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Modeling Parking Choice Behavior Using Cumulative Prospect Theory

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Abstract: In order to capture the driver's attitude and preference towards risk during the decision-making process, this paper establishes a parking choice model considering driver heterogeneity based on the cumulative prospect theory. This research innovatively considers the influence of the unreliability of cruise time on drivers' parking choice behavior and adds the psychological cost of drivers' anxiety caused by lateness into the model. At the same time, according to the driver's parking preference for parking, the latent category model is used to divide the driver into time-sensitive and money-sensitive categories. This paper analyzes the influence of unreliable cruising time on drivers' parking choice behavior and finds that drivers have the characteristics of overestimating high-probability events and underestimating low-probability events in the decision-making process. By comparing the parking choice results of rational and irrational drivers, it is found that the model considering the risk attitude of drivers in the decision-making process is more in line with reality.

Keywords: parking choice behavior; cruising time; cumulative prospect theory

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1. Introduction

The rapid increase in motor vehicles has led to a severe shortage of parking facilities in the city center, resulting in "parking difficulty" being a major issue for urban residents. During periods of high parking demand, drivers have to drive slowly on the road to look for vacant parking spaces, which causes not only environmental pollution but also road congestion. According to IBM's global parking survey, drivers spend an average of 20 min looking for a parking space [1], and 30% of traffic on the road comes from parked cruising vehicles [2]. The contradiction between the growing demand for parking and the limited increase in parking facilities in the city center is becoming more and more prominent, which affects the daily travel of residents, and the driver's cruising behavior can also create problems such as additional noise pollution and excessive carbon emissions [3].

The continuous growth of the number of motor vehicles poses a great challenge to the service capacity of transportation infrastructure [4], especially the shortage of parking facilities in the central business district of the city. The setting of on-street parking spaces increases the parking supply at a minimal cost, but it also brings many disadvantages. For example, the on-street parking spaces take up part of the road resources and can easily cause road congestion during peak travel periods. Therefore, how to improve the utilization rate of existing parking facilities is regarded as an effective way to solve the problem of parking difficulties. It is necessary to study the driver's parking choice behavior and conduct an in-depth analysis of the factors that affect the driver's parking choice behavior. Only in this way can we better formulate relevant policies to solve the problem of "parking difficulty".

2. Related Work

The study of parking choice behavior begins when the driver arrives at his destination and looks for an available parking space and ends with the driver selecting a parking space.

The early study of parking choice behavior used the questionnaire method to statistically analyze the factors affecting the driver's parking choice [5]. Subsequently, in view of these influencing factors, some scholars used the multi-objective decision-making method to recommend parking guidance and optimal parking space to drivers. For example, Leephakpreeda [6] used fuzzy knowledge-based decision-making to comprehensively consider parking costs, parking space utilization and other related factors to rank the advantages and disadvantages of parking lots. Chaniotakis et al. [7] used questionnaire surveys to obtain relevant data and adopted related models such as polynomial logit, nested logit and hybrid logit to focus on the preference of drivers to choose a behavior under the uncertainty of cruising time. Van der Waerden et al. [8] showed through multiple regression analyses that there is a significant relationship between an individual's characteristics and parking choice behavior. Caicedo [9] used constrained logit models to analyze drivers' parking choice behavior, and found that drivers generally tend to avoid higher parking costs by increasing the cruising time, and the study also considered the environmental impact of reduced stop-cruise behavior. Antolín [10] used a number of logit models to simulate the driver's choice of parking options, such as free on-street parking, paid on-street parking, and paid underground parking. With the concept of shared parking space, Ye et al. [11] incorporated the shared parking mode into the study of parking behavior. At the same time, some scholars have applied Internet of Things technology to the field of parking management to develop an intelligent parking system to help drivers better find parking spaces [12].

However, the studies based on expected utility theory treat decision-makers as "perfectly rational people", assuming that all drivers have access to objective information about any parking lot. At the same time, the expected utility theory also argues that all drivers have the same parking preference and make parking choices based on maximum utility. Obviously, this assumption is quite different from real life. In real life, people are often faced with situations where either they do not have enough time or relevant channels to collect all the information to make decisions, or they waste a lot of time and energy collecting information, and sometimes they may not be able to make optimal decisions due to time and cognitive limitations. The French economist Allais experimentally found that people's choice results do not always follow utility maximization and proposed the Allais paradox to question the rationality of the expected utility theory [13]. When the driver arrives at the destination to choose a parking location, the information obtained is dynamic, it is difficult to obtain [14], and the driver cannot process the information in the decision-making process to make a choice. Therefore, the driver's parking choice behavior should be regarded as a decision-making behavior under uncertain conditions. Kahneman and Tversky [15] proposed prospect theory, which combines the uncertainty of the decision-making environment with the bounded rationality of decision-makers and describes the process of decision-making behavior more realistically. Prospect theory proposes a nonlinear weight function and uses "sub-certainty" to resolve the Allais paradox. After the prospect theory was proposed, it was not only used in the economic field to describe the decision-making behavior of investors but also in other fields such as construction, agriculture and transportation. Luo et al. [16] set up a new travel mode choice model based on prospect function and proved the validity with an example. Wang et al. [17] and other scholars established a parking selection model based on prospect theory and analyzed the impact of parking price changes on drivers' on-street parking behavior. Ji et al. [18] studied the limited rationality of drivers and applied cumulative prospect theory to optimize the allocation of shared parking spaces in hospitals. Xue et al. [19] used prospect theory to analyze the decision-making factors that influence the owners of shared parking spaces and drivers. Most of the applications of prospect theory in the field of transportation are aimed at the choice of travelers' travel modes [20–22]. Some scholars [23] have established a model of battery electric vehicle drivers' charging behavior based on the cumulative prospect theory. In the pieces of literature on the use of prospect theory for the study of the driver's parking choice behavior, scholars paid more attention to the impact of parking fees on drivers' choice behavior [17,24].

In summary, the current research ignores the irrational state of the driver's parking choice behavior in uncertain traffic environments. At the same time, these studies only discussed the impact of the cruising time length on the driver's parking choice behavior, ignoring the impact of cruising time uncertainty on drivers. This paper considers the driver's decision-making behavior in an unreliable traffic environment and establishes a parking choice behavior model based on cumulative prospect theory. The research focus of this paper is on the impact of unreliable cruising time on the driver's parking choice behavior and the difference in parking choice behavior of drivers in rational and irrational states.

3. Methodology

3.1. Cumulative Prospect Theory

In 1979, Tversky and Kahneman proposed prospect theory to describe decision-making behavior in a risk environment. The expected utility theory believes that the decision-maker will evaluate alternatives by their utility (the sum of the product of probabilities and outcome values), and the prospect theory keenly discovers the subjective tendency of the decision-maker when making the choice behavior.

Prospect theory proposes the "reference point" and defines the gain or loss of the value relative to the reference point as the prospect value. During the experiment, the researchers found that decision-makers differed in their sensitivity to gains and losses. In view of this characteristic, prospect theory establishes different value functions for gains and losses.

Equation (1) converts the utility value x_i into a gain or loss compared to the reference point x_0. The value function, Equation (2), exhibits risk aversion to gains and risk seeking to losses. α, β are the risk preference parameters, and the value range is as follows: $0 < \alpha, \beta < 1$. Larger values of α and β indicate that people are more sensitive to risk. λ is larger than 1, which suggests that people are more sensitive to losses than gains. Larger values of λ represent the increasing degree of sensitivity. Figure 1a presents the value function.

$$\Delta x = x_i - x_0 \tag{1}$$

$$\varphi(\Delta x) = \begin{cases} \Delta x^{\alpha} & \Delta x \geq 0 \\ -\lambda(-\Delta x)^{\beta} & \Delta x < 0 \end{cases} \tag{2}$$

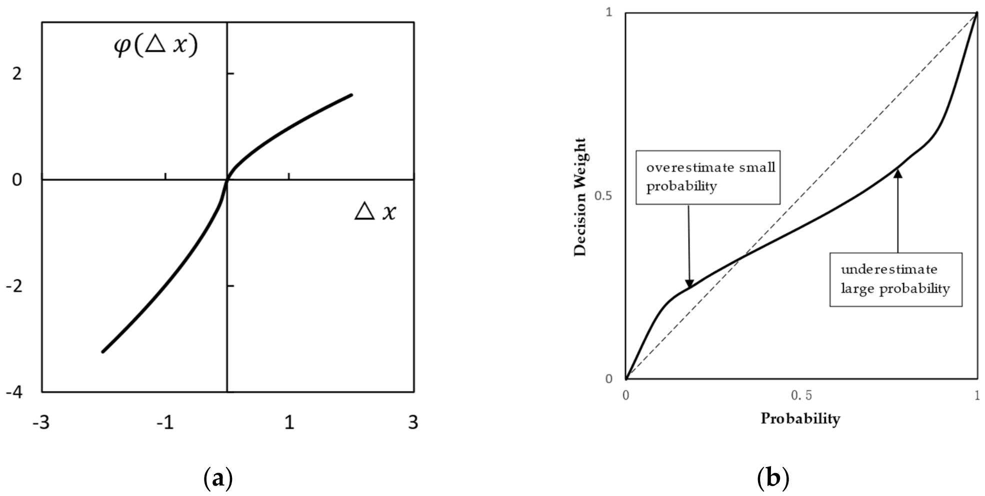


Figure 1. (**a**) Value function ($\alpha = \beta = 0.88, \lambda = 2$); (**b**) weighting function ($\gamma = \delta = 0.61$).

At the same time, the researchers also found that decision-makers overestimate small-probability events and underestimate large-probability events. That is, the decision behavior is influenced by the decision weights, not the actual probabilities. Prospect theory establishes a probability weighting function to achieve the transition between actual probabilities and decision weights.

The probability weighting function $w(p)$ is defined in Equations (3) and (4). γ and δ are the probability weighting parameters, and $0 < \gamma, \delta < 1$. The smaller γ and δ result in a more curved weighting function. The weighting function is shown in Figure 1b.

$$w^{+}(p_i) = \frac{{p_i}^{\gamma}}{\left[{p_i}^{\gamma} + (1 - p_i)^{\gamma}\right]^{1/\gamma}} \tag{3}$$

$$w^{-}(p_i) = \frac{{p_i}^{\delta}}{\left[{p_i}^{\delta} + (1 - p_i)^{\delta}\right]^{1/\delta}} \tag{4}$$

In the process of modeling travel behavior, Gao [25] found that the sensitivity of travel time gains and losses is much greater than that of travel cost gains and losses. The travelers underestimate the low-probability travel time and overestimate the high-probability travel time in the commuting mode shift behavior, and the probability weighting function presents an S-shape shown in Figure 2.

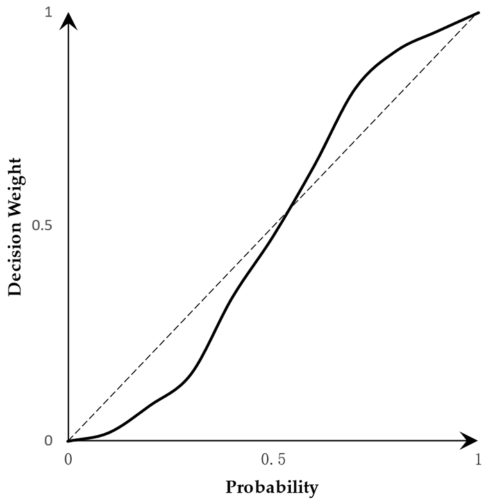


Figure 2. Improved time-weighting function ($\eta = 0.8, \gamma_t = \delta_t = 1.5$).

Gao found that the weighting functions of time and cost were distorted to different degrees, but he did not establish a modified weighting function. On this basis, Huang [26] modified the value range of the probability weighting parameters γ_t and δ_t and introduced the discrimination parameter η to obtain the optimized time probability weight-function Equations (5) and (6).

$$w_t^{+}(p_i) = \frac{\eta {p_i}^{\gamma_t}}{\left[{p_i}^{\gamma_t} + (1 - p_i)^{\gamma_t}\right]^{1/\gamma_t}} \quad \gamma_t > 1 \tag{5}$$

$$w_t^{-}(p_i) = \frac{\eta {p_i}^{\delta_t}}{\left[{p_i}^{\delta_t} + (1 - p_i)^{\delta_t}\right]^{1/\delta_t}} \quad \delta_t > 1 \tag{6}$$

Cumulative prospect theory, which is an extension of prospect theory, employs cumulative rather than single decision weights [27]. The main difference between prospect theory and cumulative prospect theory is in the weighting function, where the former works with marginal probabilities while the latter uses cumulative probabilities. In the theory of cumulative prospects, the $n_1 + n_2 + 1$ possible outcomes of the alternatives are arranged in order from smallest to largest, $x_{-n_1} < \cdots < x_0 < \cdots < x_{n_2}$, which occur with probabilities $p_{-n_1}, \cdots, p_{n_2}$. The cumulative decision weights are defined as follows:

$$\pi_i^+ = w^+(p_i + \cdots + p_{n_2}) - w^+(p_{i+1} + \cdots + p_{n_2}) \quad 0 \le i \le n_2 \tag{7}$$

$$\pi_i^- = w^-(p_{-n_1} + \cdots + p_{-j}) - w^-(p_{-n_1} + \cdots + p_{-j-1}) \quad n_1 \le -j \le 0 \tag{8}$$

Therefore, prospect theory divides people's decision-making process into two stages: the editing stage and the evaluation stage. In the editing phase, people rely on reference points to judge the likely outcomes of various decisions and to determine whether the resulting outcome is a gain or a loss. In the evaluation stage, various decision-making options are evaluated based on the results of the editing stage, and the decision with the highest prospect value is selected. The prospect value is calculated as follows:

$$U(x,p) = \sum_{i=o}^{n_2} \pi_i^+(p_i)\varphi(\triangle x_i) + \sum_{j=-n_1}^{-1} \pi_j^-(p_j)\varphi\left(\triangle x_j\right) \tag{9}$$

3.2. Latent Class Model

Even if different drivers make the same choice in the same scenario, the reasons for their decision are different. It may be affected by parking fees, walking distance, personality or habits. The factors influencing the drivers' choices of parking are very complex, and a general generalization of the characteristics of these factors can lead to ignoring the internal correlation between the various influencing factors. The latent class model was first proposed by Lazaesfeld and Henry, which can be used to explain the intrinsic correlation between variables [28]. This model makes up for the shortcomings of the structural equation model in dealing with continuous latent variables and is suitable for data with mostly categorical variables.

Latent class models use intrinsic latent categorical variables to explain the relationship between explicit categorical variables. The basic assumption of the model is that the probability distribution of explicit variables can be explained by a small number of mutually exclusive latent category variables, and each category has a relative tendency to choose explicit variables.

In Figure 3, the observable variable V_n can be directly observed, and the latent variable V_L cannot be directly observed or can be observed but needs to be synthesized by other methods. Typically, one latent variable corresponds to multiple observable variables. Latent variables can be seen as abstractions and overviews of observable variables, which, in turn, are regarded as external reflection indicators of the latent variable. The latent variable is the basis for class membership in one of several latent classes. The latent class model uses latent variables to explain the relationship between observable variables, and its basic assumption is that the probability distribution of observable variables can be explained by a small number of mutually exclusive latent variables, and each class has a specific tendency to the choice of each observable variable.

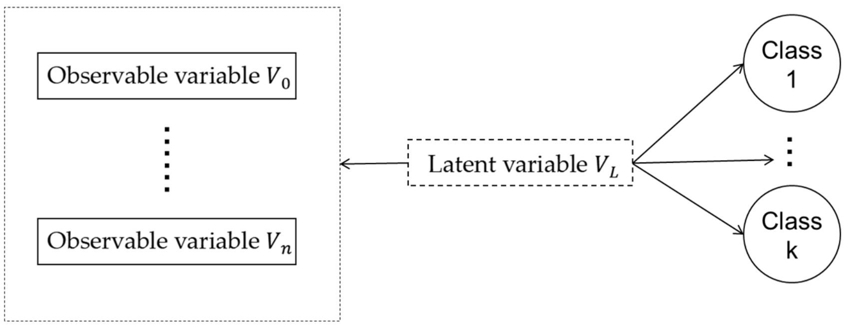


Figure 3. Concept latent class model.

The analysis process of the latent class model includes probabilistic parameterization, estimate models, determining fit and the result interpretation.

1. Probabilistic parameterization

Probability parameterization is the conversion of the probability of categorical variables into parameters, which is the first step in establishing a latent category model.

Assuming that there are three explicit variables A, B and C, and each variable has I, J and K levels, the latent variable X is with T latent categories. The choice behavior of each decision-maker can be represented by different combinations of levels of explicit variables. The latent class model assumes that latent variables (X) can explain the relationship of explicit variables (A, B and C) and maintain the local independence of explicit variables in each class. After probability parameterization, the latent class model is expressed as follows:

$$\pi_{ijk}^{ABC} = \sum_{t=1}^{T} \pi_t^X \pi_{it}^{\overline{A}X} \pi_{jt}^{\overline{B}X} \pi_{kt}^{\overline{C}X} \tag{10}$$

Constraints:

$$\sum_t \pi_t^X = 1 \tag{11}$$

$$\sum_i \pi_{it}^{\overline{A}X} = \sum_j \pi_{jt}^{\overline{B}X} = \sum_k \pi_{kt}^{\overline{C}X} = 1 \tag{12}$$

π_{ijk}^{ABC} is the joint probability of the latent class model; π_t^X is the probability of the latent variable X at the t level. Equation (11) means that the probabilities of each potential category add up to 1. $\pi_{it}^{\overline{A}X}$ is the conditional probability, which represents the probability that an individual belonging to the t potential category will respond to the i level of the observed variable A. Equation (12) shows that the sum of the conditional probabilities of each explicit variable is 1.

2. Estimate models and determine the fit

The latent class model is mainly estimated by the maximum likelihood method. In the iterative process, the EM (-expectation-maximization) and NR (Newton Rapson) algorithms are generally used, among which the EM algorithm is the most commonly used.

In the iterative process, it is necessary to find the model with the least parameters and the best goodness-of-fit. The main methods for the goodness-of-fit test are the chi-squared statistic test of likelihood ratio, Pearson test and signal evaluation index, among which the *AIC* criterion and *BIC* criterion are the most commonly used signal evaluation indexes. *BIC* is more reliable when the number of samples is thousands, and *AIC* is used when the number of samples is small. The signal evaluation index is based on the likelihood ratio chi-square test to compare different models with different parameter restrictions. The smaller the index value is, the better the parameter fit is. In order to evaluate the goodness-of-fit of the model more comprehensively, the four indexes are usually combined.

$$AIC = -2LL + CK_\beta + (C-1)K \tag{13}$$

$$BIC = -2LL + CK_\beta + (C-1)K \times \ln N \tag{14}$$

where LL is the log-likelihood value function calculated at the convergence for the parameter estimates; C is the number of latent classes; K_β is the number of elements in the utility function of the class-specified models; and K is the number of estimated [29]. The values of AIC and BIC closer to 0 indicate a better fit.

3. Result interpretation

After determining the optimal model through a goodness-of-fit evaluation, the observed data were matched to each latent class by probability estimation and comparison according to Bayesian theory. The posterior probability of the observed data being classified into each latent class is calculated by the formula. The maximum posterior probability of a latent class is used to classify the observed data into that class.

$$\hat{\pi}_{tijk}^{\overline{X}ABC} = \frac{\hat{\pi}_{ijkt}^{ABCX}}{\sum_{t=1}^{T} \hat{\pi}_{ijkt}^{ABCX}} \tag{15}$$

where, $\hat{\pi}_{tijk}^{\overline{X}ABC}$ represents the posterior probability that the observed data are classified into a latent class t. $\hat{\pi}_{ijkt}^{ABCX}$ represents the probability that the observed data are classified into a latent class t.

4. Modeling Drivers' Parking Behavior

This paper uses the cumulative prospect theory to divide the driver's parking selection process into the editing stage and evaluation stage. The editing stage determines the utility value of different parking facilities through the cost function and converts it into the loss or benefit value relative to the reference point, determines the corresponding probability of different utility values and converts the weighting function into the decision weight value. The evaluation phase calculates the foreground values for the different parking facilities, and the driver makes parking decisions based on these foreground values. The specific flow of the driver's parking selection behavior after arriving near the destination is shown in Figure 4. The relevant parameters are shown in Table 1.

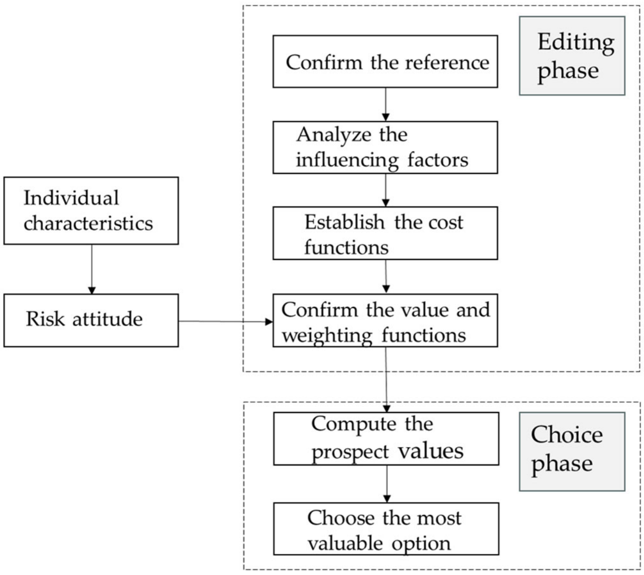


Figure 4. Choice behavior based on cumulative prospect theory.

Table 1. List of symbols used in the manuscript.

Symbol	Parameter
ε	Scale factor
μ	Travel time value
k	Parking fee
c_a	Anxiety costs
c_f	Appointment service fee
t_n	Cruise time
t_o	The point at which the driver becomes anxious
t_e	The maximum cruising time
t_f	Walking time
t_s	Detour time

Considering that shared parking spaces are not widely implemented in real life, the parking facilities in the central business district are mainly on-street parking spaces and commercial parking lots. Therefore, this paper will be based on the following assumptions when establishing the driver's parking choice behavior model.

- There are only paid on-street and off-street parking spaces around the destination;
- Off-street parking spaces can be reserved in advance, and a certain reservation service fee will be charged;
- After booking the parking space, the driver maintains the original driving speed to reach the parking space.

4.1. Edit Phase

When the driver arrives near his destination and starts looking for a vacant space, he will be faced with two options:

- Finding available on-street parking while cruising at low speeds near the destination;
- Choosing to reserve an off-street parking space and go directly to the reserved car park.

Based on the above two options, we will establish the cost function of different parking facilities and analyze the parking choice behavior of drivers through further calculations.

1. The driver chooses an on-street parking space

If the driver is lucky enough to find an available parking space within t_o, the time cost includes the cruising time t_n and the walking time t_{f1}. When the driver's cruising time is exceeded t_0, the driver gradually moves away from the destination, and the walking time t_{f2} increases. At the same time, the driver will also feel anxious during the cruise. When the driver's cruising time exceeds t_e, the on-street parking space is basically occupied, and it is difficult for the driver to find an available parking space. At this point, he has to give up looking for on-street parking and change the target to off-street parking. In this case, the time cost should be added not only to the cruising time t_n and walking time t_{f3} but also to the detour time t_s incurred by driving to an off-street parking. Therefore, the time cost function for the driver to choose an on-street parking space in different cases is represented by Equation (16).

$$c_1^t(t_n) = \begin{cases} -\left(t_n + t_{f1}\right) & 0 < t_n \le t_o \\ -\left(t_n + t_{f2}\right) & t_o < t_n \le t_e \\ -\left(t_n + t_{f3} + t_s\right) & t_e < t_n \end{cases} \tag{16}$$

The monetary cost of the driver's choice of on-street parking includes the parking fee and the psychological cost of the driver's anxiety when the cruise time exceeds t_o. Therefore, the monetary cost of on-street parking is as follows:

$$c_1^m(t_n) = \begin{cases} -k_1 & 0 < t_n \le t_o \\ -[c_a(t_n - t_o) + k_1] & t_o < t_n \le t_e \\ -[c_a(t_n - t_o) + k_2] & t_e < t_n \end{cases} \tag{17}$$

2. The driver chooses an off-street parking space

When the driver has reserved an off-street parking space, he will keep driving at a constant speed to reach the reserved parking space. To make the model even easier, we expressed the time it takes for a driver to reach a predetermined parking space at a constant speed by multiplying the cruising time t_n by a factor ε. The time cost includes driving time εt_n and walking time t_{f4}.The time cost of off-street parking is as follows:

$$c_2^t(t_n) = \begin{cases} -\left(\varepsilon t_n + t_{f4}\right) & 0 < t_n \le t_o \\ -\left(\varepsilon t_n + t_{f4}\right) & t_0 < t_n \end{cases} \tag{18}$$

If the driver arrives at the reserved parking within the designated time t_o, the monetary cost only includes the service fee for the reservation c_{f1} and parking fee k_2. When the driver fails to arrive at the reserved parking space within the specified time due to traffic congestion or other reasons, the driver needs to pay a certain penalty cost for breach of contract c_{f2}. The monetary cost of off-street parking is represented by Equation (19).

$$c_2^m(t_n) = \begin{cases} -\left(c_{f1} + k_2\right) & 0 < t_n \leq t_o \\ -\left(c_{f1} + c_{f2}\varepsilon(t_n - t_0) + k_2\right) & t_0 < t_n \end{cases} \tag{19}$$

Finally, according to the value function Equation (2), the gain or loss of time and cost of the two parking facilities relative to the reference point is calculated.

$$\varphi^t\left(c_r^t\right) = \begin{cases} \left(c_r^t - c_0^t\right)^\alpha & c_r^t \geq c_0^t \\ -\lambda\left(c_0^t - c_r^t\right)^\beta & c_r^t < c_0^t \end{cases} \tag{20}$$

$$\varphi^m\left(c_r^m\right) = \begin{cases} \left(c_r^m - c_0^m\right)^\alpha & c_r^m \geq c_0^m \\ -\lambda\left(c_0^m - c_r^m\right)^\beta & c_r^m < c_0^m \end{cases} \tag{21}$$

where, r = 1,2; c_0^t, c_0^m are the reference points for time and cost, respectively.

4.2. Assessment Phase

In the process of studying the travel mode choice of travelers, scholars find that the weight functions of time and cost are distorted in different ways [25], and this phenomenon is also reflected in the driver's parking choice behavior. Drivers are averse to uncertain cruising times when looking for parking spaces, so they tend to place higher subjective expectations on definite cruising times when making parking choice decisions.

Therefore, the prospect values of the driver's time and cost are calculated separately. Equations (5) and (6) are used to calculate the time probability weight value; Equations (3) and (4) calculate the cost probability weight value.

$$U_r^t(x,p) = \sum_{i=o}^{n_2} \pi_i^+(p_i)\varphi(\triangle x_i) + \sum_{j=-n_1}^{-1} \pi_j^-(p_j)\varphi\left(\triangle x_j\right) \tag{22}$$

$$U_r^m(x,p) = \sum_{i=o}^{n_2} \pi_i^+(p_i)\varphi(\triangle x_i) + \sum_{j=-n_1}^{-1} \pi_j^-(p_j)\varphi\left(\triangle x_j\right) \tag{23}$$

The driver's parking choice behavior model established in this paper will comprehensively consider the influence of time and money on the driver's decision-making. Therefore, the conversion factor μ is introduced to convert the time prospect value into a unit of cost. At the same time, the model also introduces the coefficient α_t, α_m to represent the driver's different preferences for time and money. Finally, we use Equation (24) to calculate the total prospect value for the different parking choices, which is U_r.

$$U_r = \mu U_r^t + U_r^m \tag{24}$$

After calculating the prospect values of all parking facilities, the probability of choosing parking facility r is calculated as follows:

$$P_r = \frac{\exp(U_r)}{\sum_{i=1}^2 \exp(U_r)} \tag{25}$$

5. Empirical Application

In this section, we will present the empirical application example to illustrate how the modeling -framework can be applied to real-world observational data. We will study the application of the parking choice model based on cumulative prospect theory in real life, analyze the parking choice preferences of different types of drivers, and discuss the influence of unreliability cruising time and irrational decision-making psychology on drivers' parking choices.

5.1. Study Area Introduction

This article selects the Guilin Road business district in Changchun as the survey area, which not only contains leisure and entertainment facilities such as shopping malls and cinemas but also contains a number of primary and secondary schools and administrative institutions. In the process of field investigation, we found that the traffic environment in the area is relatively complex, and there is an imbalance in the occupancy rate of on-street parking facilities and off-street parking facilities. The basic information on parking facilities in the Guilin Road business district is shown in Table 2. The layout of the parking facilities is shown in Figure 5.

Table 2. Information about parking facilities around Guilin Road.

Parking Location	Parking Lot Name	Number of Parking Spaces	Fees
On-street parking facilities	Xikang Road	72	¥6/h (8:00–18:00) [1]
	Tongguang Road	40	
	Longli Road	56	
	Mudan Street	19	
	Guilin Road	129	
	Xinjiang Street	12	
Off-street parking facilities	Huacaojian Building parking lot	22	¥5/h [2]
	Huoju Building parking lot	28	¥6/h
	Baihui Street 24-h parking lot	50	
	7.8 Shopping mall parking lot	70	

[1] Parking is free from 18:00 to 8:00 (+1); no charge for parking for less than 30 min; maximum daily charge is ¥40.
[2] no charge for parking for less than 10 min.

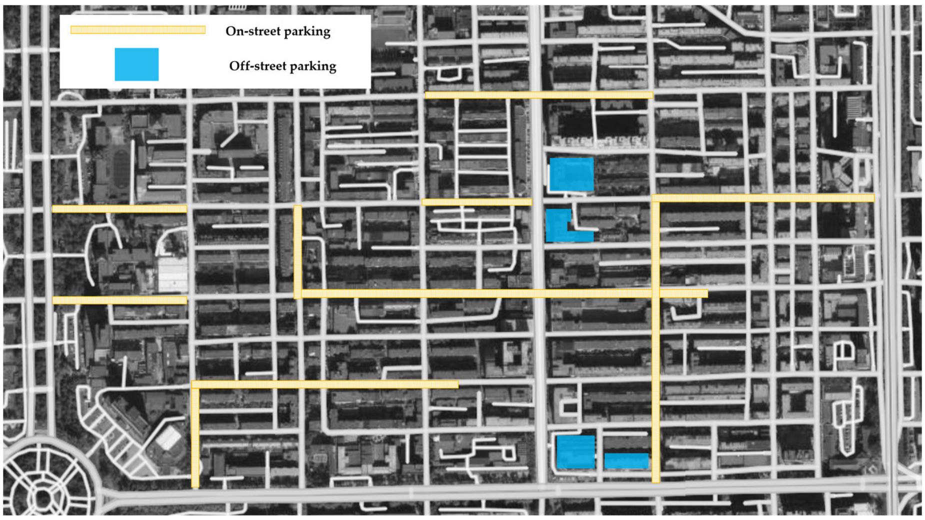


Figure 5. The location of on-street and off-street parking in the study area.

To conduct a more in-depth study of drivers' parking choices, this study conducted a two-month questionnaire survey starting from September 2022. The main content of the questionnaire included drivers' socio-economic characteristics and parking preferences. The survey focused on peak parking demand periods during weekdays and weekends. We selected drivers who had just finished parking as the subjects of this study. In the course of face-to-face interviews, we had in-depth communication with the driver about their parking choice behavior. A total of 200 survey questionnaires were distributed, and after filtering out the incomplete responses, 190 valid questionnaires were collected.

5.2. Analyzing Heterogeneous Drivers

There are many factors that affect drivers' parking choice behavior, and different drivers also have varying degrees of emphasis on these factors. In order to more accurately describe the parking choice behavior of drivers, this article introduces a latent category model to classify the parking choice preferences of drivers and calculates the target weight values of the influencing factors for different categories of drivers based on the classification results. This model is also commonly used in the transportation field to classify travelers. Gu [30] and Qiao [31] used potential category models to classify aviation and high-speed rail passengers, respectively. Scholars such as Chen [32] used to study the choice of commuting modes based on the characteristics and preferences of travelers themselves. Considering the heterogeneity of travelers' travel mode choices, potential category models are used to classify travelers. The specific steps are as follows:

1. Setting the initial number of latent classes to 1 and carrying out the goodness-of-fit test after the model is solved;
2. Increasing the number of potential categories gradually, continuing to solve the model and test the goodness-of-fit;
3. Comparing the goodness-of-fit test of each model and selecting the model with the best index as the optimal model;
4. Combining with the observed data, carrying out the estimation of the optimal model parameters and potential clustering analysis, observing the belonging category of each dataset, and, at last, outputting the classification results.

The selection of explicit variables has a very important impact on the solution results and final analysis of potential category models. Choosing the appropriate explicit variables is helpful for subsequent research and analysis. There has been a lot of research about the factors that influence drivers' choices of parking. Factors that are recurrently reported are parking fees [33], cruising time [7], walking time [9] and a number of socio-economic characteristics of the driver [8,33]. Therefore, this article selects gender, driving experience, annual household income, travel purpose, parking fees and cruising time as the explicit variables based on relevant papers. The meanings of each explicit variable at different levels are shown in Table 3.

Table 3. Explicit variables and values in the design.

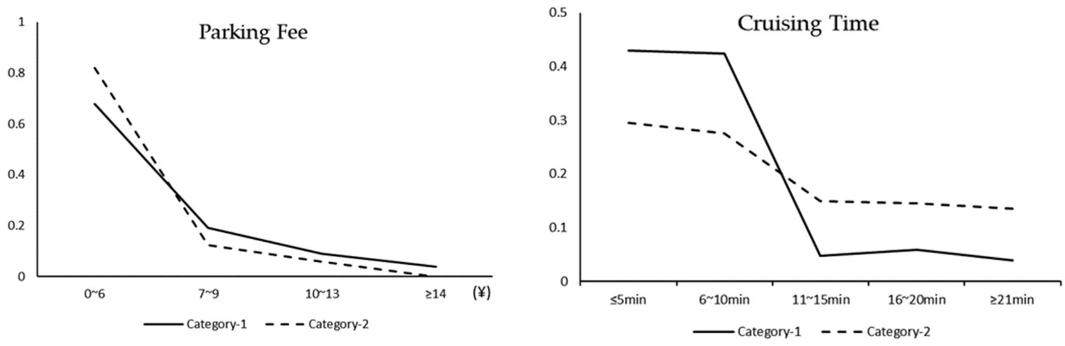
Explicit Variable	Levels	Level Values
Gender (U_1)	2	male/female
Driving Experience (U_2)	4	≤1 year2~3 years/4~5 years/≥6 years
Annual Income (U_3)	5	≤50k/60~100k/110~150k/160~200k/≥210k
Travel Purpose (U_4)	4	Work/school/shopping/others
Cruising Time (U_5)	5	≤5 min/6~10 min/11~15 min/16~20 min/≥21 min
Walking Time (U_6)	5	≤5 min/6~10 min/11~15 min/116~20 min/≥21 min
Parking Fees (U_7)	5	0~6/7~9/10~13/≥14(¥)

In the iterative process, it is necessary to find the model with the least parameters and the best goodness-of-fit. The evaluation indexes for the goodness-of-fit test are mainly G^2, χ^2 and signal evaluation indexes, among which *AIC* and *BIC* are the most commonly used signal evaluation indexes. The BIC index is more reliable when the number of samples is thousands, and the AIC index is more reliable when the number of samples is small. The signal evaluation index is based on G^2 to compare models with different parameter restrictions. The smaller the index value, the better the parameter fit. This paper uses Mplus 8.3, which is a latent variable modeling software written and published by Professors Begnt and Linda Muthen in 1987. Comparing the calculated goodness-of-fit indicators, we found that as the number of potential categories increased, the AIC and BIC values of the model continued to increase. The difference between χ^2 and G^2 when the number of categories was 2 and 3 was not significant, indicating that there was no significant optimization improvement in the goodness-of-fit of the model. As shown in Table 4, considering all indicators, the model with a 2-cluster is chosen as the ideal model.

Table 4. Latent variables classify goodness-of-fit parameters.

Models	χ^2	AIC	BIC	G^2	df
2-cluster	3173.861	2921.727	3069.110	706.006	47
3-cluster	2987.950	2925.732	3148.373	696.832	71
4-cluster	3053.971	2926.073	3223.973	717.527	95
5-cluster	2923.607	2945.810	3318.970	747.986	119

The comparison diagram of parking selection characteristics for different categories of drivers is shown in Figure 6.



(**a**) (**b**)

Figure 6. (**a**) shows the preferences of the two types of drivers in terms of parking fees; (**b**) shows the preferences of the two types of drivers in terms of cruising time.

As can be seen from Figure 6, the drivers of Category-1 and Category-2 have completely opposite preferences in terms of parking cost and cruising time. Category-1 drivers do not like to waste time cruising just to find available parking spaces. They are willing to trade higher parking fees for shorter cruising times. Therefore, we define Category-1 as a time-sensitive driver. Category-2 drivers are more inclined to cruise at low speeds on the road in search of low-cost available parking spaces. Therefore, we define 'Category-2′ as a cost-sensitive driver.

5.3. Determine the Parameters of Parking Choice Model

The parameters of the value function and the weighting function have a great impact on the accuracy of the model-solving results. The above text divides drivers into two categories based on their emphasis on cruising time and parking costs: time-sensitive and money-sensitive. This paper establishes an optimized time-weighting function (Equations (5) and (6)), so we need to recalibrate the parameters. Huang [26] recalibrated the model parameters when studying the choice of travel mode, and the effect was remarkable. Therefore, this paper cites the parameters of the time-weighting function shown in Table 5.

Table 5. Parameter of time-weighting function.

Category	η	γ_t	δ_t
time-sensitive	0.72	1.19	1.21
cost-sensitive	0.76	1.67	1.92

When many scholars [22,34] use the cumulative prospect theory in the field of transportation, the value function and the money weight function parameters directly quote the values of Tversky and Kahneman, and the final model is the error value of the final model solution result, which is small. Therefore, the relevant parameters in this paper will not be recalibrated, and the specific values are shown in Table 6.

Table 6. Parameter of the value function and cost-weighting function.

Parameter	α	λ	β	γ	δ
Coefficient	0.88	2.25	0.88	0.61	0.69

A key issue in the application of cumulative prospect theory in parking behavior selection is the determination of reference points. Considering that selecting the average value as a reference point may be simple, it can only reflect the actual value of the driver rather than the self-perceived reference value. Directly asking the driver's expected cruising time and acceptable parking rate to obtain the reference point value will better reflect the subjective perception threshold. Through the analysis of the questionnaire data, the ideal cruising time and parking cost for time-sensitive drivers was 6.72 min, ¥5.02/h; the ideal cruising time and parking cost for money-sensitive drivers was 9.35 min, ¥4.36/h.

6. Results

6.1. Impact of Unreliable Cruising Time on the Parking Choice Behavior

During the process of finding available parking spaces at the destination, drivers face many uncertain factors. When making decisions in this uncertain environment, drivers exhibit irrationality. Therefore, the use of cumulative prospect theory can better describe a driver's decision-making behavior. Drivers tend to have an aversion to unreliable cruising times, and off-street parking has more reliable cruising times because it can be booked in advance compared to on-street parking. This section focuses on how the difference in cruising time reliability affects the driver's choice between these parking facilities. Since drivers can make reservations for off-street parking in advance, the cruising time can be considered fixed. The cruising time of on-street parking is usually unreliable due to many factors. Based on the on-site investigation and asking the driver for relevant information, we set up the following three scenarios based on the specific conditions of the Guilin Road business district in Changchun. As shown in Table 7, we set the cruising time for off-street parking to 10 min based on the location of off-street parking facilities and the average speed of drivers in the study area. At the same time, we established three scenarios based on the unreliable characteristics of cruising time for on-street parking. According to the driver's parking choice behavior in different scenarios, the impact of unreliable cruising time on the driver's parking choice behavior was analyzed.

Table 7. Hypothetical scenarios with different cruising times.

	On-Street Parking	Off-Street Parking
Scenario-1	(5 min, 50%; 10 min, 30%; 15 min, 20%)	10 min
Scenario-2	(5 min, 20%; 10 min, 50%; 15 min, 30%)	
Scenario-3	(5 min, 30%; 10 min, 20%; 15 min, 50%)	

As shown in Figure 7, we can find that the driver's parking choices change as the cruising time changes. Specifically, from scenario 1 to scenario 3, the proportion of drivers in the two categories choosing off-street parking is constantly increasing, which means that there is a shift from on-street parking to off-street parking. In scenario 1, we establish that drivers have a fifty percent chance of finding on-street parking within 5 min. Compared with off-street parking spaces with a cruising time of 10 min, most drivers chose on-street parking. In scenario 3, the cruising time for off-street parking is still 10 min, but at this time, the driver is likely to spend more than 15 min to find available on-street parking. In this case, more drivers chose off-street parking. This difference reflects the driver's tendency to overestimate high-probability events in parking choice behavior. In scenario 1, the drivers subjectively overestimated the probability of "5-min cruise time for on-street parking", so most drivers chose on-street parking. In scenario 3, the drivers believe that it is likely to take them 15 min to find an on-street parking space, and at this time, the 10 min off-street parking cruising time does not seem so unbearable. Therefore, we can see in Figure 7 that most drivers choose off-street parking.

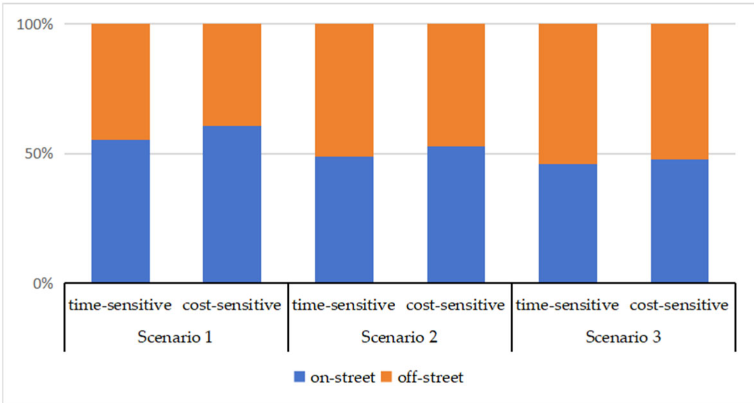


Figure 7. Impact of unreliable cruising time on the parking choice.

6.2. Impacts of Irrational Behavior on Parking Choice Behavior

The cumulative prospect theory explains the decision-making behavior of irrational decision-makers, and the parameters in the model represent the risk preferences of decision-makers. A higher value of α, β indicates that the decision-maker is more risk-averse, and a value of γ indicates the sensitivity of the decision-maker to gains and losses. Therefore, we can reason that the value of the parameter can reflect the degree of irrationality of the driver. If the values of the parameter all equal 1, we can ignore the risk pursuit and profit and loss sensitivity in the driver's decision-making process [23]. In this case, we can assume that the driver is rational in the process of making parking choices. Table 8 shows the impacts of irrational behavior on parking choice behavior.

Table 8. Impacts of irrational behavior on parking choice behavior.

Parking Space Selection	Time-Sensitive			Cost-Sensitive		
	Realistic Results	Irrational Drivers	Rational Drivers	Realistic Results	Irrational Drivers	Rational Drivers
On-street Parking	40.56%	41.05%	44.19%	67.22%	65.79%	70.56%
Off-street Parking	59.44%	58.95%	55.81%	32.78%	34.21%	29.44%

First, we find that time-sensitive drivers tend to choose off-street parking, while cost-sensitive drivers prefer on-street parking, regardless of whether the driver is rational or not. According to the survey, we found that although the parking fees per unit time for on- and off-street parking are not much different, off-street parking requires an additional reservation fee, while on-street parking is free of charge for parking outside the specified time. This results in the total cost of off-street parking being higher than that of on-street parking. At the same time, during peak parking demand periods, on-street parking occupancy rates are high, and drivers need to spend a longer time looking for parking spaces. This could explain the difference in parking choice preferences between time-sensitive and cost-sensitive drivers. Next, we compare the parking choice behavior of rational and irrational drivers with realistic situations. We can clearly find that the driver's parking choice behavior in an irrational state is closer to the realistic results. This shows that the assumption of "irrational people" can accurately describe the driver's decision-making state in real life.

7. Discussion and Future Work

This paper considers the state of the "irrational person" of the driver when making decisions and uses the cumulative prospect theory to establish a parking choice model. This study analyzes the application of the model in real life, and analyzes the influence of an uncertain cruising time and the driver's rationality on parking choice. The key findings are as follows. There are two types of drivers who need to park in the central business district, and they are divided into time-sensitive drivers and cost-sensitive drivers. There are differences in parking preferences for different types of drivers. Time-sensitive drivers are more likely to choose off-street parking, while money-sensitive drivers are the opposite. At the same time, in the face of an unreliable cruising time, the drivers show the characteristic of overestimating high-probability times, which affects their parking choice behavior. In the comparison of rational behavior and irrational behavior, we find that the parking choice behavior based on the cumulative prospect theory is closer to the real situation.

There are still some shortcomings in this study. Firstly, the model adopts the experimental parameters set by Tversky and Huang. However, the parameters of the model will vary from person to person due to the characteristics of the study area and the driver's attitude toward risk. Future research can collect drivers' parking selection behaviors from the smart parking system for more accurate parameter calibration. Another drawback comes from the limited factors that were taken into account when establishing the model. The parking cost function established in this paper only takes into account the cruising time, walking time and parking fee. During the investigation, it was learned that the parking choice behavior of some drivers was also affected by factors such as familiarity, safety and parking time in the parking lot. As we all know, the more comprehensive the factors considered in the establishment of the parking choice model, the more accurate the prediction results. In-depth research can consider adding multiple factors to the model to accurately describe the driver's parking choice behavior in complex traffic environments.

With the continuous development of science and technology, especially the application of Internet of Things technology in the field of transportation, intelligent parking systems based on the Internet of Things have also begun to appear in practical applications. Sensors are installed on parking spaces to collect information such as the availability of parking spaces. At the same time, the intelligent parking system transmits the collected information to the user and helps the user choose the best parking space [35]. The smart parking system provides drivers with optimal parking spaces based on the relevant information collected. The driver's parking choice behavior model, based on the cumulative prospect theory established in this paper, is more consistent with the driver's decision-making process in real life. Therefore, the research in this paper can help the intelligent parking system more accurately recommend the optimal parking space for drivers and improve parking efficiency. At the same time, due to the difference in drivers' personal characteristics and travel attributes, parking demand has an imbalance in time and space [36]. The paper analyzes the impact of unreliable cruising time on a driver's parking choice behavior, which helps government management departments formulate parking supply policies and adjust the supply quantity and service time of on-street parking based on drivers' parking choice behaviors. By formulating a reasonable parking supply strategy, it is possible to meet parking demand while reducing the impact of road traffic.

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