# Analysis of parking behavior in the context of urban renewal based on multi-day RP and SP data: A case study in Xi'an, China

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## ABSTRACT

The relationship between intelligent parking management and regional traffic congestion in the context of urban parcel renewal has attracted academic attention. Reasonable parking behavior analysis can effectively contribute to traffic demand management and alleviate the contradiction between parking supply and demand. To this end, this paper constructs a multinomial logit model based on Python that considers multiple factors affecting parking. First, to accommodate the multi-day behavioral variability and unobserved heterogeneity in individual characteristics ignored by traditional parking surveys, multi-day stated-preference(SP) and revealed-preference(RP) data collected in Xi'an were used to analyze people's parking choice behavioral characteristics. The questionnaires were designed by SPSS software with orthogonal design principles. Secondly, based on multi-day survey data, parameter estimation and significant factor evaluation of Multinomial logit(MNL) model are completed by using Python. Finally, the effects of parking rates, in-vehicle time and out-vehicle time on parking choice behavior are explored, and the parking behavior of passengers in different scenarios is also simulated. This paper conducted an empirical experiment in Xi'an. The research results show that in-car time and parking rate are significant factors affecting passengers' parking behavior, indicating that it is feasible to guide travelers' parking behavior and alleviate regional traffic congestion by changing the above factors. This study can provide reference for the implementation of smart parking demand management in domestic cities.

**Keywords:** Urban renewal, Parking behavior analysis, Stated-preference survey, Logit models, Intelligent parking management, Traffic demand

## 1. INTRODUCTION

In recent years, urban residential motor vehicle ownership has been increasing. The national car ownership has reached 417 million by the end of 2022. However, there is a serious mismatch between the number of existing parking facilities available and the number of cars in China, and Traffic congestion, parking difficulties and other traffic problems are increasingly serious in the context of urban land renewal. Most of the existing methods to alleviate this phenomenon are to increase urban parking lots, compared to simply increasing parking supply, implementing intelligent parking demand management can effectively alleviate the contradiction between urban parking supply and demand.

Initially, scholars worked on solving the parking problem from two perspectives: increasing the construction of parking resources and reducing parking demand. Lin[1] proposed the idea of building three-dimensional garages to increase parking spaces from the perspective of improving space utilization. With the increasing scarcity of land resources, scholars realized that the simple method of increasing parking spaces alone is never a long-term alternative and another way out needs to be found, so some scholars began to study the problem of dynamic parking pricing strategies. Espino[2] calibrated the parameters of a nested logit model constructed based on RP and SP data, and the model results showed that changes in parking costs had a more significant effect on travel mode choice than changes in transit service levels. Pierce[3]et al. adjusted parking prices based on parking occupancy rates obtained from a survey for each Seattle neighborhood and developed a method for charging for parking based on parking time differences and area differences. Ottosson[4]et al. investigated the price sensitivity of roadside parking demand by using the automatic parking transaction data obtained before and after the change of parking rate, and introduced parking occupancy rate by using the payment data to obtain the price sensitivity of parking demand. Das[5]et al. investigated the service level of on-street parking in urban streets, analyzed the parking occupancy rate by using SPSS statistical package regression analysis, and established two kinds of parking demand prediction models considering cost index (FI) and cost factor (CF), respectively, to predict

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the on-street parking demand in urban central business District (CBD). Lu[6] designed a differentiated parking scheme in Shenzhen in terms of zoning, time division and classification, and finally used a travel mode interchange scheme for fee pricing. He[7] et al. established a pricing model for on-street parking charges based on a combination of time series and regression models, which can improve the existing parking charge pricing model and predict future annual parking charge prices. Fabusuyi[8] changed the parking charge rate by calculating the price elasticity of parking demand, which affects the demand for parking spaces. Nowadays, scholars have begun to explore parking management methods under intelligent systems. DogarogluBora[9] et al. proposed that big data should be used to analyze parking information to find out the factors considered by users when choosing parking lots, including parking fee and walking distance. Kim[10] et al. proposed the establishment of a parking assistance system, which can park the vehicle in the parking space without the intervention of the driver, which is an innovative design of unmanned driving technology in the field of static traffic. Alinejad Mahyar[11] et al proposed that parking penalty fees and parking fees for all vehicles should be used to construct and maintain smart parking facilities.

In the process of smart city construction and block renewal, there are few studies exploring smart dynamic parking management, In this paper, based on RP pre-survey, SPSS was used to design a questionnaire, and the parameters of the MNL model were calibrated according to the collected multi-day parking survey data. Then, various factors in the model were analyzed, and the influence of different factors on parking choice behavior was quantified and visualized using Python. Through the collection of a large number of measured data and the simulation analysis of different parking scenarios, it provides theoretical support for solving the contradiction between parking supply and demand and traffic congestion in the process of urban renewal.

# 2. EXPERIMENTAL DESIGN AND DATA COLLECTION

## 2.1 Design of RP and SP survey

The data source was a survey of parking behaviour conducted between July and August 2022 at Xidigang parking lot. The data used for the empirical evaluation were obtained from the stated-preference(SP) and revealed-preference(RP) surveys completed by drivers at the Xidigang parking lot. The survey was conducted simultaneously through the volunteers' offline distribution of questionnaires and the drivers' online scanning and filling in questionnaires. In the survey, participants were first asked to do a RP survey, the contents of which are mentioned below. The purpose of this step is to provide reference for the follow-up questionnaire design. Participants were then asked to imagine whether they would park in the parking lot or not, given a variety of factors affecting parking. The specific contents of RP and SP survey are set as follows:

1) RP survey content setting

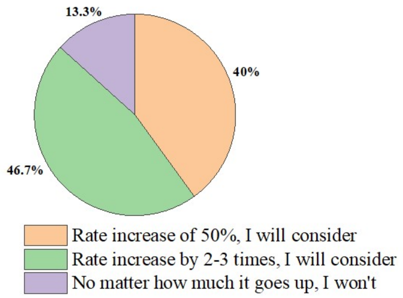
The personal attributes of travelers, actual travel behavior, and the investigation of actual parking decisions during parking incidents they experience are major components of the RP investigation. For personal attributes, mainly including gender, age, income and personality characteristics; For the actual travel behavior, the travel purpose, parking time, parking place, the frequency of taking private cars and other factors should be considered.

2) SP survey content setting

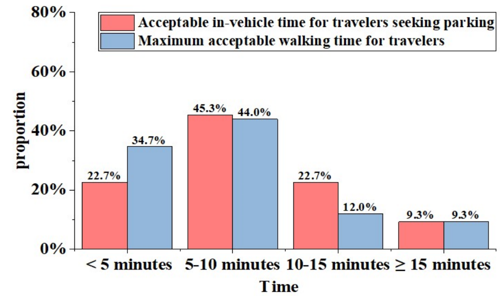
SP survey design includes three main aspects: attribute numbering determination, attribute level value design and context combination design. In order to ensure the rationality of the level value, the level value of SP questionnaire will be set according to the pre-survey results of RP.

After removing the abnormal data, the data is processed and visualized using Python and Origin. The survey results are shown in Figure 1.

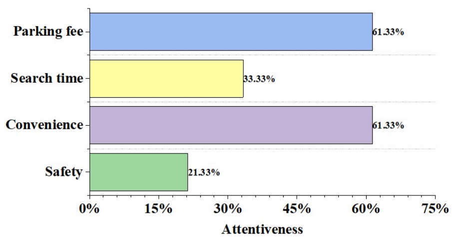
Figure 1(a) shows the responses to the question of whether travelers would consider reducing the use of private cars when faced with an increase in parking costs, and the results indicate that it is feasible to change the frequency of private car use or influence parking behavior through parking prices. Figure 1(b) shows the main concerns of parking travelers, with the most important factor of concern being the price factor of parking spaces. Figure 1(c) shows the traveler's time to find a parking space and the maximum acceptable walking time after completing parking, which provides some reference to the level of parking time and walking time attributes in the SP questionnaire. Figure 1(d) shows that with the implementation of tiered pricing (parking fees increase with parking time), the acceptable parking fees for passengers are positively correlated with their parking time, i.e., passengers generally cannot accept higher parking fees when the parking time is shorter. This provides some basis for setting the level of price attributes for dynamic parking charges in the SP questionnaire design.



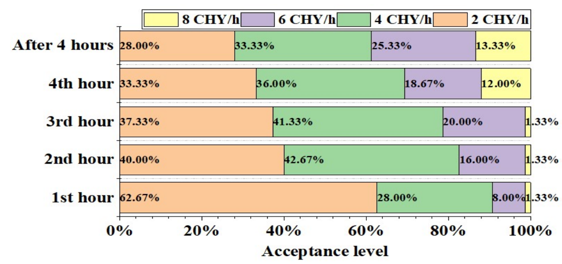

(a) Results to the question "Would you consider reducing the use of private cars if parking charges increase




(b) Travelers' main concerns when parking




(c) Acceptable in car time and maximum walking time for travelers seeking parking




(d) Maximum acceptable parking charge rates for travelers

Figure 1. RP Pre Investigation Results.

### 2.2 SP survey plan using orthogonal principle

The effectiveness of SP survey is closely related to the design of questionnaire, which needs to include the selection of limb attributes as well as attribute level values that influence the choice of respondents. In the questionnaire design of this paper, three attributes of "In-vehicle time", "Out-of-vehicle time" and "parking charge rate" are selected. Based on the distribution state of these three attributes obtained from the preliminary RP survey, certain values are added or subtracted as appropriate to form the selection of limb attribute level, as shown in Table 1. We use the orthogonal principle to complete the design of questionnaire combination. Under the condition of ensuring accuracy, the orthogonal design can effectively reduce the number of experimental combinations. After completing the orthogonal design and eliminating unreasonable combinations, we finally proposed 9 groups of orthogonal combinations, as shown in Table 2.

Table 1. Table for selecting limb attributes and attribute level definitions.

| Parking Alternatives | Properties | Level 1 | Level 2 | Level 3 |
|---|---|---|---|---|
| Alternative 1 | In-vehicle time (minutes) | 5 | 10 | 15 |
| | Out-vehicle time (minutes) | 5 | 10 | 15 |
| | parking charge rate (CHY/hour) | 2 | 4 | 7 |
| Alternative 2 | In-vehicle time (minutes) | 5 | 10 | 15 |
| | Out-vehicle time (minutes) | 5 | 10 | 15 |
| | parking charge rate (CHY/hour) | 2 | 4 | 7 |

Note: In-vehicle time in this paper is the time it takes for a traveler to enter a parking lot and find a parking space. The out-of-vehicle time in this paper is the time between the time the pedestrian parks the car in the parking space and the time he or she reaches the destination on foot.

Table 2. Orthogonal Design Table (Effective experimental combinations)

| Combination | Alternative 1 | | | Alternative 2 | | |
|---|---|---|---|---|---|---|
| | In-time | Out-time | Parking charge Rate | In-time | Out-time | Parking charge Rate |
| 1 | 5 | 15 | 4 | 15 | 10 | 2 |
| 2 | 5 | 15 | 7 | 10 | 5 | 4 |
| 3 | 10 | 5 | 7 | 5 | 15 | 4 |
| 4 | 10 | 10 | 7 | 15 | 5 | 2 |
| 5 | 10 | 15 | 4 | 5 | 5 | 7 |
| 6 | 15 | 5 | 7 | 10 | 10 | 2 |
| 7 | 15 | 10 | 2 | 10 | 5 | 7 |
| 8 | 15 | 10 | 4 | 5 | 15 | 2 |
| 9 | 15 | 15 | 2 | 5 | 10 | 4 |

Note: The unit of time in the table is minutes, and the unit of rate is yuan/h.

# 3. MODEL CONSTRUCTION AND CALIBRATION

## 3.1 Utility function of model

The choice limb utility function consists of a fixed term and a probability term. The fixed term consists of mathematical expressions for the personal characteristics of the traveler and the attributes of the choice limb, while the probability term is determined by the random factors that arise when a random event occurs. For some travelers, the choice limb attribute variables change with the parking alternative when the traveler chooses a different parking alternative.

The set of choice limbs in this paper is $A_n$ = (parking alternative 1, parking alternative 2), and the set of choice limbs is the same for each driver, Of the two options, option 1 means to choose parking, and the other means to give up parking at this point. The attribute variables of the choice limb include "parking search time", "out-vehicle time" and "parking charge rate", and the individual attribute variables include "gender ", "age", "income", "ownership of private car", "frequency of car use ". Based on the defined attribute variables, the definition table of utility variables shown in Table 3 was formed.

Table 3. The definitions of utility variables

| Select Limb | Constant term | Select limb property variables | | |
|---|---|---|---|---|
| | | out-vehicle time | in-vehicle time | parking charge rates |
| Alternative 1 | 1 | $X_{11}$ | $X_{12}$ | $X_{13}$ |
| Alternative 2 | 0 | $X_{21}$ | $X_{22}$ | $X_{23}$ |
| Unknown parameters | $ASC_1$ | $\beta_1$ | $\beta_2$ | $\beta_3$ |

| Select Limb | Traveler characteristic attribute variables | | | | |
|---|---|---|---|---|---|
| | Sex | Age | Income | Ownership | Frequency |
| Alternative 1 | $X_{14}$ | $X_{15}$ | $X_{16}$ | $X_{17}$ | $X_{18}$ |
| Alternative 2 | 0 | 0 | 0 | 0 | 0 |
| Unknown parameters | $\beta_4$ | $\beta_5$ | $\beta_6$ | $\beta_7$ | $\beta_8$ |

Note: The unit of time in the table is minutes, and the unit of parking charge rate is CHY/hour.

According to Table 3, the utility function formula for the 2 selection limbs of the traveler in making the parking choice can be derived as follows.

$$\begin{cases} U_1 = ASC_1 + \beta_1 X_{11} + \beta_2 X_{12} + \beta_3 X_{13} + \beta_4 X_{14} + \beta_5 X_{15} + \beta_6 X_{16} + \beta_7 X_{17} + \beta_8 X_{18} \\ U_2 = \beta_1 X_{21} + \beta_2 X_{22} + \beta_3 X_{23} \end{cases} \tag{1}$$

Where:

$U_1$-The utility function of Alternative 1;

$U_2$-The utility function of Alternative 2;

$ASC_1$-The constant term of Alternative 1;

$X_{ni}$-The utility variable (i = (1, 8), n = (1, 2));

$\beta_i$- The coefficient of each variable (i = (1, 8)).

### 3.2 Model fitting results

In this paper, the SP questionnaire based on the orthogonal design approach collects data on the parking preferences of travelers under different scenarios of in-vehicle time, out-of-vehicle time, and parking charge rates, which is used to build the MNL model. The value of maximum likelihood function of MNL model is - 291.24685. One of the most important information in the model conclusion is the Goodness of fit of the model. According to Mc Fadden $R^2$ formula, when only the intrinsic constant term in the selected limb is available, the value of the maximum likelihood function is estimated, and the estimated value is - 352.416.

$$\text{Mc Fadden } R^2 = 1 - \frac{LL_k}{LL_0} = 1 - \frac{-291.247}{-352.416} = 0.174 \tag{2}$$

The goodness-of-fit value of the MNL model in this study reaches 0.174 according to the above formula, which indicates the MNL model fits well. On the basis of processing the multi-day survey data, the MNL model is constructed using python and the coefficients of each attribute variable are fitted. Due to the large sample size of the data, the data were divided into ten subsamples during the significance test of the model. We identified the factors with a significance level over 5% in at least seven samples as significant factors. Therefore, the T-test results show that the significant influencing variables of parking choice behavior in Xidigang parking lot include: in-vehicle time, parking rate (the choice of limb attribute variable) and ownership (the personal attribute variable of travelers).The fitting results of a typical data sample are shown in Table 4.

Table 4. Parameter calibration results for the MNL model

| **Variable** | **Coefficient** | **Standard Error** | **z** | **Prob. z>\|Z\|** |
|---|---|---|---|---|
| X | -1.11732 | 0.79561 | -1.33 | 0.1713 |
| A | -0.01289 | 0.02289 | -0.61 | 0.5844 |
| B | -0.04817** | 0.02261 | -2.01 | 0.0421 |
| C | -0.27833*** | 0.04412 | -5.51 | 0.0000 |
| K1 | -0.39723* | 0.24135 | -1.87 | 0.0612 |
| M1 | -0.11209 | 0.14238 | -0.75 | 0.4054 |
| N1 | 0.13967 | 0.11230 | 1.31 | 0.1954 |
| P1 | 0.79631** | 0.33168 | 2.23 | 0.0287 |
| Q1 | 0.24645* | 0.12674 | 1.82 | 0.0643 |

Note: ***, **, * ⇒ Significance at 1%, 5%, 10% level.

Based on the calibration results of the parameters of the above MNL model, the specific expression of the utility function of the parking choice behavior of the passengers in the parking lot of the Xidigang can be obtained as follows.

$$\begin{cases} U_1 = -1.1173 - 0.0129X_{11} - 0.0482X_{12} - 0.2783X_{13} - 0.3972X_{14} \\ \qquad -0.112X_{15} + 0.1397X_{16} + 0.7963X_{17} + 0.2465X_{18} \\ U_2 = -0.0129X_{21} - 0.0482X_{22} - 0.2783X_{23} \end{cases} \tag{3}$$

# 4. PARKING BEHAVIOR ANALYSIS

## 4.1 Significant factor analysis

1) The Effect of Price Changes on Parking Behavior

As shown in the Figure 2, the probability of choosing a parking alternative at different parking charge rate levels can be calculated, with other conditions remaining unchanged. As the parking charge rate increases, the probability of choosing the parking alternative decreases, and the parking charge rate and the choice probability show a strong negative correlation. When the parking charge rate decreases to 1 CHY/h, the probability of choosing the parking alternative is 87%; when the parking charge rate increases to 8 CHY/h, the probability of choosing the parking alternative is 18%. Based on the above results, we can conclude that for a certain parking lot, a lower parking charge rate can attract travelers to choose to park in that parking lot, while a higher parking charge rate will lead travelers to choose other parking lots.

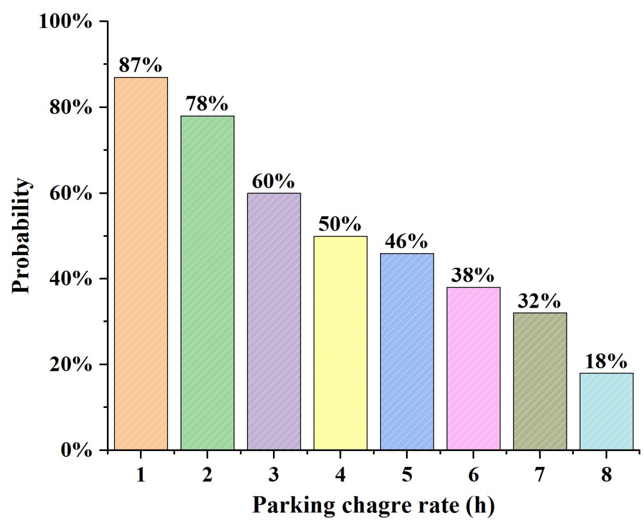



Figure 2. Choosing probability with different parking charge rates.

Note: The selection probabilities in the figure are calculated based on a scenario where the time inside the vehicle is 5 min and the time outside the vehicle is 5 min.

2) The Effect of In-vehicle/Out-vehicle Time on Parking Behavior

Under other conditions unchanged, the probability of choosing a parking alternative at different in-vehicle times are shown in the Figure 3. We can see that the in-vehicle time and selection probability show a certain negative correlation . When the change of the time in the car is small, the probability of parking selection does not change significantly. For example, when the time in the car increases from five minutes to ten minutes, the probability of parking selection only decreases by 3%. When the time in the car varies greatly, the probability of parking selection will change significantly. For example, if the time in the car increases from 5 minutes to 30 minutes, the probability of parking selection will decrease by 20%. Therefore, if we can shorten the time in the car by 10-20 minutes through certain measures, we can effectively guide the parking behavior of travelers. On the other hand, as for the probability of choosing a parking alternative at different out-vehicle time, from the figure, we can see that the out-vehicle time and the selection probability generally show a very weak negative correlation which is inconsistent with the actual logic. This abnormal result shows that our model fitting results have a certain deviation from the actual results. Although the model shows that there are outliers, after excluding outliers, the out-vehicle time and the probability of parking selection generally show a weak negative correlation which indicates that the effect of out-vehicle time on the parking behavior of traveler is not obvious.

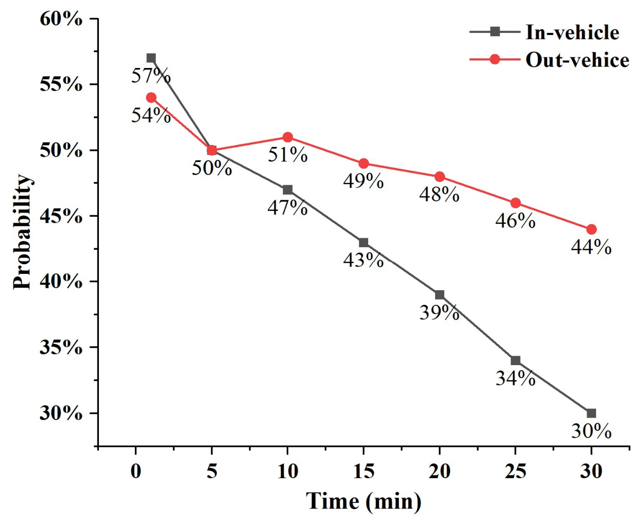



Figure 3. Choosing probability with different in-vehicle/out-vehicle time.

Note: The selection probabilities in the figure 3 are calculated based on a scenario with a parking charge rate of 4 CHY/h and an out-of-vehicle or in-vehicle time of 5 min.

### 4.2 Analysis of parking behavior selection in simulation scenarios

In summary, considering the effects of parking charge rate, in-vehicle time, and out-vehicle time on the parking selection probability, this paper simulates the selection probability of the improved parking lot compared to the original parking lot after the improvement of the current situation of the parking lot in the Xidigang Mall, and the results are shown in Table 5. The current parking situation in the parking lot of Xidigang is close to the "Parking Status" in the following table, and the choice probability of alternative 1 is 65% after reducing the time and parking charge rate at the same time; the choice probability of alternative 2 is 38% after increasing the time and parking charge rate at the same time. This shows that changing the in-vehicle time and parking charge rate at the same time will have a greater impact on the travelers' parking choice behavior. Changes in in-vehicle time and out-vehicle time are also negatively correlated with parking probability, but their strength is weaker than that of combinations including parking charge rates.

Table 5. Choosing probability of different given scenario

| | **Out-vehicle time (minute)** | **In-vehicle time (minute)** | **Parking charge rate (CHY/h)** | **Choosing probability** |
|---|---|---|---|---|
| Parking Status | 5 | 5 | 4 | — |
| Alternative 1 | 5 | 2 (-3) | 2 (-2) | 65% |
| Alternative 2 | 5 | 10 (+5) | 6 (+2) | 38% |
| Alternative 3 | 2 (-3) | 2 (-3) | 4 | 56% |
| Alternative 4 | 10 (+5) | 10 (+5) | 4 | 46% |
| Alternative 5 | 2 (-3) | 2 (-3) | 2 (-2) | 68% |

Note: The values in parentheses indicate the change comparing to parking status.

## 5. CONCLUSIONS

Based on the multi-day parking survey data collected by large parking places located in urban renewal areas, this paper uses python to build the MNL model, studies the influence of different factors on travelers' parking behaviors, and simulates travelers' parking choice behaviors under characteristic scenarios. The following conclusions are reached:

1) The multi-day RP pre-survey found that the main factors considered by travelers in the parking process included parking search time, price charged, space usage and security; 87% of travelers were found to consider reducing private car trips after the parking rate was increased.

2) Based on multi-day SP questionnaire data, the parameters of MNL model were fitted and corrected by Python, it was found that time in the car and parking rates were the most important factors influencing travelers' parking behavior in addition to personal characteristics.

3) The influence of parking price change on travelers' alternative parking choice is quantitatively analyzed, and the results showed that parking rates had an almost linear negative relationship with the probability of alternative choices, holding other external factors constant. This suggests that it is feasible to guide travelers' parking behavior and alleviate parking difficulties by varying parking rates.

Future research will further explore how to dynamically analyze the influence of various factors on travelers' parking choices in the context of smart cities; In terms of modeling methods, an optimized model considering individual heterogeneity is proposed to study parking choice behavior.

## ACKNOWLEDGEMENT

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