, Parkfee, Attitude
Shopping and entertainment	Age, Salary, Job, Education, Frequency, Parkfee, Parktime, Satisfaction
Medical treatment	Age, Salary, Drivage, Job, Education, Frequency, Parkfee, Publictransportation, Maxfee, Parktime, Maxwalktime, Maxsearchtime, Satisfaction
Going home	Age, Salary, Job, Education, Frequency, Parkfee, Parktime, Satisfaction
Picking up and dropping off children	Age, Salary, Drivage, Job, Education, Frequency, Parkfee, Parktime, Attitude, Satisfaction

4.4.2. Construction of Binomial Logit Model and Result Analysis

Taking the purpose of shopping, dining, entertainment, and travel as an example, as shown in Table 19, a total of 85 samples participated in the analysis by conducting binary logistic regression analysis on eight independent variables, and there was no missing data.

Table 19. Basic summary of binary logit regression analysis.

Name	Option	Frequency	Percentage
Y	0	33	38.82%
	1	52	61.18%
Summary	Effective	85	100%
	Deletion	0	100%
	Total	85	100%

Firstly, an analysis of the overall effectiveness of the model is conducted. From the table above, it can be seen that the null hypothesis for model testing here is whether to include independent variables (Age, Salary, Job, Education, Frequency, Parking fee, Parking time, Satisfaction). The model quality is the same for Salary, Job, Education, Frequency, Parking fee, Parking time, and Satisfaction. As shown in Table 20 (results of the likelihood ratio test for binary logit regression model), the p value is less than 0.05; therefore, the null hypothesis is rejected. The independent variables of the model are valid, and the construction of this model is meaningful.

Table 20. Likelihood ratio test of binary logit regression model.

Model	−2 log Likelihood Values	Chi-Square Value	df	p	AIC	BIC
Intercept only	113.552					
Final model	41.959	71.593	8	0.000	59.959	81.943

Table 21 presents the results of logit regression analysis. According to the statistics given in Table 21, we can obtain on-street parking selection behavior model, shown as Equation (23):

$$\text{Logit}(P) = \ln(p/1 - p) = -0.960 + 0.373 * \text{age} + 0.062 * \text{salary} - 1.177 * \text{job} + 0.529 * \text{education} - 1.036 * \text{frequency} + 1.807 * \text{parkfee} + 0.446 * \text{parktime} - 0.657 * \text{satisfaction} \quad (23)$$

Table 21. Summary of binary logit regression analysis results.

Term	Regression Coefficient	Standard	z Value	χ^2	p Value	OR Value	95% Confidence Interval of OR
Age	0.373	0.594	0.629	0.395	0.530	1.453	0.453~4.654
Salary	0.062	0.642	0.097	0.009	0.924	1.064	0.303~3.741
Job	−1.177	0.642	−1.834	3.362	0.067	0.308	0.088~1.084
Education	0.529	0.676	0.782	0.611	0.434	1.697	0.451~6.391
Frequency	−1.036	0.718	−1.444	2.084	0.149	0.355	0.087~1.449
Parkfee	1.087	0.698	2.587	6.695	0.010	6.691	1.550~23.940
Parktime	0.446	0.755	0.590	0.348	0.555	1.561	0.356~6.854
Satisfaction	−0.657	0.585	−1.123	1.260	0.262	0.519	0.165~1.632
Interface	−0.960	3.848	−0.249	0.062	0.803	0.383	0.000~722.067

Dependent variable: Y. McFadden R^2 : 0.630. Cox & Snell R^2 : 0.569. Nagelkerke R^2 : 0.772.

Taking the monthly parking fee variable as an example to explain the significance of the model, the higher the average monthly parking fee, the easier it is for travelers to accept roadside parking spaces. Similarly, the logit model for parking choice behavior under differentiated pricing of roadside parking spaces for other purposes of travel can be obtained, as shown in Tables 22–25:

Table 22. Logit model parameters of going to work.

Term	Regression Coefficient	Standard	z Value	χ^2	p Value	OR Value	95% Confidence Interval of OR
Parkfee	−0.869	0.323	−2.690	7.235	0.007	0.419	0.223~0.790
Salary	0.584	0.291	2.005	4.020	0.045	1.793	1.013~3.173
Frequency	−1.721	2.041	−0.843	0.711	0.399	0.179	0.003~9.775

Table 23. Logit model parameters of going for medical.

Term	Regression Coefficient	Standard	z Value	χ^2	p Value	OR Value	95% Confidence Interval of OR
Parkfee	−0.316	1.315	−0.240	0.058	0.810	0.729	0.055~9.605
Max fee	4.033	2.302	1.752	3.068	0.080	6.410	0.619~140.277
Parktime	1.126	2.468	0.456	0.208	0.648	3.083	0.024~388.858
Maxwalktime	−0.289	1.445	−0.200	0.040	0.841	0.749	0.044~12.721

Table 24. Logit model parameters of going home.

Term	Regression Coefficient	Standard	z Value	χ^2	p Value	OR Value	95% Confidence Interval of OR
Parkfee	0.893	0.454	1.967	3.870	0.049	2.443	1.003 ~ 5.949
Parktime	0.064	0.683	0.094	0.009	0.925	1.066	0.279 ~ 4.609

Table 25. Logit model parameters of picking up and dropping off children.

Term	Regression Coefficient	Standard	z Value	χ^2	p Value	OR Value	95% Confidence Interval of OR
Parkfee	0.561	0.729	0.770	0.593	0.125	1.753	0.420~7.331
Parktime	1.871	1.219	1.534	2.354	0.441	6.493	0.595~70.862
Attitude	−1.344	0.264	−2.155	4.646	0.031	0.261	0.077~0.885

Where p denotes the probability that Y equals 1, and $1 - p$ denotes the probability that Y equals 0. When p is below 0.5, travelers ultimately choose an on-street position for parking; otherwise, travelers do not tend to park on the street.

From the model results, it can be seen that

- 1, The higher the monthly income, the more likely it is to choose roadside parking;
- 2, The higher the level of education, the more inclined one is to choose roadside parking spaces;
- 3, The higher the monthly parking fee, the more likely it is to choose roadside parking spaces;
- 4, The longer the parking time, the easier it is to choose a roadside parking spot.

The accuracy of the model prediction is shown in Table 26 below:

Table 26. Prediction accuracy under different travel purposes.

Travel Purpose	Prediction Accuracy
Going to work	81.94%
Shopping and entertainment	81.06%
Medical treatment	81.71%
Going home	80.87%
Picking up and dropping off children	83.56%

From the above Table 26, it can be seen that the accuracy of the model prediction is relatively low under the purpose of going to work and going home. The reason is that the purpose of going to work and going home is for commuting, which belongs to rigid travel purposes. The impact of parking space attributes on parking choices is relatively small, while under the purpose of dining, shopping, entertainment, medical treatment, and picking up and dropping off children, the impact of parking space attributes on parking choices is relatively large. Therefore, the accuracy of the model prediction is relatively high.

5. Conclusions

This study processed and analyzed questionnaire data to determine the variables that can be included in the parking choice behavior model. At the same time, hypothesis

tests were conducted on the influencing factors of on-street parking choice behavior under different travel purposes, and significant influencing factors of on-road parking choice behavior corresponding to each travel purpose were determined.

This study established a binomial logit model based on the questionnaire survey data for on-street parking choice behavior of travelers under various travel purposes, and analyzed the factors and influencing mechanisms that affect on-street parking choice under each travel purpose.

This study has made an attempt to investigate the influencing factors of on-street parking choices and how these factors influence those choices. However, the study still has some limitation: (a) the sample is only from Xi'an, which may limit the generalizability of the conclusion to other cities; (b) possible deviations between hypothetical scenarios and actual decisions in SP surveys; (c) potential important factors were not included in the model, such as real-time traffic conditions and the attractiveness of specific destinations; and (d) using $p = 0.5$ as the default classification threshold may not be the optimal solution. Future work should consider conducting comparative research on multiple cities, validating SP results using GPS data, and exploring machine learning models.

In addition, according to the statistics of the questionnaire and regression, we can observe that parking price influences people's on-street parking selection. Currently, there are some on-street parking pricing strategies put into use such as SFpark in San Francisco [25]. A proper on-street parking pricing strategy is also worth researching in Xi'an. Further research can pay more attention to dynamic [26,27] and differentiated pricing [28,29] for on-street parking strategies.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study. Participation was voluntary, and respondents were informed about the study's purpose and the anonymity of their responses.

Data Availability Statement: Some or all data, models, or code generated or used during the study are available from the corresponding author by request. This data is in the form of some Excel files.

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