Exploring Taste Heterogeneity and Substitution Patterns in Dockless Bike-Sharing Parking Preferences

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Abstract

Dockless bike-sharing (DBS) is an important sustainable urban transportation mode in many cities but faces challenges with disorderly parking management. This study aims to explore the presence of taste heterogeneity and substitution patterns in DBS users' parking preferences and to determine how interpersonal variations, alternative-specific attributes, and socio-demographic characteristics affect parking choices. Based on stated-preference data collected in China, a mixed nested logit (Mixed NL) model is employed to account for both inter-alternative correlation and random taste heterogeneity. The results indicate that reducing the distance to parking and increasing monetary fines are more effective in discouraging disorderly parking than offering incentives for orderly parking or adjusting parking fees. Social influence also plays a critical role, as users are more likely to park disorderly when they observe others doing so. Meanwhile, the research also reveals that users are willing to pay an average of 0.8 CNY to reduce the distance to parking by 100 metres, and are willing to accept on average an additional 58 metres of the distance to parking in exchange for 10 minutes of free riding time. These insights into DBS users' parking behaviour enhance the understanding of the effectiveness of possible policy interventions and offer a valuable reference for developing future management strategies.

Keywords dockless bike-sharing; parking behaviour; mixed GEV model; taste heterogeneity; inter-alternative correlations; stated choice experiment

1. Introduction

Given the global drive towards a low-carbon future, sustainable transportation has become essential for reducing emissions and improving air quality. One prominent solution for promoting low-emission urban travel is the development of cycling systems, which provide an eco-friendly and efficient alternative to motorised transport. Notably, dockless bike-sharing (DBS), also known as free-floating bike-sharing, has rapidly expanded worldwide in recent years. By offering users the flexibility to pick up and drop off bikes anywhere without relying on fixed docking stations (Zhang et al., 2019), DBS presents significant advantages over traditional station-based public bicycle systems.

China, as one of the pioneers of DBS systems, operated approximately 15 million bicycles with an average of 47 million daily orders nationwide by the end of 2021 (China Road Transport Association, 2023). DBS has played an important role in easing urban traffic congestion and addressing the 'last mile' challenge in public transportation. However, it has also introduced a new challenge. Due to the limited parking resources that cannot quickly adapt to the expansion of DBS deployment, disorderly parking has become a widespread issue in China (Su et al., 2020; Zhang et al., 2019). In high-demand locations such as subway stations, office areas and commercial complexes, insufficient parking capacity often leads to an accumulation of bicycles, resulting in problems such as encroaching on pedestrian and cycling spaces and occupying restricted areas (Wang et al., 2021a, 2021b; Tang et al., 2024), as shown in Fig. 1.

(a) Parking blocking sidewalks (b) Parking occupying pedestrian crossing (c) Parking in restricted area

Fig. 1. Examples of disorderly parked DBS in Beijing, China (Photos: author)

Similar problems have also emerged in other countries, such as Austria, Singapore, the UK, the US, and Australia, leading to negative public perception and increased regulatory interventions (Laa and Emberger, 2020; Cai et al., 2023; He and Zhang, 2024). In response to stricter regulations for DBS established in some cities, such as Singapore, Vienna, Oxford, and Melbourne, some operational companies chose to exit the market because of rising costs (Laa and Emberger, 2020). Amsterdam opted to impose a temporary ban on all DBS systems in 2017 specifically due to excessive use of private bike parking spaces (O'Sullivan, 2017). These phenomena illustrate that disorderly parking not only negatively affects cyclists, pedestrians as well as the city's appearance, but also severely impacts the sustainability of shared-micromobility systems.

Understanding users' parking preferences is crucial for designing more effective interventions targeting the root causes of disorderly parking. Few studies have examined how users' socioeconomic characteristics, psychological factors, and environmental factors influence the decision between disorderly and orderly parking (Wang et al., 2021a, 2021b; Huang et al., 2023; Wang et al., 2023). Several policy interventions have been suggested, such as offering rewards for orderly parking behaviour, imposing penalties for disorderly parking behaviour, and enhancing public awareness regarding orderly parking practices (Su et al., 2020; Gao L. et al., 2021; Tang et al., 2024). However, due to limitations in research methods, most studies have only highlighted the effect of incentives in promoting orderly parking behaviour, but few have investigated what the most efficient level of incentives is. Identifying the optimal incentive is crucial for achieving the desired behavioural guidance while ensuring efficient resource use and maximizing impact. Additionally, there has been a lack of in-depth exploration into the possibility of taste heterogeneity among different individuals. In the context of car parking, taste heterogeneity has been shown to be a major factor in parking type choice, influencing the impact of substantive factors such as access, search, and egress time, as well as attitudes toward potential fines for illegal parking (Hess and Polak, 2004). Accordingly, exploring taste heterogeneity in the influences of different factors and policy interventions on parking preferences among DBS users would be valuable in obtaining a more accurate understanding of user behaviour.

This paper aims to fill the research gap by examining the presence of deterministic and random taste heterogeneity in users' preferences and quantifying the distribution of the values users place upon different utility factors influencing parking choices. To achieve this, we first conducted a stated preference experiment, enabling the analysis of various attributes that might impact users' behaviour, and then employed a mixed nested logit model, which allows for both interpersonal random taste heterogeneity and inter-alternative correlations, to explore the extent to which individual characteristics and alternative-specific attributes influence users' parking decisions and how this varies among individuals.

The study contributes to the literature in two key ways: (1) Our results reveal the presence of deterministic and random taste heterogeneity in DBS users' parking preferences and quantify the impact of the random variation on coefficient estimates for specific attributes (e.g., proximity to designated parking areas, perceived behaviour of other users, potential rewards, fines, and parking fees). (2) By evaluating the effectiveness of policy interventions and estimating the marginal rate of substitution (e.g., willingness to pay for reduced distance to parking, the trade-off between rewards and the distance to parking), this study generates insights for policymakers and operators seeking to promote orderly parking. Although the present paper focuses solely on the DBS system, we strongly believe that the observations are also applicable to other dockless shared-micromobility systems, such as shared e-scooters and shared e-bikes, which experience similar disorderly parking problems (Liazo et al., 2022; Meng et al., 2024).

The remainder of this paper is organised as follows. Section 2 provides a review of existing studies on DBS parking challenges and management. Section 3 introduces the stated choice experiment design and data collection process. Section 4 describes the applied modelling framework. Section 5 presents and discusses the estimation results and the marginal rate of substitution, such as willingness to pay and value of time. Section 6 discusses the implications and limitations of our work and presents the conclusions.

2. Literature review

2.1. *Parking management strategies for DBS*

Existing literature has proposed various parking management strategies for dockless bike-sharing (DBS) systems, which are summarised in Table 1. Considering that DBS parking problems are largely driven by insufficient parking supply, previous studies have primarily addressed these challenges from planning and operational perspectives, which can be regarded as a supply-side approach. Establishing parking spots that match demand is a critical management strategy that has been widely studied (Zhang et al., 2019; Hua et al., 2020; Arif and Margellos, 2022). Hua et al. (2020) used trip data from Mobike and the dockless bike-sharing survey in Nanjing to estimate parking demand, then applied clustering methods to identify virtual stations where bikes tend to congregate. Arif and Margellos (2022) developed a scenario optimization model to jointly determine the capacities and locations of parking spots, accounting for uncertainties in parking demand and points of interest within the area. Electric fence technology is considered an effective method to regulate users' parking behaviour. Zhang et al. (2019), Liazo et al. (2022) and Cai et al. (2023) propose methodological frameworks to optimize electric fence planning, with the aim of maximizing parking demand coverage. However, demand-based parking spot optimization strategy has some limitations. For example, inaccurate predictions of parking demand can lead to failures in matching supply with actual needs (Meng et al., 2024). Furthermore, this approach largely overlooks parking compliance, i.e., even with sufficient parking facilities, users may still choose to park disorderly due to inconvenience or the absence of mandatory enforcement (Si et al., 2024). While geo-fencing techniques can promote orderly parking by preventing users from locking bicycles outside designated parking areas, the high infrastructure costs (Cai et al., 2023) limit broad adoption, and issues with position recognition accuracy may still allow disorderly parking (Wang et al., 2019).

Another key strategy to promote the balance between parking supply and demand is the repositioning of DBS systems. There is a considerable amount of current research on this topic, which can be divided into two types: static bicycle repositioning problems (SBRP) and dynamic bicycle repositioning problems (DBRP) (Liang et al., 2024). SBRP typically rebalances stations overnight and cannot explicitly respond to demand fluctuations that occur during the day (Pal and Zhang, 2017; Du et al., 2020). DBRP is used to match travelers' dynamic parking and pick-up demand fluctuations during the daytime (Tian et al., 2020; Cheng et al., 2021; Zhou et al., 2023; Liang et al., 2024). Tian et al. (2020) developed a flow-type task window to fit the strong time-sensitive demand fluctuation, which could help complete each rebalancing within an average of 4 minutes. Liang et al. (2024) proposed a general mixed-integer programming model for multi-period rebalancing problems and simulated 1-minute time-slots (a level of detail fine enough to approximate real-time demand) to evaluate the performance of the proposed method. Although previous studies have done a lot of work to enable the supply to match real-time demand via rebalancing strategies, there is still a lot of demand lost (Tian et al., 2020; Liang et al., 2024). Additionally, rebalancing measures are often constrained by DBS companies' operational cost controls and the limited availability of labor (Wang et al., 2023).

TABLE 1

Summary of parking management strategies for DBS

Research category	Approaches	Literature
Parking spots planning	Parking facility planning	Hua et al., 2020; Arif and Margellos, 2022
	Electric fence planning	Zhang et al., 2019; Liazo et al., 2022; Cai et al., 2023
Bicycle repositioning	Static bicycle repositioning	Pal and Zhang, 2017; Du et al., 2020
	Dynamic bicycle repositioning	Tian et al., 2020; Cheng et al., 2021; Zhou et al., 2023; Liang et al., 2024
User-based strategies	Incentive-based approaches	Chiariotti, 2020; Cheng et al., 2021; Fukushige et al., 2022
	Penalty-based approaches	Bao et al., 2023

Parking spots planning and bicycle repositioning strategies can balance parking supply and demand to some extent, helping to mitigate disorderly parking caused by insufficient parking spaces. However, it does not directly regulate users' parking behaviour. Some studies have explored incentive-based approaches (Chiariotti, 2020; Cheng et al., 2021; Fukushige et al., 2022), using incentive measures to encourage DBS users to rent bicycles in surplus stations or return bikes to deficient stations. Fukushige et al. (2022) proposed a potentially cost-effective strategy for rebalancing DBS by offering incentives to users, either to walk farther to access a bicycle (origin-based incentives) or to bring a bicycle to an undersupplied area (destination-based incentives). Their findings suggest that users are willing to walk an additional 3.8 minutes per dollar (around 0.52 minutes per CNY) at origins and 4.2 minutes per dollar (around 0.58 minutes per CNY) at destinations in response to such incentives. Bao et al. (2023) suggested a strategy that integrates parking infrastructure and penalties, and evaluated the impact of punitive measures on promoting standard parking.

TABLE 2

Previous work on DBS users' parking behaviour or intention

Research Methods	Literature	Analysis Methods	Key findings
Rating scale survey (intentions)	Zhao and Wang (2019)	Hierarchical regression analysis	• Attitude, subjective norm, social norms and perceived behavioural control influence DBS users' parking intention.
	Wang et al. (2021a)	Ordered logit model	• Social norms, reciprocity, communication responsibility, and institutional environment influence proper DBS parking intention.
	Wang et al. (2021b)	Ordinary Least Squares	• Descriptive social norms influence disorderly parking intention.
	Wang, M. et al. (2023)	Partial least squares (PLS-SEM)	• Perceived invulnerability promotes disorderly parking intention.
Rating scale survey (behaviours)	Jiang et al. (2019)	Factor analysis	• Factors such as user self-discipline and parking space influence DBS disorderly parking behaviour.
	Wei et al. (2022)	Principal component analysis	• Measures such as co-enhanced standardised parking or the improvement of parking facilities can help relieve disorderly parking.
	Huang et al. (2023)	Process macro model	• Rewards are more effective than punishments in promoting orderly parking. • Injunctive norms show a stronger influence than descriptive norms.
	Tang et al. (2024)	Structural equation model (SEM)	• Punishment, personal norm, and descriptive norm positively influence users' orderly parking behaviour.
	Si et al. (2024)	Bootstrap and regression analyses	• Both economic incentives and punitive measures increased DBS users' willingness to park correctly. • Punitive measures were marginally more effective than incentives.
Stated preference (SP) survey	Gao L. et al. (2021)	Mixed Logit model	• Both positive and negative incentives can encourage DBS users to park legally. • Users' heterogeneous characteristics could exert influences on the effect of policy compliance.
	Bao et al. (2023)	Binary logistic model	• Factors predicting parking compliance included gender, age, occupation, usage behaviour, and travel preferences.
Field experiments	Su et al. (2020)	Logistic and probit models	• Warning messages and monetary incentives shifted users' parking behaviour more than social norm interventions.
Revealed preference (RP) method	Wang, Y. et al. (2023)	Spatial clustering and decision trees methods	• There is significant spatiotemporal heterogeneity in inconsiderate parking. • Inconsiderate parking behaviour is influenced by riding distance, as well as the density of surrounding catering service places, lifestyle services, sports and leisure places, hotels and hostels.

2.2. *User parking behaviour in DBS system*

Studying users' parking behaviours is essential for developing effective parking management policies to address DBS parking problems. Table 2 provides insights into the related studies on users' parking behaviours and intentions. Most of them have examined the factors influencing users' choices and preferences between disorderly and orderly parking (Wang et al., 2021a, 2021b; Wang, M. et al., 2023; Wang, Y. et al., 2023; Bao et al., 2023; Huang et al., 2023; Tang et al., 2024). For example, Wang et al. (2021a) identified the lack of a shared definition of 'orderly parking' as the most significant factor affecting DBS parking, alongside social norms, reciprocity, communication responsibility, and the institutional environment. Wang et al. (2021b) further demonstrated that descriptive social norms shape users' attitudes toward orderly parking directly and indirectly, and then influence the orderly parking intention. Tang et al. (2024) proposed that the severity and certainty of punishment, along with personal and descriptive norms, positively affect users' attitudes toward orderly parking, which, in turn, influence their parking behaviour. Other factors, such as past parking behaviour (Wang, M. et al., 2023a), socioeconomic characteristics (Wang et al., 2021a, 2021b; Bao et al., 2023; Wang, M. et al., 2023), DBS usage patterns (Bao et al., 2023), and the built environment (Wang, Y. et al., 2023) have also been shown to significantly influence parking behaviour.

Additionally, few studies have evaluated the influence of behaviour interventions aimed at addressing disorderly parking (Su et al., 2020; Gao L. et al., 2021; Si et al., 2024). Su et al. (2020) used a randomised field experiment to assess the effectiveness of warning messages and monetary incentives in promoting orderly parking behaviour, finding that both interventions improved compliance. Similarly, Si et al. (2024) explored the impact of penalties and incentives on user compliance, showing that penalties were more effective in encouraging orderly parking within designated electronic fences. Gao L. et al. (2021) established a mixed logit model to determine how positive and negative incentive measures affect parking behaviour, demonstrating that monetary rewards are more effective at promoting orderly parking than financial penalties.

2.3. *Research gap*

Understanding parking behaviour is essential for DBS parking management, since users' compliance with parking regulations directly impacts the effectiveness of planning and operational measures. However, research focusing on DBS usage from a behavioural perspective has received relatively limited attention, leaving notable gaps that call for further exploration.

Firstly, the possibility of explained and unexplained taste heterogeneity among users has been widely ignored in previous studies on DBS parking behaviour. Similar to other decision-making behaviour, individuals show significant differences in their responses to changes in various attributes of a given alternative within the specific parking context, and neglecting these differences may lead to bias and poorer model fit (Hess and Polak, 2004). Only one study by Gao L. et al. (2021) has considered random taste heterogeneity in the model, indicating that the impact of factors such as travel purpose, gender, number of companions, and willingness to incur penalties or accept rewards varies among individuals. However, the deterministic and random taste heterogeneity in initial preferences for specific parking alternatives, as well as in responses to alternative-specific attributes, have not been adequately explored.

Secondly, past studies were mainly based on rating scale survey to identify the factors influencing parking intention or behaviour, and to analyse the relationships between them (Huang et al., 2019; Jiang et al., 2019; Zhao and Wang, 2019; Wang et al., 2021a, 2021b; Wei et al., 2022; Wang, M. et al., 2023; Si et al., 2024; Tang et al., 2024). However, this method have certain limitations. For instance, it collects respondents' attitudes or preferences toward specific items, but it lacks contextualization and the process of choice trade-offs. Regarding other methods, field experiments (Su et al., 2020) allow for the direct observation of behaviour in controlled settings but cannot fully account for variations in attributes. The RP method (Wang, Y. et al., 2023) relies on respondents' observed choices or previous behaviour, limiting the ability to explore attributes or alternatives that do not exist (Helveston et al., 2018). Few studies have employed the SP survey. There is a lack of sufficient understanding of users' responses to new parking alternatives or attributes that emerge under policy interventions.

Thirdly, as proposed by Su et al. (2020), exploring the relationship between the value of the reward and the distance people are willing to walk or the time they are willing to spend would be valuable for setting appropriate incentive prices. However, no research has been conducted in this area to date.

3. Survey and data

3.1. *The definition of orderly and disorderly parking for DBS and its current status in China*

As of now, there is no standardised definition of orderly and disorderly parking for DBS in both academic and operational fields (Wang et al., 2021a; Heinen and Buehler, 2019). Jiang et al. (2019) and Wang et al. (2021a) provided a broader definition of disorderly parking as parking outside the designated areas, while Gao L. et al. (2021) defined it more specifically as occupying a bicycle lane, sidewalk, or walkway for the blind, as well as overcrowded parking when legal parking spaces are fully occupied. Su et al. (2021) and Si et al. (2024) further considered whether bicycles within designated areas were properly placed, taking into account their positioning and alignment. Different cities or districts in China have established specific definitions of disorderly parking based on their unique conditions and management objectives. For example, some places have implemented geo-fencing technology, using GPS to restrict users to end rides only in designated areas to promote orderly parking, with parking outside the geo-fenced boundaries considered disorderly (Zhang et al., 2019). In contrast, in places lacking designated parking areas, the definition of disorderly parking is more ambiguous (Wang et al., 2021a).

In typical scenarios, bicycle parking resources are limited and dispersed. The nearest parking areas to high-traffic destinations, such as busy public transportation stations and work, educational or residental locations, are often insufficient to meet demand (Van der Spek and Scheltema, 2015; Heinen and Buehler, 2019). Without enforced requirements, DBS users want to park their bicycles as close as possible to the destination and lack adequate motivation to park bicycles in more distant parking areas, leading to the accumulation of bicycles near the destinations. This results in bicycles overflowing onto sidewalks, bicycle lanes, and even motor lanes. Accordingly, this research is focused on addressing this critical issue. We proceeded under the assumption that clearly designated parking areas exist, and define orderly parking as parking within designated parking areas, focusing specifically on the situation where the nearest designated parking area to the destination is saturated.

3.2. *Survey design*

The survey was divided into four components, collecting data on: 1) current DBS usage and parking information, such as riding frequency, average riding time, past parking behaviour, past penalty experiences for disorderly parking, and reasons for past disorderly parking; 2) responses to stated choice (SC) tasks; 3) responses to self-report scale statements; and 4) respondents' socio-demographic characteristics, including gender, age, education, income, occupation, and bike ownership. Based on the objectives here, only stated preference (SP) data and socio-demographic information were employed in the modeling process. The following section outlines the process involved in designing the SC components.

3.2.1. *SP scenario design*

We used SC tasks in the survey to understand how people react to different parking options and management methods that do not currently exist in real parking scenarios. In the questionnaire, we presented respondents with hypothetical decision-making scenarios, which were based on a typical DBS travel situation. Detailed explanations and a graphical illustration were provided, as shown in Fig. 2. The text was originally written in Chinese for data collection and then translated into English for illustration in this paper. Different from previous studies, the designated paid parking area was also included as one of the parking options. Although paid parking areas are currently uncommon in practice and primarily used for private bicycle storage, it remains valuable to explore as a potential management strategy for DBS and allows us to evaluate how users trade off between cost and convenience. Fig. 3 gives an example of the SC tasks.

Fig. 2. Illustration of the choice scenario in SP survey.

	Another designated free parking area	Designated paid parking area	Disorderly parking
Distance from the destination	200m (The round trip takes 4 min)	100m (The round trip takes 2 min)	
Reward	30 min free ride coupon		
Parking fee		￥1	
Fine			￥5
Number of other people parking disorderly			High (more than 10 people)
Choice question:	○	○	○

Fig. 3. Example of SC tasks in the questionnaire.

3.2.2. *Experiment design*

The SC experimental design was developed using the Ngene software (ChoiceMetrics, 2018). SC tasks include three parking alternatives: 1) free parking area, 2) paid parking area, and 3) disorderly parking, which individuals were asked to choose between. All three alternatives were labeled in the experiment, meaning that the label itself conveys information to respondents, allowing for the estimation of label-specific preference parameters and constants (Louviere et al., 2000).

Based on a systematic review of the literature (Fukuda and Morichi, 2007; Wang et al., 2021a; Gao et al., 2021b), as well as the specific objectives and scope of this research, five attributes were ultimately included, which are summarised in Table 3. Not every attribute applies to all three alternatives. Specifically, "distance to parking" serves as a general attribute for the two orderly parking alternatives. "Reward" is linked to the free parking area, while the "parking fee" attribute pertains to the paid parking area. Additionally, the "fine" and the "other people" attributes are associated with the disorderly parking alternative.

Increasing the number of levels leads to greater design complexity and a higher number of choice tasks (Louviere et al., 2000). To balance statistical efficiency with respondents' cognitive burden, three levels were assigned to attributes such as distance to parking, parking fee, and the number of other people parking disorderly. For the reward and fine attributes, an explicit zero level was included to enable the estimation of presence-versus-absence effects on choice behaviour. All of the attribute levels were determined such that they extended beyond current observed real-world levels while varying within reasonable ranges, providing sufficient variation needed to estimate the attribute's sensitivity, while also ensuring feasibility and realism for respondents in the survey (Song et al., 2018). To better reflect practical conditions and avoid dominated alternatives, two constraints were applied to the attribute levels in the experiment design: (1) the parking cost in the paid parking area must be lower than the fine for disorderly parking when the fine is non-zero, and (2) the distance to the free parking area must exceed the distance to the paid parking area.

TABLE 3

Overview of attributes and their levels

Attributes	Attribute Descriptions	Another designated free parking area	Designated paid parking area	Disorderly parking
Reward	The free riding coupon for parking in a more distant free parking area (min)	0/ 10/ 20/ 30	–	–
Distance to parking	Additional distance needed to park in another designated free or paid parking area (m)	200/ 500/ 800	100/ 200/ 300	–
Parking fee	Charges imposed by the designated paid parking area (CNY)	–	0.5/ 1/ 2	–
Fine	Monetary penalties automatically deducted for disorderly parking bikes (CNY)	–	–	0/ 1/ 3/ 5
Other people	Number of other users who disorderly park bikes outside designated parking areas.	–	–	No others/ Low (≤10 people)/ High (>10people)

Note: *CNY/USD ≈0.138 during survey period*

It is important to note that this research adopts the free riding time coupon as the reward to encourage users to park bicycles in designated parking areas, rather than relying on the monetary reward frequently used in previous studies (Su et al., 2020; Wang et al., 2021a, 2021b; Gao et al., 2021b). In practical situations, various factors impacting the financial sustainability of monetary incentives, such as cost implications and budget constraints, could significantly influence DBS companies' willingness and ability to implement monetary rewards for orderly parking. In contrast, non-monetary incentive types, such as free riding time coupons, appear to be easier to implement and have been increasingly explored by DBS companies (Beijing News, 2024) and in some academic studies regarding DBS users' choices in recent years (Shen et al., 2018; Li et al., 2019; Kirkman, 2019; Si et al., 2024). In the SC tasks, we presented respondents with both the distance to parking and the corresponding round-trip time to the destination, calculated based on average speeds. It is assumed that cycling from the destination to the designated parking area would be at an average speed of 10 km/h (see Long and Zhao, 2020 for the statistical average cycling speed of bike-sharing in Chinese cities), while the return to the destination would be on foot at an average speed of 4 km/h (see Romanillos and Gutierrez, 2019; Jia et al., 2022).

A D-efficient design (Bliemer and Rose, 2024) was used to achieve a low D-error, corresponding to a higher level for the Fisher information, which facilitates more precise parameter estimates. A swapping algorithm (ChoiceMetrics, 2018) was applied to minimize D-error and maximize attribute level balance. Due to the absence of prior information on the coefficients, we initially conducted a pilot study using non-informative priors (small positive or negative values) (Rose and Bliemer, 2009; Bliemer and Collins, 2016). A total of 50 samples were collected in the pilot study, which was conducted in June 2024. The final experimental design was subsequently generated based on the information obtained from the pilot survey, resulting in the design of 12 SC tasks for each respondent. The S-estimate, which indicates the smallest sample size needed for all parameters to be statistically significant, was calculated to be 200 in the final D-efficient design, suggesting that a sample size above 200 is likely adequate to draw meaningful conclusions (Rose and Bliemer, 2013).

3.3. *Data collection*

The survey was implemented using an online questionnaire developed using the online tool Credamo (https://www.credamo.world/#/) in July 2024. Credamo is a professional survey platform in China with a commercial panel of over 3 million members (Credamo, 2022), covering all provinces and administrative regions. It has been widely used in numerous studies (Tang et al., 2023; Si et al., 2024). We imposed a strict constraint on the recruited samples, restricting them to individuals who had previously used DBS. Participants could receive a bonus of CNY 2 (approximately USD 0.27), which would be credited to their electronic accounts. The average response time for all respondents is about 8 minutes. In total, 703 participants completed the survey. After reviewing the survey responses, the final analysis included 600 valid responses, following the manual exclusion of 103 respondents with dubious survey responses, which were excluded based on specific criteria, such as instructed response items (Meade and Craig, 2012), response time (Huang et al., 2012) and long strings of the same response category (Johnson, 2005). The effective response rate was 85%.

3.4. *Descriptive statistics*

A detailed summary of the respondents' socio-demographic (e.g., gender, age, income, education level, occupation, bike ownership) and DBS usage characteristics (e.g., usage frequency, average riding duration, city of residence), including income distribution, is provided in Appendix 1. Among those who provided valid responses, 58% were female. Young people made up the majority of respondents, with 60% aged 21-30 and 23% aged 31-40, which is similar to the user profile of DBS reported by iiMedia Research (2022), where 81% of users are aged between 22 and 40. The sample displayed a relatively high level of academic achievement, with 70% holding a bachelor's degree and an additional 19% having a master's degree or higher, aligning with the educational characteristics of shared mobility users reported in the *Green Development Report on Shared Mobility* (2017). The majority of respondents (72%) were employed full-time, while 22% were students. Monthly income levels among respondents were relatively evenly distributed across the sample.

Regarding DBS usage, 85% of respondents used DBS at least once per week. Most respondents (61%) reported an average riding duration of 11-20 minutes, which was consistent with the observations from WRI (2020). Additionally, CAUPD (2024) shows that the average duration of a single bike ride is approximately 12.1 minutes in 2024. Overall, the demographic and usage characteristics of the sample in this survey matched the user profile of China's DBS market as described in existing reports, indicating the representativeness of the sample.

Although approximately 22% of respondents are located in cities where geo-fencing technology has been implemented, its potential influence on their acceptance of and responses to the choice scenario, which was designed without considering geo-fencing, is expected to be limited. This is because geo-fencing in these cities has typically been implemented only in a small portion of the city area, while free-floating parking remains permitted in most parts of the city. In addition, some cities have simultaneously adopted an incentive-based approach as part of their parking management strategy, alongside geo-fencing. Given the clearly described scenarios in the SP survey, the perceived impact of geo-fencing on the findings is considered negligible in this study. The choice proportions for free parking, paid parking and disorderly parking in the survey were 41%, 39%, and 20%, respectively. Despite being a hypothetical option not currently existing in real-world settings, paid parking exhibited a relatively high selection rate, suggesting that respondents regarded it as a valid alternative.

4. Modelling framework

4.1. *Utility specification*

In our work, discrete choice models were estimated based on the principles of random utility maximization (McFadden, 1973), assuming that an individual will select the alternative that provides the highest utility. The random utility function U_{ni} for alternative i for respondent n, consisting of a deterministic component V_{ni} and a random component ε_{ni}, is specified as shown in Eq. (1)

$$U_{ni} = V_{ni} + \varepsilon_{ni} = \delta_{ni} + \beta_n' x_{ni} + \varepsilon_{ni}, \tag{1}$$

where δ_{ni} represents the alternative specific constants (ASCs) capturing the average effect on utility of all factors not included in the model, x_{ni} are attributes associated with alternatives i as faced by respondent n, β_n represents the weight or importance that respondent n attaches to the corresponding attribute in the choice process and can be positive or negative depending on the attribute. Relaxing the assumption of homogeneity across individuals, we can incorporate deterministic taste heterogeneity into the models by allowing for interactions between estimated parameters and individual socio-demographic characteristics. For example, δ_{ni} can be written as a deterministic function of an observed vector z_n^{δ} of individual characteristics ($\delta_{ni} = \delta_i + \omega_{z,i} z_n'^{\delta}$, where $\omega_{z,i}$ represents the extent to which each individual characteristic influences the overall perception for different alternatives) (Bhat, 2000). In the case of a continuous interaction (see for example Hess et al., 2007; Axhausen et al., 2008), the interaction term could be expressed as

$$f(z_n^{\beta}, x_{ni}) = \beta_x \left(\frac{z_n^{\beta}}{\overline{z^{\beta}}} \right)^{\eta_{z,x}} x_{ni}, \tag{2}$$

where z_n^{β} is the observed value for a given socio-demographic variable such as income for respondent n, $\overline{z^{\beta}}$ gives the mean value across the sample population. The estimate of $\eta_{z,x}$ gives the elasticity of the sensitivity to x_i with respect to changes in z^{β}; if $\eta_{z,x}$ is negative, an increase in z^{β} will lead to a decrease in sensitivity towards x_i, with the opposite applying in the case of positive values for $\eta_{z,x}$. β_x captures the marginal utility of changes in attribute x_i at the average value of z^β in the same population.

4.2 *MNL and NL model*

Assuming the random error terms ε_{ni} to be identically and independently distributed (i.i.d.) across alternatives and respondents with a type I extreme value (or Gumbel) distribution, we developed a multinomial logit (MNL) model (McFadden, 1973) as the base. The probability of respondent n choosing alternative i from the set of alternatives J is then given by

$$P_{ni} = \frac{e^{V_{ni}}}{\sum_{j \in J} e^{V_{nj}}} \tag{3}$$

The restriction imposed by the MNL model on the distribution of random error terms leads to the independence from irrelevant alternatives (IIA) property, resulting in identical cross-elasticities between all pairs of alternatives (Wen and Koppelman, 2001). To address these limitations, we developed the nested logit (NL) model (Williams, 1997) within the closed-form generalised extreme value (GEV) framework (McFadden, 1978), which expands the MNL by offering more flexible specifications of error terms ε_{ni} to handle correlations between alternatives. In the NL model, alternatives are divided into different nests (B_1, $B_2 \dots B_K$), and λ_k is used to measure the degree of independence in unobserved utility among alternatives within nest B_k. We would then have $0 < \lambda_k \leq 1$, while a higher value of λ_k indicates greater independence and lower correlation among these alternatives (Train, 2009). The choice probability of respondent n choosing alternative i within nest B_k is given by Eq. (4), which can be decomposed into a marginal probability P_{nB_k} and a conditional probability $P_{ni|B_k}$.

$$P_{ni}(\beta) = P_{ni|B_k} P_{nB_k} , \tag{4}$$

$$P_{nB_k} = \frac{e^{\lambda_k I_{nk}}}{\sum_{\ell=1}^{K} e^{\lambda_\ell I_{n\ell}}} , \tag{5}$$

$$P_{ni|B_k} = \frac{e^{V_{ni}/\lambda_k}}{\sum_{j \in B_k} e^{V_{ni}/\lambda_k}} , \tag{6}$$

where

$$I_{nk} = \ln \sum_{j \in B_k} e^{V_{nj}/\lambda_k} . \tag{7}$$

4.3. *Mixed GEV models*

In order to capture potential random variations in respondents' preferences, we developed mixed multinomial logit (MMNL) models (McFadden and Train, 2000). The most widely used formulation of the MMNL is based on random coefficients, which is referred to as the random-coefficients logit (RCL) model (Train, 2009). In our research, we considered three types of distributions for coefficients: normal, log-normal, and negative log-normal distributions. We assumed that ASCs follow a normal distribution, based on the a priori assumption that different individuals may perceive parking alternatives as either advantageous or disadvantageous, as expressed in Eq. (8), where θ_δ is a vector of parameters (including mean μ_{δ_i} and standard deviation σ_{δ_i}) characterizing the distribution and ξ_{ni} are the draws from the selected distribution for each respondent n. Similarly, we assumed the coefficient of the reward attribute to follow a log-normal distribution, while those of distance to parking, parking fee, and fine to follow negative log-normal distributions, ensuring the positive or negative effects of these attributes, as shown in Eq. (9).

$$f(\delta_i \mid \theta_\delta) = \mu_{\delta_i} + \sigma_{\delta_i}\xi_{ni}, \xi_{ni} \sim N(0,1) \quad (8)$$

$$f(\beta_x \mid \theta_\beta) = \pm\exp(\mu_{\beta_x} + \sigma_{\beta_x}\xi_{nx}), \xi_{nx} \sim N(0,1) \quad (9)$$

While the RCL model introduces random taste heterogeneity, it does not accommodate potential correlation among alternatives. Another formulation of the MMNL model is the error-components logit (ECL), which is conceptually different, yet mathematically equivalent to the RCL model (Ben-Akiva and Bierlaire, 2003, Hess et al., 2004; Train, 2009). Instead of assuming inter-individual variations in taste parameters, the ECL model introduces inter-alternative correlations by allowing certain alternatives to share common error components in their utility. The ECL can be implemented by assigning a dummy variable to each nest of alternatives. With K non-overlapping nests, the error component term can be expressed as

$$\tau'_n \varphi = \sum_{k=1}^{K} \tau_{nk} d_{ik}, \quad (10)$$

where $\tau_{nk} \sim N(0, \sigma_\tau)$ is a random term with zero mean, shared by all alternatives in the nest k, and σ_τ captures the magnitude of the correlation. d_{ik}=1 if the alternative i belongs to the nest k, and 0 otherwise. The terms in φ represent error components associated with each nest, defining the stochastic portion of utility along with ε_{ni}.

Although the MMNL model allows for both random taste heterogeneity and flexible substitution patterns, it still suffers from important issues of identification (Walker, 2001). Mixed GEV models have been shown to avoid the identification issues associated with MMNL models and offer advantages in computational efficiency (Hess et al., 2004; Haghani et al., 2015). Additionally, the Mixed NL model offers a computational advantage by reducing the number of random coefficients, while the ECL model requires an additional random terms to represent each separate nests (Hess et al., 2004; Haghani et al., 2015). Accordingly, we developed a mixed nested logit (Mixed NL) model, which incorporates a correlation structure, enabling the evaluation of choice probabilities within the NL framework and calculating unconditional probabilities by integrating over the probability distribution of the coefficients. The unconditional probability for choosing alternative i is obtained by integrating Eq. (4) over the possible values of β weighted by its function Eq. (11).

$$P_{ni}(\theta) = \int_\beta P_{ni}(\beta) f(\beta \mid \theta) d\beta = \int_\beta \frac{e^{V_{ni}/\lambda_k} \left(\sum_{j \in B_k} e^{V_{ni}/\lambda_k}\right)^{\lambda_k - 1}}{\sum_{\ell=1}^{K} \left(\sum_{j \in B_\ell} e^{V_{nj}/\lambda_\ell}\right)^{\lambda_\ell}} f(\beta \mid \theta) d\beta \quad (11)$$

5. Empirical analysis

5.1. Specification procedure

Five models were established using a step-wise approach. The MNL model was initially created as the basis for comparison, assuming that no correlation existed between the alternatives. We then estimated a NL model, incorporating a nesting parameter to account for potential heightened correlations among the two orderly parking alternatives. Following that, the model was extended to a RCL model, which included random parameters to accommodate interpersonal random taste heterogeneity. A MMNL incorporating random coefficients and error components, and a Mixed NL model, were finally estimated to simultaneously account for both inter-alternative correlations and random taste heterogeneity. It should be noted that the MMNL model with both random coefficients and error components is referred to as the ECL model in this paper to distinguish it from the RCL model.

For model identification purposes, the free parking area alternative was assumed as the base alternative for all models, with the corresponding alternative-specific constants (ASC) parameter fixed at 0. The attribute for the effect of the number of other people parking disorderly was dummy-coded and entered the utility functions as categorical variables to describe whether others were parking disorderly, with 'no others' set as the reference category (fixed at 0). Other attributes entered the utility function linearly. To identify sources of heterogeneity, possible deterministic taste heterogeneity in the parameters was tested by incorporating interaction terms. It was observed that accommodating deterministic heterogeneity found an improvement of model fit, as evidenced by all the selection criteria considered (Likelihood Ratio test, $p < 0.001$). Higher model fit indicators were found when interacting respondents' gender and age with the ASC for the disorderly parking alternative, and respondents' income with parking fee as a continuous interaction. Although incorporating riding frequency and duration covariates could offer meaningful insights, these variables did not yield statistically significant effects (see Appendix 2). Therefore, they were excluded from the final model in favor of model parsimony. Rather than exploring the interactions between the income characteristic and ASC for alternatives, we specified a continuous interaction term between income and parking fee to capture how sensitivity to parking fees varies across income. A negative value of the interaction parameter indicates that respondents with higher income are less sensitive to parking fees, and vice versa. It should be noted that the midpoint approach (Bhat, 1994; Von Fintel, 2007) was used to handle grouped and missing income data, enabling the estimation of the continuous interaction. Additionally, to account for potential correlation in unobserved utility components, we tested all theoretically valid nesting structures among the three alternatives. As shown in Appendix 3, the specification that grouped the free parking area and the paid parking area into an "orderly parking" nest exhibited the strongest substitution pattern between alternatives, so this nesting structure was adopted in the final NL and Mixed NL models.

5.2 Estimation results

All models in this paper were estimated in R using Apollo (Hess and Palma, 2019), with 500 MLHS draws (Hess et al., 2006) for numerical approximation of the MMNL integrals. The model selection criteria and estimation results for five models are presented in Table 4 and Table 5, respectively. Moving from left to right, goodness-of-fit gradually improves, as seen from the values of final *LL*, *AIC*, *BIC*, and Adjusted ρ^2, indicating that the explanatory power of the models progressively increases with the rising specification complexity, while maintaining a good balance between model fit and complexity. The better performance of the Mixed NL model compared to the MNL, NL and RCL models could also be confirmed by likelihood ratio (LR) tests. For example, the LR test yields a value of 54.64 with a corresponding p-value of < 0.01 when comparing the Mixed NL and RCL models, indicating that the improvement in model fit is statistically significant. Specifically, the Mixed NL model outperforms the other models by allowing for both interpersonal variations in DBS parking preferences while also allowing for correlation between the orderly parking alternatives (Hess, 2004). Notably, the Mixed NL model achieves a goodness-of-fit nearly equivalent to (and marginally better than) that of the ECL model, which is consistent with the findings of Haghani et al. (2015). Moreover, the Mixed NL model demonstrated better performance in capturing the effects of key variables. In particular, it was able to reveal a significant difference between the coefficients for $\beta_{\text{other people low}}$ and $\beta_{\text{other people high}}$, whereas the ECL model failed to do so. Therefore, the following analysis will focus on the estimation results of the Mixed NL model.

TABLE 4

Model selection criteria of the DBS parking choice models

Goodness–of–fit measures	Multinomial logit	Nested logit	Random-coefficients logit	Error-components logit	Mixed nested logit
Number of choice observations	7200	7200	7200	7200	7200
Number of estimated parameters	10	11	16	18	18
LL (final)	-5591.88	-5572.85	-4667.5	-4641.59	-4640.18
AIC	11203.75	11167.69	9367.01	9319.17	9316.35
BIC	11272.57	11243.39	9477.12	9443.04	9440.23
Adj. ρ^2	0.2918	0.2941	0.4079	0.4109	0.4111

Fig. 4 presents a graphical representation of the probability distributions of utility coefficients. Significant random interpersonal taste heterogeneity was identified for six coefficients: ASC for paid parking area alternative, ASC for disorderly parking alternative, reward, distance to parking, parking fee, and fine parameters. We assume that the ASCs follow a normal distribution. The mean estimates for ASCs of the paid parking area and disorderly parking alternatives are significantly negative, while disorderly parking ASC shows the lowest mean, suggesting a general preference for the free parking area over the paid one and disorderly parking is perceived most negatively. The standard deviation of the ASC for the disorderly parking alternative is relatively high, indicating the significant variability in respondents' preferences for disorderly parking. Interaction terms further reveal that females and older individuals have an even stronger aversion to disorderly parking, which is consistent with Wang et al. (2021a) and Su et al. (2020), suggesting that socio-demographic characteristics significantly influence the overall perception of parking alternatives.

The coefficient of reward is assumed to be log-normally distributed, while the estimated mean and standard deviation are both statistically significant. The sign of the coefficient is arbitrary when interpreting the direction of the effect, but it does influence the magnitude of the effect. Specifically, the more negative the mean parameter, the smaller the magnitude of the marginal utility, indicating lower sensitivity to the reward attribute. Given that previous research primarily evaluated monetary rewards as an incentive measure (Gao L. et al., 2021; Wang et al., 2021a, 2021b), this research demonstrates that offering free riding time coupons as rewards also significantly encourages users to park at more distant locations, although the effect is relatively modest.

A negative log-normal distribution is employed for the coefficients of distance to parking, parking fee and fine. The mean and standard deviation of the three coefficients are all significant. As seen from the interaction term, individuals with higher incomes show lower sensitivity to parking fees. However, the significance of the $\eta_{\text{income, parking fee}}$ declines as model complexity increases, and becomes statistically insignificant in the Mixed NL model, which suggests that the taste heterogeneity for parking fees is mainly captured by the random component instead of the interacting covariate.

TABLE 5

Model estimation results for MNL, NL, RCL, ECL and Mixed NL models

Parameters	Multinomial logit		Nested logit		Random-coefficients logit		Error-components logit		Mixed nested logit	
	Est.	Rob. t_rat.	Est.	Rob. t_rat.	Est.	Rob. t_rat.	Est.	Rob. t_rat.	Est.	Rob. t_rat.
Means of utility coefficients										
$\delta_{\text{free parking area}}$	0	—	0	—	0	—	0	—	0	—
$\delta_{\text{paid parking area}}$	-0.643	-8.08***	-0.557	-9.12***	-1.113	-8.75***	-1.116	-9.10***	-0.883	-8.98***
$\delta_{\text{disorderly parking}}$	-1.444	-5.38***	-1.187	-4.70***	-2.262	-4.52***	-2.095	-4.02***	-1.765	-4.16***
$\omega_{\text{female, disorderly parking}}$	-0.339	-2.70***	-0.319	-2.69***	-0.544	-1.84*	-0.602	-2.42**	-0.617	-2.73***
$\omega_{\text{age, disorderly parking}}$	-0.191	-2.31**	-0.187	-2.38**	-0.525	-3.05***	-0.599	-3.31***	-0.422	-2.96***
β_{reward}	0.030	14.93***	0.024	12.85***						
$\beta_{\text{distance to parking}}$	-5.583	-26.34***	-4.401	-16.00***						
$\beta_{\text{parking fee}}$	-0.898	-18.42***	-0.666	-12.25***						
$\eta_{\text{income, parking fee}}$	-0.144	-3.43***	-0.144	-3.38***	-0.104	-2.26**	-0.094	-2.23**	-0.083	-1.59
β_{fine}	-1.341	-24.57***	-1.260	-24.18***						
$\beta_{\text{no others}}$	0	—	0	—	0	—	0	—	0	—
$\beta_{\text{other people}}$	0.546	7.63***	0.560	8.47***	0.813	5.61***				
$\beta_{\text{other people low}}$							0.846	5.45***	0.650	5.02***
$\beta_{\text{other people high}}$							0.831	4.81***	0.901	6.39***
Standard deviations of utility coefficients										
$\sigma_{\delta_{\text{paid parking area}}}$					0.576	3.53 ***	0.537	3.14***	0.512	4.84***
$\sigma_{\delta_{\text{disorderly parking}}}$					2.392	12.54***	-2.084	-12.20***	2.046	11.94***
$\tau_{\text{orderly parking}}$							1.124	3.64***		
Location parameters on log-scale										
$\mu_{\beta_{\text{reward}}}$					-3.131^	-38.81***	-3.168^	-38.74***	-3.478^	-33.12***
$\mu_{\beta_{\text{distance to parking}}}$					2.287^^	53.14***	2.328^^	53.56***	2.025^^	29.52***
$\mu_{\beta_{\text{parking fee}}}$					0.456^^	7.70***	0.448^^	7.65***	0.165^^	1.96**
$\mu_{\beta_{\text{fine}}}$					1.260^^	13.49***	1.310^^	20.00***	1.075^^	13.44***
Log-scale standard deviations										
$\sigma_{\beta_{\text{reward}}}$					-0.467^	-3.49***	-0.610^	-6.91***	0.690^	6.55***
$\sigma_{\beta_{\text{distance to parking}}}$					-0.493^^	-9.95***	-0.491^^	-19.65***	-0.489^^	-16.44***
$\sigma_{\beta_{\text{parking fee}}}$					0.517^^	5.02***	-0.548^^	-9.09***	0.472^^	4.04***

$\sigma_{\beta_{\text{fine}}}$			-0.665^^	-7.00***	0.693^^	9.36***	-0.642^^	-9.33***
Nesting coefficient								
$\lambda_{\text{orderly parking}}$	0.706	15.79***					0.657	13.31***

Note:
* Signify confidence at 90%, ** Signify confidence at 95%, *** Signify confidence at 99%.
^ means the coefficient is log-normally distributed by assumption, ^^ means the coefficient is negative log-normally distributed by assumption.
For coefficients assumed to follow a log-normal or negative log-normal distribution, the estimated parameters correspond to the location parameter on log-scale and log-scale standard deviation for the log-transformed coefficients (i.e., log(β) or log(-β)). These parameters define the log-normal probability density function, but do not represent the mean and standard deviation of the coefficients (i.e., β) themselves.

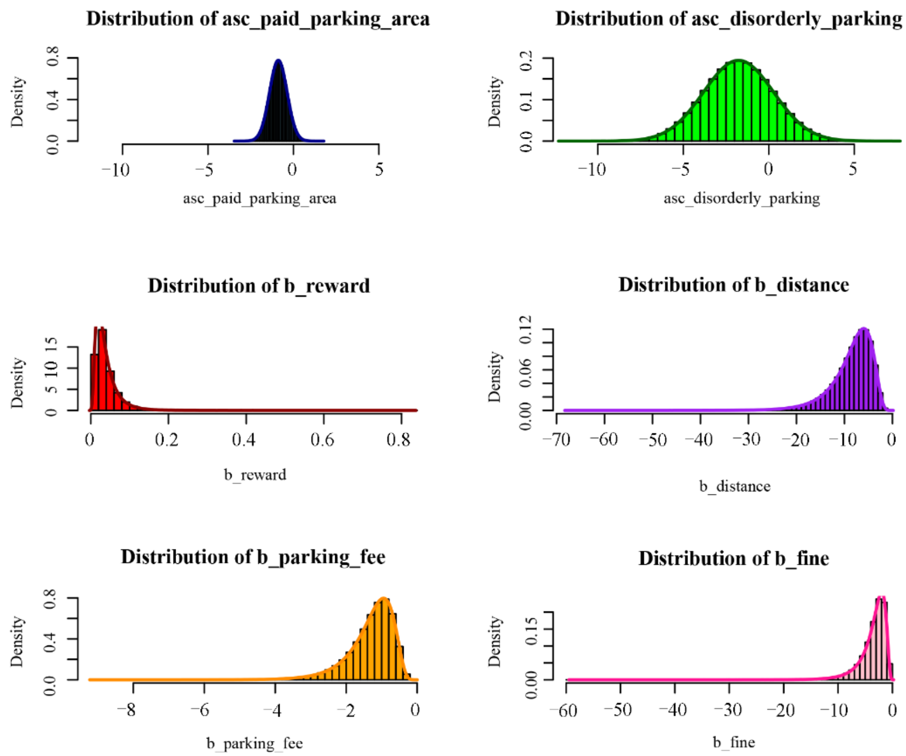

Fig. 4. Probability distribution for random utility coefficients estimated based on the Mixed NL model.

The positive coefficient for the dummy variable representing other people's behaviour implies that when others park disorderly, respondents are more likely to do the same. This can be explained by the theory of descriptive norms proposed by Cialdini et al. (1990), which suggests that individuals' behaviour is guided by the perception of how other people behave in a given context. While many users believe that orderly parking is better for the environment and society, they may still park disorderly when observing others doing so (Fukuda and Morichi, 2007; Wang et al., 2021b). Compared with the other three models, the Mixed NL model revealed a significant difference between the coefficients for $\beta_{\text{other people high}}$ and $\beta_{\text{other people low}}$, indicating that a higher number of people parking disorderly increases the utility of choosing disorderly parking more than a lower number does. It implies that, compared with low-perceived descriptive norms, high-perceived descriptive norms can lead to a greater level of moral disengagement, which has been supported by findings in other literature (Rinker and Neighbors, 2013; Zhao et al., 2017). The nesting parameter ($\lambda_{\text{orderly parking}}$) is significant at the 99% level of confidence and takes a value of 0.657, implying a high correlation between the unobserved utilities of the free parking area and paid parking area alternatives. This correlation pattern is further supported by the significant variance of the error component term associated with these two alternatives in the ECL model.

5.3. Analysis of policy intervention effectiveness

For assessing the impact of changes in policy interventions, model predictions were conducted in Apollo (Hess and Palma, 2019), with the prediction algorithm set to perform 500 runs. We first generated forecasts based on the base values of the explanatory variables as specified in the SC experiment and subsequently predicted the new choice probabilities of each alternative at the observation level resulting from the percentage change in the values of five explanatory variables. The predicted probabilities of choosing specific alternatives under several policy interventions can be observed clearly, as shown in Fig.

5. It should be noted that no single base value is reported for each attribute in Fig. 5, as the relative changes are derived from all choice tasks, each of which is assigned different attribute values. The base values and their corresponding adjusted values after applying relative changes are provided in Appendix 4. For example, in choice task 1, the distance to the free parking area is 800m, and a 30% reduction corresponds to a decrease of 240m. In contrast, in choice task 4, where the distance to the free parking area is 500 m, a 30% reduction corresponds to a decrease of 150m. In Fig. 5, relative changes ranging from −30% to +30% were applied to all choice tasks, and the choice probabilities represent the overall predicted changes aggregated across all tasks.

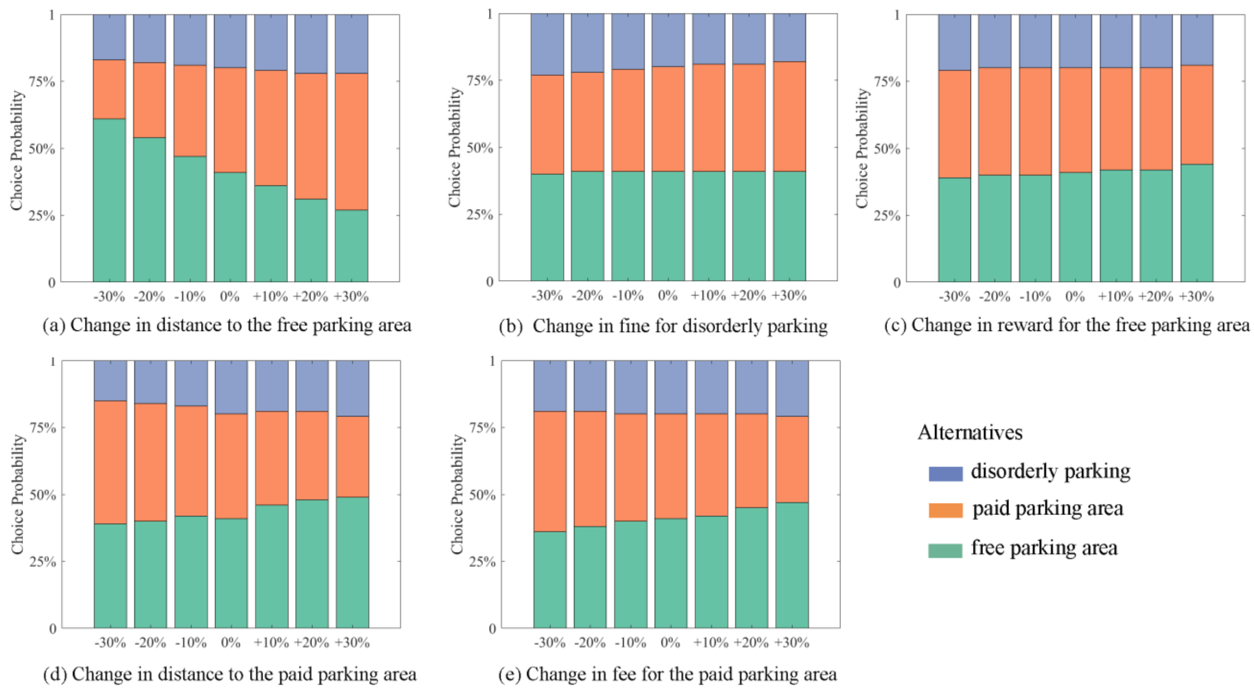

Fig. 5. Choice probability under policy interventions based on the Mixed NL model.

Reducing the distance to designated parking areas, whether paid or free, has been shown to reduce disorderly parking rates. Under the original scenario, the choice probabilities for the free parking area, paid parking area, and disorderly parking are 41%, 38%, and 21%, respectively. A 30% reduction in the distance to the free parking area results in a 3% decrease in the probability of choosing disorderly parking, while a 30% increase in distance leads to a 2% rise. In comparison, reducing the distance to the paid parking area by 30% yields a 5% decrease in the probability of disorderly parking, whereas a 30% increase leads to a 1% rise. These results suggest establishing high-density DBS parking facilities, which enable users to access designated parking areas within a relatively short distance when the parking areas near the destination are fully occupied, have the potential to discourage disorderly parking behaviour. This finding aligns with Meng et al. (2024), which demonstrated a potential non-linear relationship between the density of shared scooter parking corrals and parking non-compliance rates. To further examine behavioural sensitivity, we calculated direct and cross choice elasticities in response to a 1% increase in each attribute, as shown in Table 6. The choice elasticities of the disorderly parking alternative in response to a 1% increase in the distance to the free and paid parking areas are 0.40 and 0.30, respectively, both lower than that of the free and paid parking alternatives. This indicates that while reductions in the distance to parking do help lower disorderly parking rates, the main shift in choice occurs between the free and paid parking alternatives.

Implementing monetary punitive measures can also help reduce parking non-compliance, which is consistent with Gao et al. (2021). More specifically, a 30% reduction in fines for disorderly parking increases the probability of such behaviour by 3%, while a 30% increase in fines results in a 2% decrease. The choice elasticity of disorderly parking with respect to a 1% increase in the fine is 0.36. In comparison, a 30% increase or decrease in rewards only leads to a 1% shift in the probability of disorderly parking, indicating a limited behavioural response to free riding reward changes. Among all the policy interventions examined, the choice elasticity of disorderly parking in response to changes in the reward is the lowest.

TABLE 6

Choice elasticities in response to a 1% increase in attribute values

	distance to parking (free)	reward	distance to parking (paid)	parking fee	fine
free parking area	-1.40	0.18	0.50	0.35	0.04
paid parking area	1.26	-0.14	-0.69	-0.45	0.14
disorderly parking	0.40	-0.11	0.31	0.16	-0.36

Furthermore, adjustments to parking fees exhibit the potential in influencing the probabilities of choosing free or paid parking alternatives, demonstrating the effectiveness of pricing mechanisms in influencing parking behaviour. However, they have weak impact on disorderly parking behaviour. The choice elasticity of disorderly parking with respect to a 1% increase in the parking fee is 0.16.

Overall, only the choice elasticities of the free and paid parking alternatives in response to a 1% increase in the distance to the free parking area exceed 1, which can be considered relatively elastic. This suggests that users are sensitive to changes in the distance to free parking areas. In contrast, the choice elasticities associated with a 1% increase in other attributes fall below 1, indicating relatively inelastic responses (Hensher et al., 2015). This finding demonstrates that relying on a single policy intervention may be insufficient to address the problem of disorderly parking. A combination of policy interventions may be necessary to achieve more effective parking management outcomes.

5.4. Willingness to pay interpretation

Willingness to pay (WTP) values were calculated based on parameter estimates for each model, as presented in Table 6. During the survey period, the exchange rate was CNY/USD = 0.138. For models with fixed coefficients, the mean values and robust standard errors of WTPs were computed using the Delta method (Train, 2009), while WTP distributions were derived through a simulation approach for the random coefficient models (Hensher and Greene, 2003; Daly et al., 2011). Specifically, the random coefficients were simulated at the individual level. To illustrate this intermediate step, we provide in Appendix 5 the transformed estimates of coefficients with log-normal and negative log-normal distributions. The empirical distribution of WTP was then derived from the distribution of the ratio of these individual coefficients. Since all random coefficients for attributes follow either a positive or negative log-normal distribution, this ensures that moments of the WTP distributions (e.g., mean and variance) can be calculated (Daly et al., 2012). The WTPs produced by the four models are similar in magnitude. However, an overall increase in the mean value and wider quartiles can be observed as model complexity increases, which is consistent with findings in empirical discrete choice studies (Hess et al., 2004; van den Berg, 2010; Teye, 2014). This indicates that ignoring random taste heterogeneity and substitution patterns can lead to a risk of biased results. The broad range of WTP values also confirms that individuals place different values on distance to parking and time to/from parking. The subsequent analysis thus mainly focuses on the Mixed NL model. The following analysis mainly focuses on the Mixed NL model.

Starting with the WTP for the reduced distance to parking, we first derived the distributions of the marginal utilities for the distance to parking and parking fee attributes. Then, we generated 500 random draws and calculated the ratio of the marginal utility of distance to parking to the marginal utility of parking fee for each sample in this set. Given that both distance to parking and parking fee follow a negative log-normal distribution, the WTP for distance to parking also follows a log-normal distribution, with an estimated mean of CNY 0.81 per 100 metres saved. This result could not be found directly in other research, but similar analysis can be found in Guo et al.'s (2023) study, in which the WTP for a reduction of 100 metres in the picking up distance of DBS was calculated as CNY 0.45 using the NL model. Some studies also focused on the WTP for private bicycle parking (Van Lierop et al., 2018; Kohlrautz and Kuhnimhof, 2025). Kohlrautz and Kuhnimhof (2025) estimated the WTP of cyclists at RWTH Aachen University for various types of bicycle parking facilities and found that the average WTP for reducing the walking distance by 100 metres exceeds 0.20 euros (around CNY 1.58) per day. Van Lierop et al. (2018) observed that 43% of cyclists in Montreal, Canada, were willing to pay over 0.50 dollars (around CNY 3.63) per day for secured bicycle parking.

TABLE 7

WTP calculations for MNL, NL, RCL, ECL and Mixed NL models

Models		Mean and percentiles of distribution				Changes against Mixed NL		
		mean	robust s.e.	s.d.	interquartile range	mean	s.d.	interquartile range
Multinomial logit	WTP (CNY/100 m)$_{\text{parking fee distance to parking}}$	0.62	0.03			-23%		
	VoT (CNY/1 h)$_{\text{parking fee time to/from parking}}$	20	1.02			-24%		
	MRS (m/10 min)$_{\text{distance to parking reward}}$	-54	4.00			-7%		
	MRS (min/10 min)$_{\text{time to/from parking reward}}$	-1.12	0.08			-15%		
Nested logit	WTP (CNY/100 m)$_{\text{parking fee distance to parking}}$	0.66	0.03			-19%		
	VoT (CNY/1 h)$_{\text{parking fee time to/from parking}}$	21.05	1.07			-20%		
	MRS (m/10 min)$_{\text{distance to parking reward}}$	-55	3.77			-5%		
	MRS (min/10 min)$_{\text{time to/from parking reward}}$	-1.15	0.07			-13%		
Random -coefficient logit	WTP (CNY/100 m)$_{\text{parking fee distance to parking}}$	0.81		0.66	0.63	0%	6%	3%
	VoT (CNY/1 h)$_{\text{parking fee time to/from parking}}$	25.8		19.4	19.3	-2%	-8%	-5%
	MRS (m/10 min)$_{\text{distance to parking reward}}$	-56		42.8	42.0	-3%	-29%	-14%
	MRS (min/10 min)$_{\text{time to/from parking reward}}$	-1.23		1.10	1.00	-7%	-24%	-12%
Error -components logit	WTP (CNY/100 m)$_{\text{parking fee distance to parking}}$	0.86		0.73	0.67	6%	18%	10%
	VoT (CNY/1 h)$_{\text{parking fee time to/from parking}}$	27.3		25.2	22.2	3%	19%	9%
	MRS (m/10 min)$_{\text{distance to parking reward}}$	-56		51.4	45.5	-3%	-15%	-7%
	MRS (min/10 min)$_{\text{time to/from parking reward}}$	-1.20		0.94	0.95	-9%	-35%	-17%
Mixed nested logit	WTP (CNY/100 m)$_{\text{parking fee distance to parking}}$	0.81		0.62	0.61			
	VoT (CNY/1 h)$_{\text{parking fee time to/from parking}}$	26.4		21.1	20.3			
	MRS (m/10 min)$_{\text{distance to parking reward}}$	-58		60.1	49.0			
	MRS (min/10 min)$_{\text{time to/from parking reward}}$	-1.32		1.44	1.14			

We also show value of time (VoT) in addition to WTP. Specifically, we replaced the distance to parking attribute with parking time in the model under the assumption that all respondents travel at an average and constant speed, and then re-estimated the parameters. The VoT was derived from the ratio of the marginal utility of parking time to the marginal utility of the parking fee, with the mean value of the VoT distribution estimated at 26.4 CNY per hour. It is important to note that the VoT estimated in this study reflects the overall value of time to/from parking, including both the time required to access the parking area and the walking time from there to the final destination. VoT-related research in China is relatively limited, and there is a lack of official statistical data (Song et al., 2018). Gao K, et al. (2021) estimated the value of travel time for DBS trips in Shanghai to be CNY 30.2 per hour. Kou et al. (2017) obtained the average value of commuting times for public transport and car travel as CNY 11.34 per hour and CNY 17.81 per hour, respectively in Beijing. The VoT estimates obtained in this study are broadly of the same order of magnitude as those reported in the relevant literature.

Additionally, the marginal rate of substitution (MRS) values for the trade-offs between the distance to parking and reward were calculated by dividing the coefficient of the reward attribute by the coefficient of distance to parking, reflecting how individuals trade off increased the distance to parking against the rewards offered. The estimated mean of the MRS distribution for each 10-minute free riding reward is 58 metres, indicating that respondents are willing to accept an additional 58 metres of the distance to parking in exchange for receiving a 10-minute free riding reward. According to the *Standards for the Provision of Non-Motorised Vehicle Parking Facilities in Urban Road Spaces in Beijing* (2023), for areas around the entrances and exits of public transportation with limited space, the establishment of non-motorised vehicle parking facilities is recommended within a range of 50 to 100 metres. Similarly, the MRS between parking time and reward was calculated by dividing the coefficient of the reward attribute by the coefficient of parking time. The results suggest that respondents are willing to spend an average of 1.32 extra minutes proceeding to a designated parking area in exchange for receiving a 10-minute free riding reward.

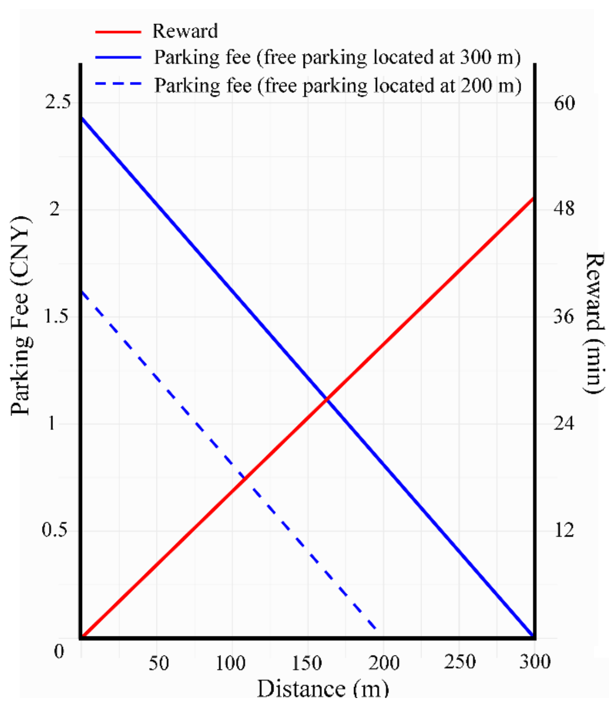

Fig. 6. Conceptual illustration of WTP and MRS variation with distance.

A conceptual illustration of how mean values of WTP and MRS vary with changes in the distance to parking is presented in Fig. 6. The red solid line represents the required riding time reward to encourage users to park in the free parking area as the distance increases. The blue solid and dashed lines indicate the users' willingness to pay for different locations of paid parking areas when the free parking area is located 300m and 200m from the destination, respectively. When the free parking area is located 300 metres from the destination, an average free-riding reward of 51.7 minutes is required to incentivize users to park there. Under this situation, if there is a paid parking area available at the destination, users would be willing to pay approximately CNY 2.4 to reduce the distance to parking. These insights, based on the mean values, may serve as a valuable reference for DBS companies in designing appropriate parking fees and reward levels. However, it is important to note that, at the individual level, the acceptable walking distance does not necessarily increase linearly with the reward. This subsection primarily focuses on the implementation of paid parking areas and incentive-based approaches to encourage the use of remote parking options. While the findings provide useful insights for designing parking management strategies, they have limited direct relevance to policy interventions specifically aimed at reducing disorderly parking.

6. Discussion and conclusion

Dockless bike-sharing has rapidly gained popularity in recent years, offering a sustainable and convenient mode of transportation. However, the accompanying disorderly parking has emerged as one of the most challenging problems for city administrators. This paper presents an in-depth investigation of users' parking preferences in DBS trips, in order to provide a reference for developing targeted policy interventions that encourage orderly parking.

6.1. Theoretical Implications

The present research offers several theoretical implications for the literature on bicycle parking behaviour.

Firstly, this study expands the literature on DBS parking management from the user-based perspective. While prior studies have primarily addressed parking problems through supply-side strategies, such as the planning of designated parking areas and bicycle rebalancing (Zhang et al., 2019; Tian et al., 2020), these approaches often face practical challenges in implementation (Wang et al., 2019; Si et al., 2024; Meng et al., 2024). By examining users' parking preferences and evaluating the behavioural effects of different policy interventions, this study provides a behavioural foundation for the development of more direct parking management strategies to improve parking compliance. There is still a lack of in-depth empirical investigations on this topic.

Secondly, this research improves the modelling of DBS user behaviour by employing a mixed nested logit model that simultaneously accounts for both random taste heterogeneity and inter-alternative correlations. While deterministic taste heterogeneity associated with socioeconomic demographics such as gender and age, has been widely acknowledged in existing studies (Su et al., 2021; Gao et al., 2021; Si et al., 2024), interpersonal random taste heterogeneity has received comparatively little attention (Gao et al., 2021). The present research confirms that different orderly parking alternatives are strongly correlated, and there is significant random taste variation in how users respond to alternative-specific attributes such as proximity to designated parking areas, parking fees, rewards, and fines. Incorporating random taste heterogeneity allows for more accurate estimation of key measures, including the WTP, VoT, and MRS, as ignoring such heterogeneity may lead to biased results (Hess et al., 2004; van den Berg, 2010; Teye, 2014).

Thirdly, the findings of this study may be extended to other forms of micromobility, such as shared e-scooters and private bicycle parking, which also face challenges related to disorderly parking. The behavioural characteristics identified through this study, particularly interpersonal random taste heterogeneity and the influence of the distance to parking, incentives, parking fees and descriptive norms on cyclist parking behaviour, may also be applicable to other forms of micromobility. However, it should be noted that unlike shared micromobility users, private bicycle cyclists are also influenced by factors such as the risk of theft (van Lierop et al., 2018; Jonkeren and Kager, 2021; Kohlrautz and Kuhnimhof, 2025) and the value of the bicycle (Kohlrautz and Kuhnimhof, 2025), which should be taken into account when designing parking management strategies for private bicycles.

Finally, from a methodological perspective, this paper contributes to the limited application of mixed GEV models, which is underutilised in practice due to computational complexity and the lack of estimation options in most commercial econometric software. In the present research, we estimated the model using Apollo, which facilitates for the mixing of any underlying kernel model.

6.2. Practical Implications

The present research provided insights for DBS companies and local governments to improve parking compliance and reduce disorderly parking.

First, the findings indicate that users tend to avoid disorderly parking, particularly female and older individuals. Therefore, it is essential to establish a clear and consistent definition of disorderly parking behaviour and to explicitly communicate it to users to avoid ambiguity. Confusing or inconsistent rules may undermine users' understanding and hinder parking compliance. Furthermore, it is important to consider the taste heterogeneity when developing parking management strategies, as suggested by Kohlrautz and Kuhnimhof (2025). For example, educational and guidance messages could be more actively directed toward male and younger users via the DBS app to enhance parking compliance.

Secondly, we discovered that reducing the distance to parking and imposing monetary penalties for disorderly parking are obviously effective in discouraging such behaviour. When parking spaces near the destination are saturated, users are less willing to proceed to other designated parking areas as the distance to parking increases. This highlights the need for planning high-density DBS parking facilities, especially around high-demand destinations (Meng et al., 2024). In addition, DBS companies should strive to implement technological solutions that enable the prompt identification of disorderly parking and the enforcement of penalties (Tang et al., 2024). Furthermore, this study found that DBS users are willing to accept an average of 58 additional metres of the distance to parking for a 10-minute free riding reward, which provides a practical reference for designing incentive measures to promote orderly parking.

Thirdly, we found that descriptive norms significantly impact users' utility when choosing parking behaviour. When users observe a greater number of others engaging in disorderly parking, they are more likely to exhibit similar behaviour. This suggests that timely detection and repositioning of disorderly parked bicycles are crucial for preventing the accumulation of bicycles.

Finally, this study considers paid parking as a potential management strategy when the designated free parking area is located far from the destination. We found that users are willing to pay approximately CNY 0.81 to reduce the distance to parking by 100 metres. Paid bicycle parking has mainly been studied in relation to private bicycles, including cases in the Netherlands (Molin and Maat, 2015), Canada (van Lierop et al., 2018), and Germany (Kohlrautz and Kuhnimhof, 2025), but has not yet been considered in the context of DBS. Nevertheless, we believe that paid parking could still be explored as a viable strategy for managing DBS parking. Given that DBS companies often lack incentives to actively manage parking due to cost concerns, allowing them to operate paid parking spaces near high-demand locations such as metro stations or business districts under government authorization and charge parking fees directly through the app may offer a profitable model. This could encourage greater operator involvement in parking management and reduce the burden currently placed primarily on local governments.

6.3. Limitations

One limitation of this study is the insufficient consideration of the ordering effect in the stated choice experiment design. The presentation order of alternatives within the choice set has been recognised to influence choice outcomes in some literature (Garbarski et al., 2016; Boxebeld, 2024). To improve the validity of stated preference data, future research should consider implementing mitigative measures, such as randomizing the positions of labeled alternatives in the choice set and then incorporating position indicators into the model specification to account for potential ordering effects. Another limitation of the experimental design lies in the presentation of both the distance to parking and the corresponding round-trip time in the SC tasks. The intent was to assist respondents who may not have a clear perception of distance, as time is often a more intuitive reference in travel contexts. However, because time and distance are distinct concepts, and individuals may perceive or respond to them differently, this approach may have influenced how respondents evaluated the attribute, which was not fully accounted for in the experimental design. Moreover, the SC survey did not explicitly state that fines would be strictly enforced, which may have led some respondents to infer the likelihood of enforcement based on their prior experiences, potentially introducing bias. Nevertheless, this should not have substantial influence on the estimated direction of the fine coefficient.

From a methodological perspective, this study relies solely on SP data, which is useful for examining hypothetical choices by hypothesizing alternatives and attributes, but it has potential limitations related to the veracity of individuals' stated responses, which may lead to inconsistencies with users' realistic parking preferences (Helveston et al., 2018). In addition, the assessment of the effectiveness of policy interventions derived based on the study sample and the SP scenario offers theoretical insights, but may have limited generalisability to real-world conditions. Combining RP and SP data in model estimation could overcome the weaknesses of each data source. It is recommended to use the pooled RP and SP data in the future to reduce bias from hypothetical choice situations. Additionally, some latent factors such as personal attitudes, ascription of responsibility, awareness of consequences, and personal norms have also been proven to influence users' parking choices in previous studies (Wang et al., 2021b; Tang et al., 2024). However, this type of data is not reflected in the data used to develop the present model. Future studies are encouraged to integrate latent variables into discrete choice models, to enhance the understanding of the impact of unobserved factors on DBS users' decision-making processes.

6.4. Conclusions

This paper developed a mixed nested logit model to simultaneously account for both random taste heterogeneity and inter-alternative correlations in dockless bike-sharing parking preference. Based on the SP data collected in China, this study examined how DBS users' parking choices are influenced by socioeconomic characteristics and alternative-specific factors, while also evaluating the effectiveness of various policy interventions. The findings confirm the existence of random taste heterogeneity in preferences for the distance to parking, rewards, fines, and parking fees, and demonstrate that reducing the distance to parking and imposing penalties are effective strategies for discouraging disorderly parking. Users' willingness to accept additional distance to parking in exchange for free riding time rewards, as well as their willingness to pay to reduce the distance to parking, was also estimated. This study contributes to the literature on DBS parking management by extending the empirical understanding of parking behaviour. Moreover, the results offer empirical evidence for local governments and DBS operators in formulating more effective parking policies to mitigate disorderly parking.

CRediT authorship contribution statement

Shujing Zhang: Conceptualization, Methodology, Investigation, Formal Analysis, Data curation, Writing – original draft. **Thomas O. Hancock**: Conceptualization, Methodology, Writing - review & editing. **Stephane Hess**: Conceptualization, Methodology, Writing - review & editing. **Shunping Jia**: Conceptualization, Writing - review & editing, Supervision.

Acknowledgement

Thomas O. Hancock and Stephane Hess acknowledge support from the European Research Council through the advanced grant 101020940-SYNERGY.

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Appendix 1. Demographics and usage characteristics of the survey respondents.

Characteristics	Categories	Number	Percentage (%)
Gender	Male	252	42
	Female	348	58
Age group	≤20	25	4.2
	21-30	362	60.3
	31-40	140	23.3
	41-50	51	8.5
	≥51	22	3.7
Income per month (CNY)	≤2000	69	11.5
	2001–4000	104	17.3
	4001–6000	95	15.8
	6001-8000	94	15.7
	8001–10000	89	14.8
	≥10001	141	23.5
	I'd rather not to say.	8	1.3
Education level	High school/technical secondary school	20	3.3
	Junior college	45	7.5
	Undergraduate	422	70.3
	Master	106	17.7
	Ph.D. and above	7	1.2
Occupation	Employed full time	431	71.8
	Employed part time (less than 24 hours/week)	7	1.2
	Self-employed or unemployed	26	4.3
	Retired	2	0.3
	Student	134	22.3
Bike ownership	No	235	39.2
	Yes	365	60.8
Use frequency	Once every few months or less	34	5.7
	At least once a month	59	9.8
	1-2 times a week	244	40.7
	3-5 times a week	194	32.3
	Once a day or more	69	11.5
Average riding duration(min)	≤10	57	9.5
	11–20	367	61.2
	21–30	148	24.7
	≥30	28	4.7
City of residence	Cities with geo-fencing implementation	129	21.5
	Cities without geo-fencing implementation	471	78.5

Note: *CNY/USD ≈0.138 during survey period*

Appendix 2. Model estimation results for MNL, NL, MMNL, Mixed NL models incorporating riding frequency and duration covariates.

Parameters	Multinomial logit		Nested logit		Mixed multinomial logit		Mixed nested logit	
	Est.	Rob. t_rat.	Est.	Rob. t_rat.	Est.	Rob. t_rat.	Est.	Rob. t_rat.
Means of utility coefficients								
$\delta_{\text{free parking area}}$	0	—	0	—	0	—	0	—
$\delta_{\text{paid parking area}}$	-0.644	-8.08***	-0.558	-9.13***	-1.096	-8.84***	-0.859	-8.80***
$\delta_{\text{disorderly parking}}$	-1.446	-5.38***	-1.191	-4.72***	-2.15	-4.37***	-1.743	-4.04***
$\omega_{\text{female, disorderly parking}}$	-0.356	-2.84***	-0.332	-2.80***	-0.671	-2.55**	-0.575	-2.62***
$\omega_{\text{age, disorderly parking}}$	-0.189	-2.28**	-0.185	-2.36**	-0.545	-3.45***	-0.473	-3.40***
β_{reward}	0.043	4.62***	0.034	4.70***				
$\omega_{\text{riding frequency, reward}}$	-5.9979e-04	-0.31	-6.0351e-04	-0.42	-7.7179e-04	-0.244	-4.4152e-04	-0.19
$\omega_{\text{riding duration, reward}}$	-0.005	-1.75*	-0.003	1.63	-0.008	-1.82*	-0.005	-1.65*
$\beta_{\text{distance to parking}}$	-7.045	-10.43***	-5.592	-8.94***				
$\omega_{\text{riding frequency, distance to parking}}$	0.155	1.18	0.138	1.28	0.282	1.17	0.156	0.79
$\omega_{\text{riding duration, distance to parking}}$	0.414	2.244**	0.138	2.10**	0.592	1.87*	0.354	1.37
$\beta_{\text{parking fee}}$	-0.899	-18.46***	-0.667	-12.21***				
$\eta_{\text{income, parking fee}}$	-0.148	-3.52***	-0.149	-3.50***	-0.111	-2.46**	-0.102	-2.21**
β_{fine}	-1.343	-24.50***	-1.262	-24.07***				
$\beta_{\text{no others}}$	0	—	0	—	0	—	0	—
$\beta_{\text{other people}}$	0.549	7.66***	0.562	8.49***	0.827	6.02***		
$\beta_{\text{other people low}}$							0.666	5.25***
$\beta_{\text{other people high}}$							0.893	6.29***
Standard deviations of utility coefficients								
$\sigma_{\delta_{\text{paid parking area}}}$					0.566	3.38 ***	0.423	3.32***
$\sigma_{\delta_{\text{disorderly parking}}}$					2.304	12.92***	-1.96	-11.63***
Location parameters on log-scale								
$\mu_{\beta_{\text{reward}}}$					-2.749^	-11.42***	-3.043^	-12.23***
$\mu_{\beta_{\text{distance to parking}}}$					2.53^^	24.51***	2.232^^	17.14***
$\mu_{\beta_{\text{parking fee}}}$					0.447^^	7.59***	0.190^^	2.45**
$\mu_{\beta_{\text{fine}}}$					1.278^^	18.84***	1.097^^	15.16***
Log-scale standard deviations								
$\sigma_{\beta_{\text{reward}}}$					-0.401^	-3.31***	-0.427^	-3.96***
$\sigma_{\beta_{\text{distance to parking}}}$					-0.405^^	-8.87***	-0.443^^	-7.83***
$\sigma_{\beta_{\text{parking fee}}}$					-0.538^^	-7.68***	-0.537^^	-8.114***
$\sigma_{\beta_{\text{fine}}}$					-0.666^^	13.06***	-0.642^^	-9.33***

Nesting coefficient				
$\lambda_{\text{orderly parking}}$	0.706	15.57***	0.690	14.68***

Note:
* Signify confidence at 90%, ** Signify confidence at 95%, *** Signify confidence at 99%.
^ means the coefficient is log-normally distributed by assumption, ^^ means the coefficient is negative log-normally distributed by assumption.
For coefficients assumed to follow a log-normal distribution, the estimated means and standard deviations refer to the parameters that directly define the probability density function of the log-normal distribution; the same applies to negative log-normal distribution.

Appendix 3. Estimate results of alternative nesting structures.

Estimate results	$NL_{orderly\_parking}$	$NL_{paid\_disorderly}$	$NL_{existing}$
$\lambda_{orderly\ parking}$	0.706		
$\lambda_{paid\ disorderly}$		0.727	
$\lambda_{existing}$			1.891
Goodness-of-fit			
Number of estimated parameters	11	11	11
LL (final)	-5572.85	-5571.95	-5487.31
Adj. ρ^2	0.2941	0.2942	0.3049
AIC	11167.69	11165.89	10996.63
BIC	11243.39	11241.59	11072.33
Likelihood ratio test (value)	38.06	39.86	209.14
Likelihood ratio test (p value)	$6.86\times e^{-13}$	$2.728\times e^{-10}$	$2.116\times e^{-47}$

Appendix 4. Base values and corresponding adjusted attribute values used in the prediction.

Attributes	Relative changes	Choice tasks											
		1	2	3	4	5	6	7	8	9	10	11	12
Distance to parking (free)/m	-30%	560	560	560	350	350	350	350	140	560	140	350	560
	-20%	640	640	640	400	400	400	400	160	640	160	400	640
	-10%	720	720	720	450	450	450	450	180	720	180	450	720
	base	**800**	**800**	**800**	**500**	**500**	**500**	**500**	**200**	**800**	**200**	**500**	**800**
	10%	880	880	880	550	550	550	550	220	880	220	550	880
	20%	960	960	960	600	600	600	600	240	960	240	600	960
	30%	1040	1040	1040	650	650	650	650	260	1040	260	650	1040
Rewards/ CNY	-30%	7	14	7	0	21	14	0	21	7	14	0	21
	-20%	8	16	8	0	24	16	0	24	8	16	0	24
	-10%	9	18	9	0	27	18	0	27	9	18	0	27
	base	**10**	**20**	**10**	**0**	**30**	**20**	**0**	**30**	**10**	**20**	**0**	**30**
	10%	11	22	11	0	33	22	0	33	11	22	0	33
	20%	12	24	12	0	36	24	0	36	12	24	0	36
	30%	13	26	13	0	39	26	0	39	13	26	0	39
Distance to parking (paid)/m	-30%	210	70	140	70	140	140	210	70	140	70	210	210
	-20%	240	80	160	80	160	160	240	80	160	80	240	240
	-10%	270	90	180	90	180	180	270	90	180	90	270	270
	base	**300**	**100**	**200**	**100**	**200**	**200**	**300**	**100**	**200**	**100**	**300**	**300**
	10%	330	110	220	110	220	220	330	110	220	110	330	330
	20%	360	120	240	120	240	240	360	120	240	120	360	360
	30%	390	130	260	130	260	260	390	130	260	130	390	390
Parking fee/CNY	-30%	0.35	0.35	0.7	1.4	0.35	1.4	0.7	0.35	0.7	0.35	0.35	1.4
	-20%	0.4	0.4	0.8	1.6	0.4	1.6	0.8	0.4	0.8	0.4	0.4	1.6
	-10%	0.45	0.45	0.9	1.8	0.45	1.8	0.9	0.45	0.9	0.45	0.45	1.8
	base	**0.5**	**0.5**	**1**	**2**	**0.5**	**2**	**1**	**0.5**	**1**	**0.5**	**0.5**	**2**
	10%	0.55	0.55	1.1	2.2	0.55	2.2	1.1	0.55	1.1	0.55	0.55	2.2
	20%	0.6	0.6	1.2	2.4	0.6	2.4	1.2	0.6	1.2	0.6	0.6	2.4
	30%	0.65	0.65	1.3	2.6	0.65	2.6	1.3	0.65	1.3	0.65	0.65	2.6
Fine/ CNY	-30%	0.7	0.7	0	3.5	2.1	0	3.5	0	2.1	0	3.5	2.1
	-20%	0.8	0.8	0	4	2.4	0	4	0	2.4	0	4	2.4
	-10%	0.9	0.9	0	4.5	2.7	0	4.5	0	2.7	0	4.5	2.7
	base	**1**	**1**	**0**	**5**	**3**	**0**	**5**	**0**	**3**	**0**	**5**	**3**
	10%	1.1	1.1	0	5.5	3.3	0	5.5	0	3.3	0	5.5	3.3
	20%	1.2	1.2	0	6	3.6	0	6	0	3.6	0	6	3.6
	30%	1.3	1.3	0	6.5	3.9	0	6.5	0	3.9	0	6.5	3.9
Number of other people parking disorderly		**0**	**2**	**2**	**2**	**1**	**2**	**0**	**0**	**1**	**1**	**0**	**1**

Appendix 5. Transformed estimates of coefficients with log-normal and negative log-normal distributions.

Models	Parameters	Distribution	mean	s.d.	interquartile range
Random -coefficient logit	β_{reward}	log-normal distribution	0.049	0.02	0.03
	$\beta_{\text{distance to parking}}$	negative log-normal distribution	-11.117	5.83	6.67
	$\beta_{\text{parking fee}}$	negative log-normal distribution	-1.802	1.00	1.12
	β_{fine}	negative log-normal distribution	-4.398	3.27	3.27
Error -components logit	β_{reward}	log-normal distribution	0.051	0.03	0.04
	$\beta_{\text{distance to parking}}$	negative log-normal distribution	-11.574	6.05	6.92
	$\beta_{\text{parking fee}}$	negative log-normal distribution	-1.819	1.08	1.18
	β_{fine}	negative log-normal distribution	-4.716	3.71	3.60
Mixed nest logit	β_{reward}	log-normal distribution	0.039	0.03	0.03
	$\beta_{\text{distance to parking}}$	negative log-normal distribution	-8.536	4.44	5.09
	$\beta_{\text{parking fee}}$	negative log-normal distribution	-1.319	0.66	0.76
	β_{fine}	negative log-normal distribution	-3.600	2.57	2.62