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Spatial-temporal heterogeneity and built environment nonlinearity in inconsiderate parking of dockless bike-sharing

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ABSTRACT

Although previous studies have shed light on the travel behaviour of dockless bike-sharing (DBS) users, little research focused on their inconsiderate parking behavior. Unlike the travelling behavior, the choice of parking location is closely linked to the different built environments surrounding the parking locations. Therefore, to improve the efficiency of governance, it is vital to explore the parking patterns and heterogeneous influences of the built environment on inconsiderate parking and formulate targeted measures. This paper measures the coordinates of prohibited parking areas in the field to identify inconsiderate parking. Based on big data from Mobike DBS and data on the built environment, the paper empirically analyzes the heterogeneous spatiotemporal distribution patterns of inconsiderate parking with clustering and decision trees. The influencing factors of inconsiderate parking and their nonlinear effects are further analyzed using random forest and partial dependence plots (PDP). The results show that there is significant spatiotemporal heterogeneity in inconsiderate parking, in which different clusters reflect various characteristics of the built environment. Furthermore, marginal effect analysis finds that influencing factors such as riding distance, catering service places, lifestyle services, sports and leisure places, and hotels and hostels have a strong effect on inconsiderate parking behavior, and show nonlinear effects with optimal allocation intervals. Therefore, targeted strategies should be carried out in terms of dynamic temporal adjustment, precise spatial layout, differential management according to time and zone, and cause-assisted administration. The paper's results provide important decision-making support for inconsiderate parking.

1. Introduction

Dockless bike-sharing (DBS) has become popular as a green and flexible mode of transport for an increasing number of cities. DBS has been shown to reduce emissions of CO_2 and noxious gases, diminish traffic congestion, and improve accessibility (Li and Kamargianni, 2018; Zhang and Mi, 2018; Qin and Liao, 2021). However, the characteristics of DBS, such as dockless parking and mass deployment, have also led to inconsiderate parking and inefficient utilization of resources, which not only renders the urban traffic space more confined and affects normal traffic and overall order but also acts as a major obstruction to convenient usage by citizens

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and the operation and management of shared bicycles by enterprises and governments (Gao et al., 2021; Laa and Emberger, 2020). Therefore, reducing inconsiderate parking in DBS will be critical.

Inconsiderate parking usually refers to parking shared bikes in prohibited parking areas designated by DBS companies. However, the prohibited parking areas set up by bike-sharing companies are relatively simple and do not fully match the prohibited parking areas specified by laws and regulations. For example, in Beijing, the prohibited parking areas set up by Mobike are mainly in Chang'an Street, crowded hutongs and grassy parks. Prohibited parking areas such as hospital entrances, intersections and pedestrian crossings (see Fig. 1) are usually not designated. The negative externalities associated with inconsiderate parking in these areas cannot be ignored, as there have been many reports of DBS parked in front of hospitals, preventing patients from entering or leaving. The banned parking areas analysed in this paper are based on legislation and regulations, combined with field research, which can more comprehensively identify inconsiderate parking, disorderly parking and other behaviours that cannot be identified by the banned parking areas set up by the company.

At present, DBS users have insufficient motivation, awareness and cooperation for considerate parking. Therefore, the management of inconsiderate parking in DBS mainly depends on enterprises and governments. Enterprises mainly use operational planning and user intervention to manage inconsiderate parking. However, inconsiderate parking behaviour is complex and diverse, and has differentiated spatial and temporal characteristics (Gu et al., 2019; Hui et al., 2022). The existing operational planning cannot flexibly respond to the changing patterns of inconsiderate DBS parking, and has high management costs and pressures. According to Baoshan District, Shanghai, in December 2021, DiDi Bike will have about 20,000 bikes in Baoshan District, with 43 operators and maintenance staff, responsible for 400 bikes per capita; Meituan Bike will be responsible for 3,000 bikes per capita in Baoshan District, and the labour supply is not enough to meet the daily operation and maintenance demand. Therefore, there is an urgent need for managers to clarify the spatial and temporal patterns and mechanisms of indiscriminate parking, and improve the efficiency of operation, maintenance, guidance and management accordingly.

The government mainly uses parking space planning to regulate DBS parking, but the number, size and location of parking spaces require comprehensive consideration of factors such as the number of bicycles, hotspot parking spaces and the surrounding built environment, and systematic planning from the urban management level. Inconsiderate DBS parking shows greater heterogeneity in different built environments (Liu et al., 2018; Xing et al., 2020; Wu et al., 2021), such as in front of hospitals and near metro stations, where inconsiderate parking is more likely to occur. This heterogeneity implies the need for differentiated parking policies. Therefore, an in-depth study of the spatio-temporal patterns and heterogeneous influences of the built environment on inconsiderate parking is a crucial development direction for the management of inconsiderate parking in DBS.

Previous studies on DBS have focused on riding characteristics rather than parking characteristics (Wu et al., 2021; Chen and Ye, 2021; Wang et al., 2022), and there is a lack of understanding of the characteristics and patterns of inconsiderate parking. In terms of the analysis of factors that influence inconsiderate parking, the literature mainly explores the influence of socioeconomic attributes, psychological characteristics, and external incentives of DBS users on inconsiderate parking using a stated preference (SP) experimental approach (Gao et al., 2021b; Su et al., 2020; Wang et al., 2021a; Gao et al., 2021a). There is a lack of evidence, based on big data, on the impact of the external environment on inconsiderate parking. Moreover, prior literature analyzes the main factors that affect DBS parking, including the intensity of cycling, natural environment, psychological attitudes, and built environment (Guo et al., 2022), with the built environment as the key factor that affects the use of DBS. Many scholars have analyzed the influence of the built environment on DBS usage (Wu et al., 2021; Chen and Ye, 2021; Guo and He, 2020; Ji et al., 2018; Duran-Rodas et al., 2019) and the interaction between the built environment and temporal attributes (Mateo-Babiano et al., 2016; Li et al., 2022), but few studies have analyzed the influence of the built environment on patterns of inconsiderate DBS parking.

This paper measures prohibited parking zones in the field based on existing regulations and used big data on regional parking data from Mobike to analyze the spatial and temporal distribution characteristics of parking, especially inconsiderate parking. Using a machine learning approach, the influence of the built environment and temporal attributes on heterogeneous parking patterns has been further investigated. The influence factors of inconsiderate parking are also explored by considering trip characteristics, the built

(a) Parked in a pedestrian crossing (b) Parked in a motor lane

Fig. 1. Inconsiderate parking of DBS (Picture from the internet. http://k.sina.com.cn/article_1893892941_70e2834d02000t791.html?cre=tianyi&mod=pcpager_fin&loc=38&r=9&rfunc=32&tj=none&tr=9 and https://baijiahao.baidu.com/s?id=1697735490955295445).

environment, and weather factors based on a random forest (RF) method. The nonlinear effects of the influencing factors based on partial dependence plots (PDP) are further analyzed to better depict the internal influence mechanism (Chen et al., 2021). Based on study results, suggestions for targeted management are proposed from the perspectives of dynamic adjustment in time, precise spatial layout, differential management in time zones, and cause-assisted management.

The paper makes four main contributions. First, based on big data from Mobike DBS, we analyze the heterogeneous spatiotemporal pattern of inconsiderate parking. Second, we measure the coordinate range of inconsiderate parking areas through extensive field investigation and matched it with Mobike's data in ArcGIS to overcome the difficulties of identifying inconsiderate parking. Third, we identify the spatial and temporal heterogeneity of the built environment near parking spots by clustering and decision tree analysis. This provides important evidence and information that forms the basis for subsequent targeted management measures. And fourth, we further examine the nonlinear effects of key variables on inconsiderate parking and offer targeted policy implications.

The paper is organized as follows. Section 2 reviews the relevant literature and Section 3 introduces the data and research methodology. Section 4 reports on the empirical analysis, Section 5 discusses the results and suggests targeted governance measures, and Section 6 concludes.

2. Literature

2.1. Research on DBS usage and parking

Existing research links DBS origins and destinations as OD pairs to analyse DBS usage characteristics, including distance, frequency and duration of DBS trips (Xing et al., 2020; Wang et al., 2022; Ji et al., 2020). These dynamic characteristics are not present in parking behaviour. Many studies also used the average trips of departure and arrival within an area to characterise DBS usage (Liu and Lin, 2019; Wu et al., 2021). The characteristics of DBS usage by analysing both the origin and destination of DBS trips have been explored in the literature. However, some studies have found differences in DBS departure and arrival patterns (Guo et al., 2022). For example, in terms of time, arrivals are high but departures are low in school mornings and the opposite is true in the evenings (Faghih-Imani et al., 2014; Faghih-Imani and Eluru, 2016b). The number of DBSs departing and arriving from residential areas differs between weekends and weekdays (Noland et al., 2016; Zhang et al., 2017). Spatially, Sun et al. (2018) and Liu and Lin (2019) found that DBS users were more likely to choose commercial areas as destinations, but less likely to depart from commercial areas and around parks. Liu and Lin (2019) found that a safe and comfortable cycling environment increased departures rather than arrivals. All of these findings point to the importance of analysing park characteristics separately.

And DBS parking is usually associated with the purpose of the trip. Xing et al. (2020) used K-means clustering based on trip records and their surrounding POI data to show that on weekdays, DBS origins and destinations typically fall into one of five categories: dining, transportation, shopping, work, and residential. Zhang et al (2021) applied a regression model that considered built environment factors at both origin and destination and found that most rides ended at a metro station. In summary, previous studies have only examined parking decisions as one aspect of car trips. Even when they mentioned parking behaviour, most studies only discussed where drivers preferred to park and did not explore whether the parking location was appropriate. As a result, the characteristics and patterns of inappropriate parking are rarely considered.

2.2. Impact of the built environment on DBS

Most studies on the impact of the built environment on DBS have been conducted in two ways. First, by directly analyzing the impact of the built environment on DBS usage (El-Assi et al., 2017). Many studies have found that areas around residential and commercial districts (Wu et al., 2021; Chen and Ye, 2021) and near metro and bus stations (Guo and He, 2020; Ji et al., 2018; Lin et al., 2019) and entertainment venues (Duran-Rodas et al., 2019; Ma et al., 2020) often account for a significant number of DBS trips. And second, by analyzing both temporal factors and the built environment to explore the impact of built environment attributes on different types of temporal usage of shared bikes (Faghih-Imani and Eluru, 2016a; Faghih-Imani and Eluru, 2016b; Mateo-Babiano et al., 2016). For example, Xu et al. (2019) found that residential density, commercial density, and the number of intersections on roads were associated with temporal patterns of usage. Li et al. (2022) found that the impact of built environment variables on DBS usage varied by spatial characteristics. Some studies have analyzed DBS usage patterns and types of usage (Ma et al., 2020; Liu and Lin, 2022; Zhang et al., 2021), but few have examined the impact of the built environment on spatiotemporal patterns of DBS usage. We only found one study, by Liu and Lin (2019), that analyzed the influence of the built environment and temporal attributes on different spatiotemporal patterns by establishing an interaction term between built environment attributes and temporal periods. However, their study focused on usage patterns and lacked insight into the formation of parking patterns and the heterogeneity of the built environment in terms of DBS parking patterns.

In terms of methodology, the literature has used three main approaches to analyse the impact of the built environment. The most commonly used is the regression model (Zhang et al., 2017), including the ordinary least squares (OLS) model (Liu et al., 2019), the geographically weighted regression (GWR) model (Li et al., 2022), and the negative binomial regression (Guo and He, 2020).The regression model ignores the non-linear effects of the influencing factors (Chen and Ye, 2021; Li et al., 2022). The second is the decision tree model. For example, Chen and Ye (2021) used gradient-boosted regression trees (GBDT) to explore the nonlinear effects of the built environment on DBS. Ding et al. (2018) used the gradient-boosted decision tree (GBDT) model to analyse the effects of the built environment on distance travelled. However, the GBDT model is overly sensitive to anomalous data. The third is random forest. For example, Wang et al. (2022) used a Random Forest (RF) model to investigate the effect of influencing factors on the number of trips at origin and destination, and used a Partial Dependency Diagram (PDP) to investigate the non-linear effects of influencing factors. Chen et al. (2021) used random forest to analyse the ranking of built environment factors affecting multimodal transport. Existing research suggests that decision tree and random forest (RF) models have the advantage of being non-parametric and can capture complex non-linear relationships between variables (Wang et al., 2022).

2.3. The characteristics and factors that influence inconsiderate parking

The literature on the factors that influence inconsiderate parking concentrates on the effect of psychological characteristics on bike-sharing users. Gao et al. (2021) employed a stated preference survey with 453 respondents and showed that monetary rewards and fines, as positive and negative incentives, motivated people to park their shared bikes in areas near their destinations where parking was not saturated. Su et al. (2020) found that warning messages and rewards encouraged regulated parking through random field experiments. Wang et al. (2021a) used questionnaires and demonstrated that social norms influenced users' orderly parking via personal norms. Wang et al. (2021b) and Wei et al. (2022) found that social norms, moral norms, reciprocity, communication responsibility, and institutional environment play an important role in regulating DBS parking behavior. These studies have analyzed the influence of the sociodemographic characteristics and psychological factors of users on inconsiderate parking behavior but have not considered the effects of the built environment, weather, and other external factors, and therefore lack the foundation to make recommendations on infrastructure, etc.

3. Data sources and research methods

3.1. Data sources and data processing

This study uses regional big data provided by Mobike DBS, Beijing's points of interest data, and weather data to analyze the spatiotemporal characteristics of shared bike parking and the factors that influence inconsiderate parking. DBS riding data consist of specific trip information generated within a 1.5 km radius of Beijing West Railway Station from August 1, 2018, to October 31, 2018, provided by Beijing Mobike Technology Co. The study area covers a radius of 1.5 km around Beijing West Station and is shown as the red circled area in Fig. 2. As one of the four major railway passenger stations in Beijing, with an average daily passenger flow of over

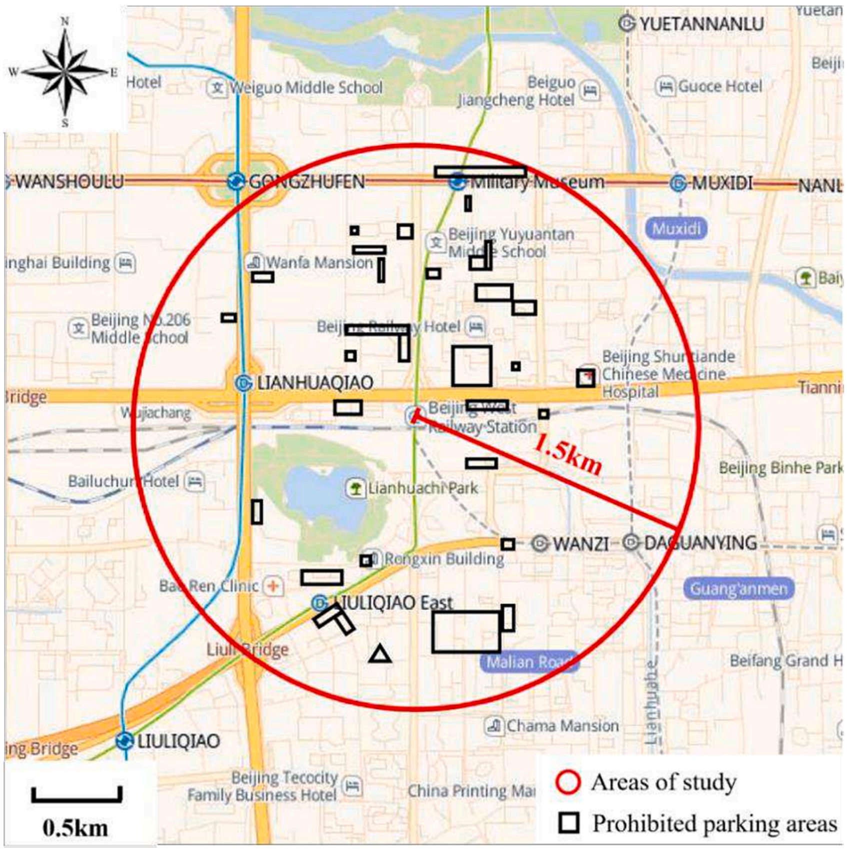


Fig. 2. The identified inconsiderate parking areas and total study area.

200,000, Beijing West Railway Station is a premium railway station that connects travellers nationwide. It is conducive to the study of the role of shared bikes in intercity travel, and can well reflect the articulating role of transport hubs. In addition, the study area covers all types of the built environment and can reflect concurrent parking patterns within a sufficiently large area to be representative. The full sample dataset specifically contains the trip order ID, latitude and longitude of origin, latitude and longitude of destination, total ride duration, total ride distance, ride start time and end time, the centre point to which the ride trip belongs, and the order date for each trip.

Riding characteristics include whether it was inconsiderate parking, riding distance, riding duration, parking time, parking date, week and whether it was a holiday. The riding distance, riding duration and date of parking are continuous variables. Whether the parking is inconsiderate, parking time, week and whether it is a holiday are dummy variables.

The parking time consists of a series of dummy variables: whether the parking time is from 0:00 to 4:00 (end_time1), whether the parking time is from 4:00 to 8:00 (end_time2), whether the parking time is from 8:00 to 12:00 (end_time3), whether the parking time is from 12:00 to 16:00 (end_time4) and whether the parking time is from 16:00 to 20:00 (end_time5). The week is represented by four dummy variables: whether it is Monday (Mon), whether it is Tuesday (Tue), whether it is Wednesday (Wed) and whether it is Thursday (Thur).

Points of interest (POIs) are geographic information commonly used in electronic maps to identify specific facilities in space and often provide the main data support in studies related to the urban built environment. To further study the effect of land usage elements in the built environment on shared bike parking behavior, we collected 12 categories of POI data using the Gaode API platform; each includes the latitude and longitude coordinates of a specific point of interest and the category to which it belongs. These 12 categories of POI data provide a detailed overview of the locations of travel activities in residents' urban lives. According to the latitude and longitude of the destination of each trip, the number of POIs within 100 m of the destination (parking location) of each trip is extracted.

The weather has an important influence on riding and parking behavior. This study employs the variables of air quality index, weather conditions, wind power, and the average temperature of a day to characterize the weather. The data are from the China Meteorological Data Network. Average temperature, wind power and the air quality index are continuous variables, and weather conditions is a dummy variable, which consists of two binary variables, whether it is sunny (sunny) and whether it is rainy (rainy). Table 1 shows the basic data set, which mainly consists of three dimensions: riding characteristics, the built environment, and weather factors.

Table 1
Data sets and related explanations.

	Variate	Meaning	Average	Standard deviation	Min	Max	Observation
	incon_pa	Inconsiderate parking (yes = 1)	0.08	0.27	0	1	522,739
Riding data	tt	Riding duration (minute)	9.62	7.60	3	120	522,739
	end_time1	Parking time: 0:00–4:00 (yes = 1)	0.01	0.08	0	1	522,739
	end_time2	Parking time: 4:00–8:00 (yes = 1)	0.15	0.36	0	1	522,739
	end_time3	Parking time: 8:00–12:00 (yes = 1)	0.26	0.44	0	1	522,739
	end_time4	Parking time: 12:00–16:00 (yes = 1)	0.20	0.40	0	1	522,739
	end_time5	Parking time: 16:00–20:00 (yes = 1)	0.08	0.28	0	1	522,739
	dis	Riding distance (meters)	1406.86	1359.60	30	19,979	522,739
	ds	Date of parking (1–92)	47.96	27.89	1	92	522,739
	Mon	Whether it is a Monday (yes = 1)	0.13	0.34	0	1	522,739
	Tues	Whether it is a Tuesday (yes = 1)	0.15	0.36	0	1	522,739
	Wed	Whether it is a Wednesday (yes = 1)	0.18	0.39	0	1	522,739
	Thur	Whether it is a Thursday (yes = 1)	0.16	0.36	0	1	522,739
	weekend	Whether it is a holiday (yes = 1)	0.26	0.44	0	1	522,739
Built environmental data	POI1	Number of catering service places	4.52	7.17	0	42	522,739
	POI2	Number of public facilities	0.38	0.74	0	4	522,739
	POI3	Number of companies	0.57	1.65	0	11	522,739
	POI4	Number of transportation facilities	1.98	2.32	0	11	522,739
	POI5	Number of scientific and educational institutions	1.26	2.76	0	16	522,739
	POI6	Number of financial and insurance institutions, etc	0.85	1.67	0	11	522,739
	POI7	Number of hotels and hostels	0.73	1.30	0	16	522,739
	POI8	Number of living service places	4.03	5.25	0	27	522,739
	POI9	Number of sports and leisure places	0.46	0.88	0	4	522,739
	POI10	Number of healthcare facilities	0.52	1.10	0	10	522,739
	POI11	Number of government offices	1.02	2.09	0	16	522,739
	POI12	Number of business residences	4.52	7.17	0	42	522,739
Whether factors	tem	Average temperature (℃)	19.90	6.72	8.5	31.5	522,739
	sunny	Whether it is sunny (yes = 1)	0.34	0.47	1	1	522,739
	rainy	Whether it is rainy (yes = 1)	0.18	0.38	1	1	522,739
	wind	Wind power (1–6)	1.70	0.75	1	3	522,739
	air	Air quality index	59.94	35.34	21	198	522,739

Note: The number of POIs in the table is calculated with a search radius of 100 m, centred on the parking location.

We dropped data in which the latitude and longitude of the destination in the sample data exceeded the boundaries using the location selection function of ArcGIS. We only retained riding data for distances between 30 m and 20,000 m, since shared bikes are generally used by residents to travel short distances. Trips of less than 30 m were likely to have been made by users who stopped riding after riding a short distance because the bike had mechanical problems; trips of more than 20,000 m usually last more than two hours and they are likely to be made by users who forget to lock the bike after riding. Such rides are abnormal and were excluded to ensure the validity of the results. Similarly, we filtered orders with travel times of less than 2 min or greater than 120 min.

3.2. Delineation of prohibited parking areas

We critically calibrated our identification of prohibited parking areas through field measurements. The literature and the setting of prohibited parking areas for DBS mainly concern military, administrative, and attraction areas, and the delineation of prohibited areas were broad—for example, near Tiananmen Square in Beijing and the east side of Chang'an Street did not allow shared bike parking. However, such arrangements were not effective in binding users, and inconsiderate parking in pedestrian crossings and underground passages was not accurately identified. Therefore, in this paper, we accurately measured prohibited parking areas by conducting field research based on laws and regulations. The mapping algorithm is imported into the ArcGIS map module to accurately construct strictly delineated criteria. This enabled us to lay a solid foundation for precisely identifying users' inconsiderate parking behavior at a later stage.

No variable in Mobike's riding data identifies whether riders parked inconsiderately. Therefore, based on the literature and the Beijing Regulations on the Management of Non-Motorized Vehicles and Technical Guidelines on the Technical Design of Bicycle Parking Areas, we identified some of the following areas as prohibited DBS parking areas by examining inconsiderate parking areas in the field.

① Prohibited parking areas in and around military areas: Signs in front of military zones usually indicate that parking is prohibited.
② National Tax Administration: The path in front of the National Tax Administration.
③ Crossroads: Shared bikes should not be parked at crossroads, especially at intersections of major roads.
④ In front of hospitals: Shared bikes should not be parked in densely populated areas such as hospitals.
⑤ In front of train stations: Prohibited parking zones are identified by lines painted in front of train stations.
⑥ In front of companies: For instance, prohibited parking zones at banks or Beijing Post Centres.
⑦ Underground passages: Parking is prohibited inside underground passages, which obstructs pedestrian traffic.
⑧ Particularly narrow pavement: a one-way pavement that is less than 2 m in width and where shared bikes cannot be parked.
⑨ On overpasses.

We measured and defined a total of 32 prohibited parking areas, which are shown in Fig. 2. We also used ArcGIS to locate each prohibited parking area within the map and determine whether each parking location POInt was within a prohibited parking area based on latitude and longitude, and set the binary variable: If the bike is parked within a prohibited parking zone it is 1 and otherwise 0.

3.3. Research methodology

3.3.1. Spatiotemporal pattern mining

This paper analyzes the temporal characteristics, spatial characteristics, and spatiotemporal interaction characteristics of the inconsiderate parking of DBS. First, we used descriptive statistics to analyze the main temporal and spatial characteristics of inconsiderate parking and focused on the characteristics of daily peak value, weekly peak value, and the spatial accumulation of parking and inconsiderate parking.

A STING (Statistical Information Grid) clustering algorithm was used to cluster the spatial distribution of DBS parking(Bureva et al., 2017), and the decision tree CART algorithm was used to analyze the influencing factors of the spatial aggregation formation of shared bikes and explore the space–time interaction characteristics of inconsiderate parking. A STING clustering algorithm is a multi-resolution clustering technology based on a grid that divides the spatial area of the input object into rectangular units, and the space can be divided by hierarchical and recursive methods (Dong et al., 2018). A STING clustering algorithm based on grid density shows better performance in terms of accuracy, noise reduction, parameter sensitivity, and calculation efficiency (Hireche et al., 2020). The first step in STING grid clustering is to rasterise the vector data - which contains latitude and longitude coordinates. The iteration starts from 1 m * 1 m, and it is found through trial and error that the 1 m * 1 m parameter setting can maintain good computational efficiency and accuracy, so the study area is rasterised into cells of 1 m * 1 m squares, and the number of parking locations and POI elements in each cell is recorded to facilitate a comprehensive analysis between POI elements and parking behaviour.

The decision tree is a process of classifying data through a series of rules. Decision trees are divided into classification trees and regression trees. Classification trees make decision trees for discrete variables, and regression trees make decision trees for continuous variables (Zhou et al., 2020). We used the classification tree CART algorithm. The algorithm uses a boosting method to improve the model's accuracy. The software has a fast calculation speed, occupies fewer memory resources, is very robust in the face of data omission and many input fields, and improves execution efficiency and classification accuracy (Hou et al., 2020).

3.3.2. Analysis of influencing factors

(1) Model selection

We applied big data on shared bikes to analyse the influence of the built environment, weather and riding characteristics on inconsiderate parking. Most studies have used a regression model to investigate the factors that influence DBS usage (Ma et al., 2020; Faghih-Imani and Eluru, 2015). A regression model is a parameter estimation model that captures the significance of the relationship between the dependent and independent variables. Decision tree and random forest (RF) models capture complex non-linear relationships among variables. And many studies have shown that random forests can achieve higher predictive accuracy than polynomial logistic regression (Wang et al., 2022), especially for unbalanced datasets such as inconsiderate parking of DBS. In addition, random forests are relatively robust to outliers and noise in large datasets. These advantages make RF a powerful integrated learning technique for dealing with complex, non-linear and high-dimensional data (Zhou et al., 2020).

Therefore, the regression model, decision tree model and random forest have their advantages in analysing the influencing factors that need to be further compared and evaluated. The typical evaluation metrics are accuracy, recall rate, F1 score and AUC score (Zhou et al., 2020; Islam and Amin, 2020). We compared the predictive accuracy of the logit model, decision tree model, and RF model with inconsiderate parking as the dependent variable and the built environment, driving characteristics, and weather conditions as the independent variables. This procedure divides 80 % of the data set into a training set and 20 % into a test set. We compared the generalisation ability of the models by comparing the accuracy, F1-score, recall rate and AUC of each model, and the results are shown in Table 2.

From the results in Table 2, we can see that the F1 score of the RF model is the largest, which indicates that the RF model is the most robust of the three; the accuracy and recall rates are also at a more average level. In addition, the AUC of the RF reaches 0.94, which is the closest to 1, which indicates that the RF model works best. Overall, the RF model fit is excellent and the predictive accuracy is outstanding, so we adopted it for our analysis.

(2) Parameter determination

To improve the predictive accuracy of the RF model, it is necessary to adjust the parameters according to the model's learning effect on the research data; after parameter adjustment, it is possible to obtain an optimized RF model. In the RF algorithm, the out-of-bag error rate is usually used as an indicator to test the predictive accuracy of the model. In the construction of k decision trees, since the training set samples are drawn randomly and with put-back, the probability of each sample being drawn is $1/k$. After k draws, the probability of a sample's not being drawn is $(1-1/k)k$. With a large enough sample size, the probability of a sample not being drawn is $\lim_{k\to\infty}\left(1-\frac{1}{k}\right)^k = \frac{1}{e} \approx 36.8\%$. Therefore, for each training set, about 36.8 % of samples do not participate in the generation process of the decision tree and are thus out-of-bag samples; each tree is predicted for its out-of-bag samples. The ratio of the number of prediction errors to the total number of samples is the out-of-bag error rate (OOB error rate) of the RF, and the smaller the OOB error rate, the better the model construction. We calculated the OOB error rate for different sub-tree sizes at maximum depths of Sqar and None, as shown in Fig. 3. We can see that the OOB error is the smallest, at 800 trees. Based on the results of the parameter adjustment, 800 trees is the optimal number of decision trees, and the maximum growth depth of the decision tree is the default value of None, with a minimum OOB error rate of 0.07035. We built the RF model by taking the system default value of 2 for the minimum number of samples for the node division of our decision tree and 1 for the minimum number of samples for the leaf nodes.

4. Empirical results

4.1. Temporal characteristics

4.1.1. Daily peak variation

As shown in Fig. 4(a), from August to October the daily parking quantity shows a "double peak", with the morning peak occurring between 07:00 and 09:00 and the evening peak between 17:00 and 19:00. During these two periods, DBS parking quantity is high and the demand for bicycles varies considerably over short periods, in line with the morning and evening peak hours of residents' trips. This suggests that DBS is to some extent an important supplement to residents' travel patterns; it enriches their travel structure and travel chains during morning and evening peaks. The maximum number of parked bikes in the evening peak is smaller than in the morning peak and the rate of decline in parking after the evening peak is also slower, which is coincident with the realistic

Table 2
Model evaluation index scores.

	Logit Model	CART Decision Tree Model	Random forest Model
Accuracy	91.87 %	91.17 %	93.01 %
F1 score	1.55 %	46.97 %	51.22 %
Recall rate	0.78 %	47.83 %	44.88 %
AUC	0.6778	0.7145	0.9460

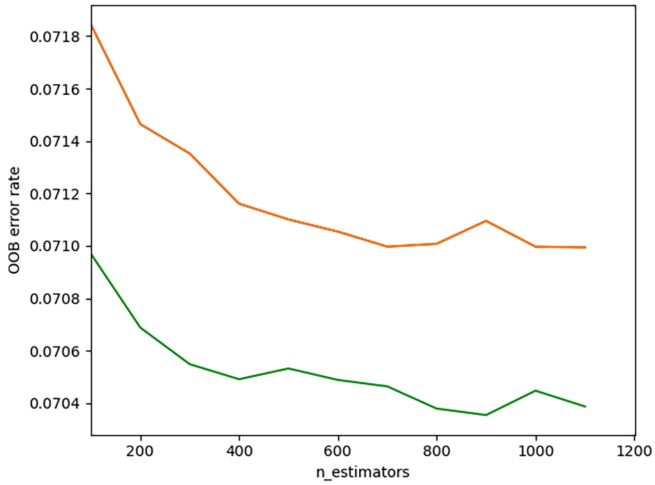


Fig. 3. Out-of-bag error rates for different subtree volumes Note: The green line denotes the out-of-bag error rate at the default value of None for the maximum depth and the red line denotes the out-of-bag error rate at the maximum depth of Sqar. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

characteristic of residents' less constrained activity time after work.

As can be seen in Fig. 4(b), the peaks and trends in the amount of inconsiderate parking during the day are generally consistent with the total amount of parking. However, during the morning peak, the peak of inconsiderate parking is earlier, the amount of variations is relatively higher than during the evening peak, and the variations are also more dramatic, all of which indicates that people travel more intensively and more hurriedly in the morning.

As can be seen in Fig. 4(c), the rate of inconsiderate parking is lower for residents during the morning and evening peak hours. At night, from 9 p.m. to 5 a.m., the rate of inconsiderate parking is higher. Moreover, the closer to the peak of parking, the denser the flow of traffic and the faster the rate of inconsiderate parking declines. A possible reason for this is that awareness of face and herd mentality (Zhao et al., 2019) has an important influence on normative parking. Since prohibited parking areas are generally equipped with no parking signs, people tend to park their bikes in reasonable locations out of moral restraint and social norms when there is a high volume of people nearby (Wang et al., 2021b). Another possible reason is that people tend to park their bikes in areas in which shared bikes are concentrated, and cyclists often decide where to park their bikes based on where other bikes are parked. In this case, only a small percentage of bikes are parked away from the "hordes", so the percentage of inconsiderate parking is relatively low. Also, the rate of inconsiderate parking fluctuates considerably throughout the day, particularly in the early morning and at night, which may explain the increasing trend in user violation behavior during this time due to the lack of external constraints.

4.1.2. Weekly peak variation

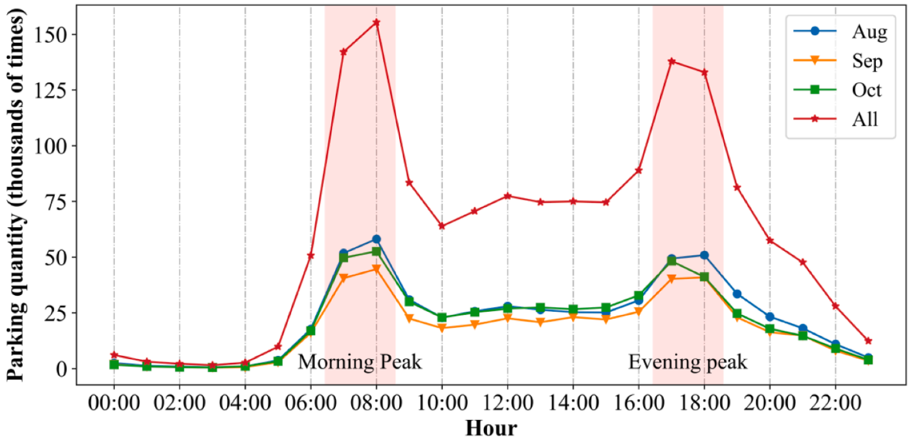
We plotted the time series of total weekly parking quantities for August, September, October, and the 3 months overall. As can be seen in Fig. 5(a), the overall trend in weekly parking quantities rises from Monday to Wednesday and then slowly decreases from Wednesday. The maximum number of bikes is parked on Wednesday and the minimum number is on Saturday and Sunday. This reflects the fact that DBS in the city mainly serve commuting needs and satisfies the demand of residents who are going to work or school. Wednesday, arguably, is the day DBS users are most motivated to work. Fig. 5(b) shows a consistent trend in the amount of inconsiderate parking and the amount of parking.

Fig. 5(c) shows that the rate of inconsiderate parking is more volatile in September, while the rate of inconsiderate parking is relatively stable in August, October, and overall. However, there is a trend of gradual increase from Monday to Sunday in all four lines. In addition, the rate of inconsiderate parking was higher in August than in the other two months. This may attributable to the higher temperatures in August, which make for poorer weather conditions for riding compared with the other two months; users' emotions can also be affected by the heat. Fig. 5(c) and (d) both show that the rate of inconsiderate parking is higher on holidays than on weekdays. The probable reason for this is that residents are more relaxed, with no school or work on holidays, so they are a bit weaker in terms of self-restraint and causing the rate of inconsiderate parking to be higher.

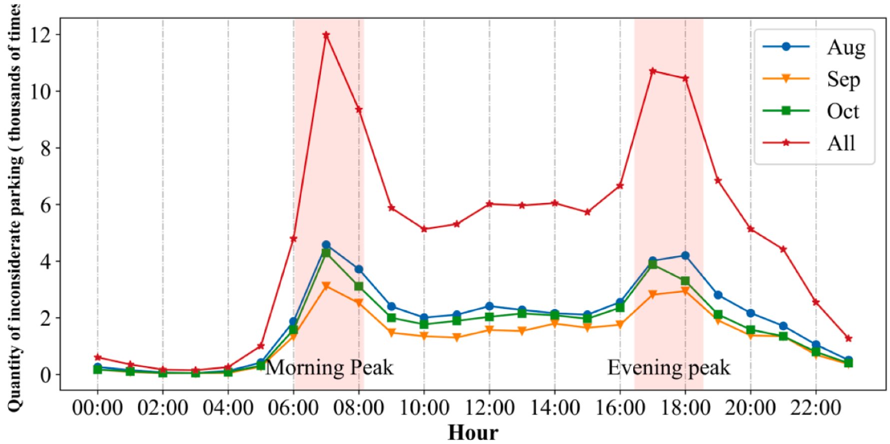
4.2. Spatial characteristics

4.2.1. Accumulation characteristics

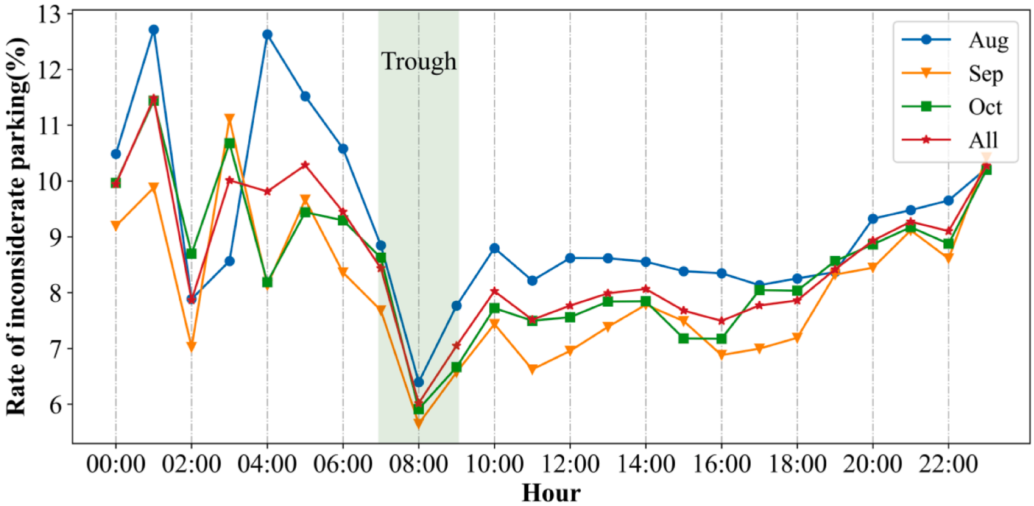
To compare differences in the distribution of DBS space on weekdays and holidays, we drew space heat maps of the full samples on Mondays and Sundays in August, September, and October, as shown in Fig. 6. As can be seen in Fig. 6, the Liuliqiao East, Wanzi, Daguanying, Military Museum, and Carrefour subway stations are the most popular areas for parking, whether on holidays or working days, which shows that subway stations and supermarkets have always been hot areas for shared bikes parking. The distribution of shared bikes in Daguanying and Liuliqiao East in Fig. 6(a) is more than that in Fig. 6(b) (i.e., the red is darker), which indicates that



(a) Variations in daily parking



(b) Variations in daily inconsiderate parking



(c) Variations in the daily rate of inconsiderate parking

(caption on next page)

Fig. 4. Variations in daily parking patterns of shared bikes Note: (a)-(c) plot the variations in daily parking quantity, daily inconsiderate parking quantity, and the rate of inconsiderate parking per day respectively, in which the rate of inconsiderate parking = inconsiderate parking quantity/parking quantity.

compared with holidays, DBS are more distributed around subway stations on weekdays, which is consistent with the characteristic whereby shared bikes mainly play a role in commuting on weekdays.

The distribution of shared bikes around Carrefour supermarkets in Fig. 6(b) is more (in darker red) than that in Fig. 6(a), which indicates that more shared bikes are parked near shopping malls and supermarkets on holidays than on weekdays, which corresponds to the fact that residents' main activities on holidays are shopping and entertainment.

4.2.2. Spatial clustering

According to the STING clustering method introduced in Section 3, the clustering results of data on the full sample are shown in Fig. 7. Samples are divided into five categories according to the spatial distribution. ① mainly includes Shengjin Homeland and Yuelin People's Square. The land use types are mainly living service places and housing, so this is labelled Residential Living. ② mainly includes office buildings and companies and thus is labelled Workplace. ③ has a small scope and is mainly concentrated near the overpass of the W.3rd Ring Road Middle, so it is labelled Overpass Facility. ④ mainly includes Beijing West Railway Station—a transportation hub that connects the whole country—and is labelled West Station Hub. ⑤ mainly includes Daguangying station and is labelled Metro Station Hub.

4.3. Spatiotemporal characteristics

4.3.1. Temporal characteristics of different spatial areas

We analyzed the characteristics of the different area categories in different temporal periods. Fig. 8 presents the variation in daily parking for the five categories. Fig. 8(a) plots the variation in daily parking for the residential Living category, which has a distinct evening peak, a lower morning peak, and a smaller midday peak (overall left low and right high). Fig. 8(b) plots the daily parking variation in the Workplace category, in which the morning peak is more pronounced than the evening peak (high left and low right), which is consistent with people commuting to work in the morning and returning home in the evening. Fig. 8(c) plots the daily parking variation for the Overpass Facility category, in which both the morning and evening peaks are evident (balanced double peak), which is consistent with the overpass's function as a public facility serving people's commute. Fig. 8(d) plots the daily parking variation for the West Station Hub category and shows a relatively high level of parking throughout the day, with midday parking consistently remaining at a more elevated level than the other categories, with the morning peak having less fluctuation. Fig. 8(e) plots the daily parking variation in the Metro Station Hub category, which shows a double-peak feature, with the morning peak being more elevated than the evening peak and the morning peak variation being more intense and concentrated. This is consistent with the characteristic whereby people are relatively rushed in the morning and relatively free to leave after school and work. Depending on differences in the built environment and parking time characteristics in each category, it is necessary to manage the different categories by division.

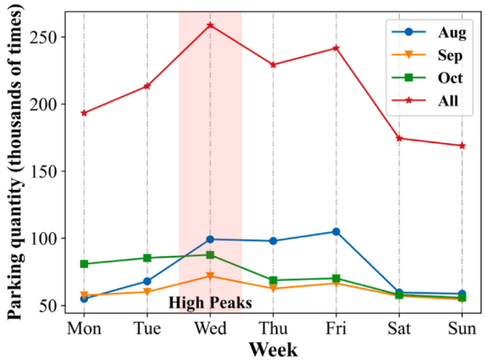
4.3.2. Characteristic analysis of spatial clusters

To examine the characteristics of the spatial clusters, a decision tree analysis was conducted using the category variable as the target variable and the dataset described in Section 3 as the feature variables. We used the CART package that comes with R software for the analysis, and the results are shown in Fig. 9.

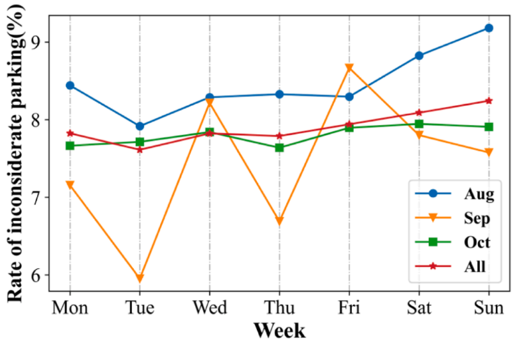
We can see in Fig. 9 that most of the factors with a significant influence are Points of Interest (POIs), an indication that the characteristics of the built environment are quite different in spatial clusters. For instance, in node 1 and node 15, POI 9 (sports and leisure places) and POI 5 (science, education, and culture) are more intense in the ④ West Station Hub category, while POI 1 (food and beverage service) and POI 5 (science, education, and culture) are less intense in the ⑤ Metro Station Hub category. The differences in the built environment between the different spatial clusters result in different parking densities and rates of inconsiderate parking in the different clusters.

The contribution of the different factors is shown in Table 3, which derives the differences between the factors in the different spatial clusters. We found the greatest variation in the built environment of public facilities, science, education and culture, and sports and leisure places had the greatest influences in the different spatial clusters, with a total effect contribution of over 90 %. Parking for shared bikes, such as bike stands and under the flyovers, is common in the vicinity of public facilities. Scientific and educational institutions are the main destinations for students, and young people prefer shared bikes as a new and inexpensive means of transport; thus bikes are more densely distributed in the vicinity of those facilities. There are also differences in the characteristics of POIs in different spatial clusters, such as business residences, government offices, and living service places.

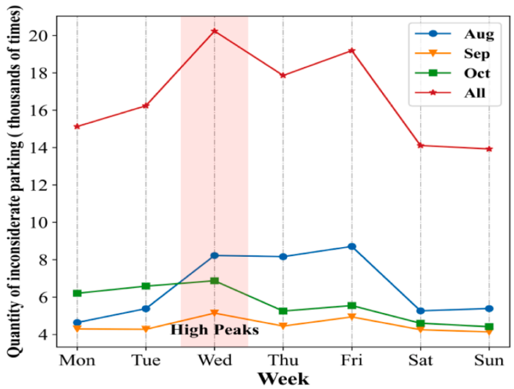
We focus on the characteristics of inconsiderate parking in different clusters. There are also some differences in the inconsiderate parking of spatial clusters. As can be seen from the results in Fig. 9, node 3, the distribution of inconsiderate parking is more important in ④, the West Station Hub category; conversely, there is little inconsiderate parking near POI 11 (business residences). A possible reason for this is that business residences are generally managed in separate zones with stricter requirements for DBS parking - with clearly marked no parking signs and largely dedicated parking spaces - so that residents' parking behaviour is more normative. The West Station Hub area has higher passenger traffic, with complex transport modes and a high number of foreign visitors who are unfamiliar with adequate local parking and therefore tend to park inconsiderately.



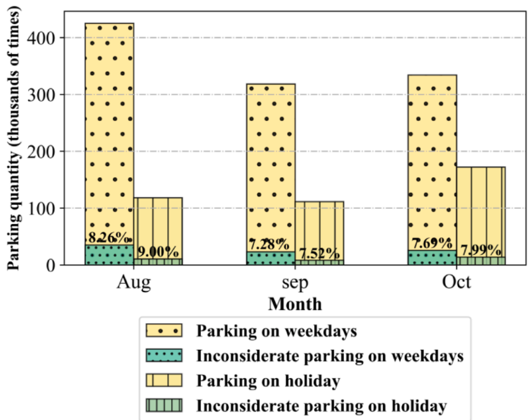
(a) Variations in weekly volume of parking



(b) Variations in the volume of inconsiderat



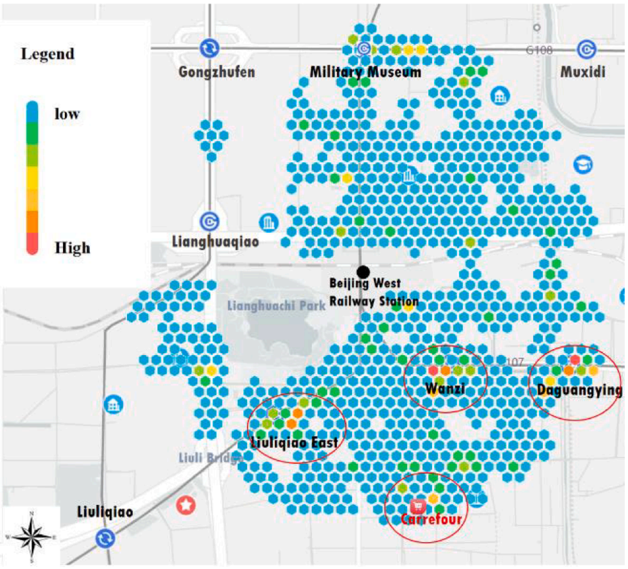
(c) Variations in the weekly rate of inconsiderate parking



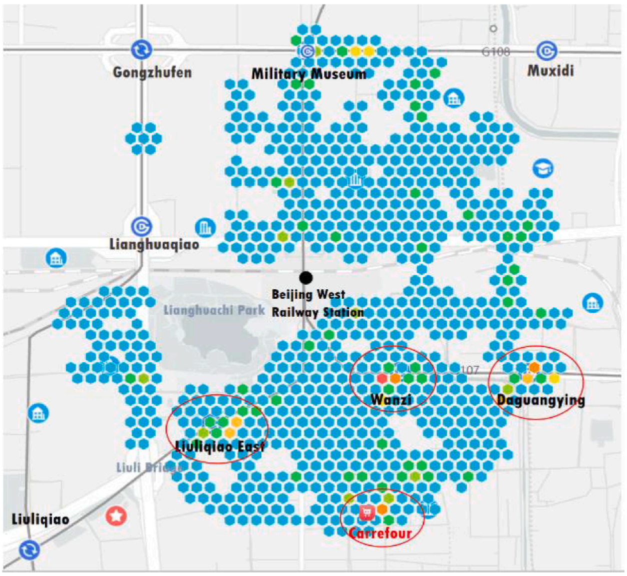
(d) Variations in parking on weekdays and holidays

(caption on next page)

Fig. 5. Weekly Variations in shared bike parking Note: (a)-(c) plot the variation in weekly parking quantity, weekly inconsiderate parking quantity, and the rate of weekly inconsiderate parking respectively; (d) plots the frequency of weekday parking and inconsiderate parking for August, September and October, and the frequency of holiday parking and inconsiderate parking.



(a) Spatial distribution on weekdays



(b) Spatial distribution on holidays

Fig. 6. Heat map of the spatial distribution of shared bikes Note: (a) depicts the spatial distribution of shared bikes parked on Mondays from August to October, which reflects the spatial distribution of weekday parking, and (b) depicts the spatial distribution of shared bikes parked on Sundays from August to October, which reflects the spatial distribution of holiday parking. Red to blue indicates high to low parking volume. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Sports and leisure places are mainly places for recreation and leisure, and the positive externalities of exercise brought by bike-sharing rides coincide with the purpose of users' trips; thus the use of shared bikes to reach sports and leisure places venues increases accordingly. The different categories of spatial clustering reflect different distributions and characteristics in terms of spatiotemporal patterns.

(a) Full sample spatial distribution (b) STING clustering results

Fig. 7. Clustering results of the spatial distribution of DBS Note: (a) depicts the full sample spatial distribution and (b) depicts STING grid clustering results based on the full sample spatial distribution. Different colours correspond to different classifications, and specific category symbols are marked in the figure.

4.4. Mechanisms of inconsiderate parking formation

4.4.1. Relative importance analysis

This paper constructed a random forest to analyze the effects of riding characteristics, the built environment, and weather on inconsiderate parking, and the influence of factor variables, in order of importance, is shown in Table 4. The most influencing factor is riding distance. From the perspective of riding characteristics, riding distance, riding duration, and the date of the ride are the more important variables. It is intuitive that the longer and farther the ride—the more intense the ride—the more tired the user will feel (Silva-Cavalcante et al., 2018), and the greater the probability of inconsiderate parking at the destination. The date of parking is also an important factor, with a low level of parking and inconsiderate parking from 15 September to 10 October, which may be linked to the National Day holiday. During the National Day holiday, residents' main activity is not commuting but rather travelling and relaxing and the usage of DBS decreases, resulting in less parking and inconsiderate parking as well.

From a built environment perspective, catering service places, living service places, and sports and leisure places are the more highly ranked factors. All three land use types are recreational and catering service places, which suggests that the motivation for people to use shared bikes influences their inconsiderate parking behavior. The selection of bike-sharing parking locations is influenced by geographic factors (land use, built environment, and access to public transport infrastructure), demographic factors, traffic factors, and economic factors (Faghih-Imani and Eluru, 2015) as well as psychological factors. When a destination is a place of entertainment and leisure, people will be in a relaxed mood, which will reduce their self-restraint and moral restraint and thus influence inconsiderate parking.

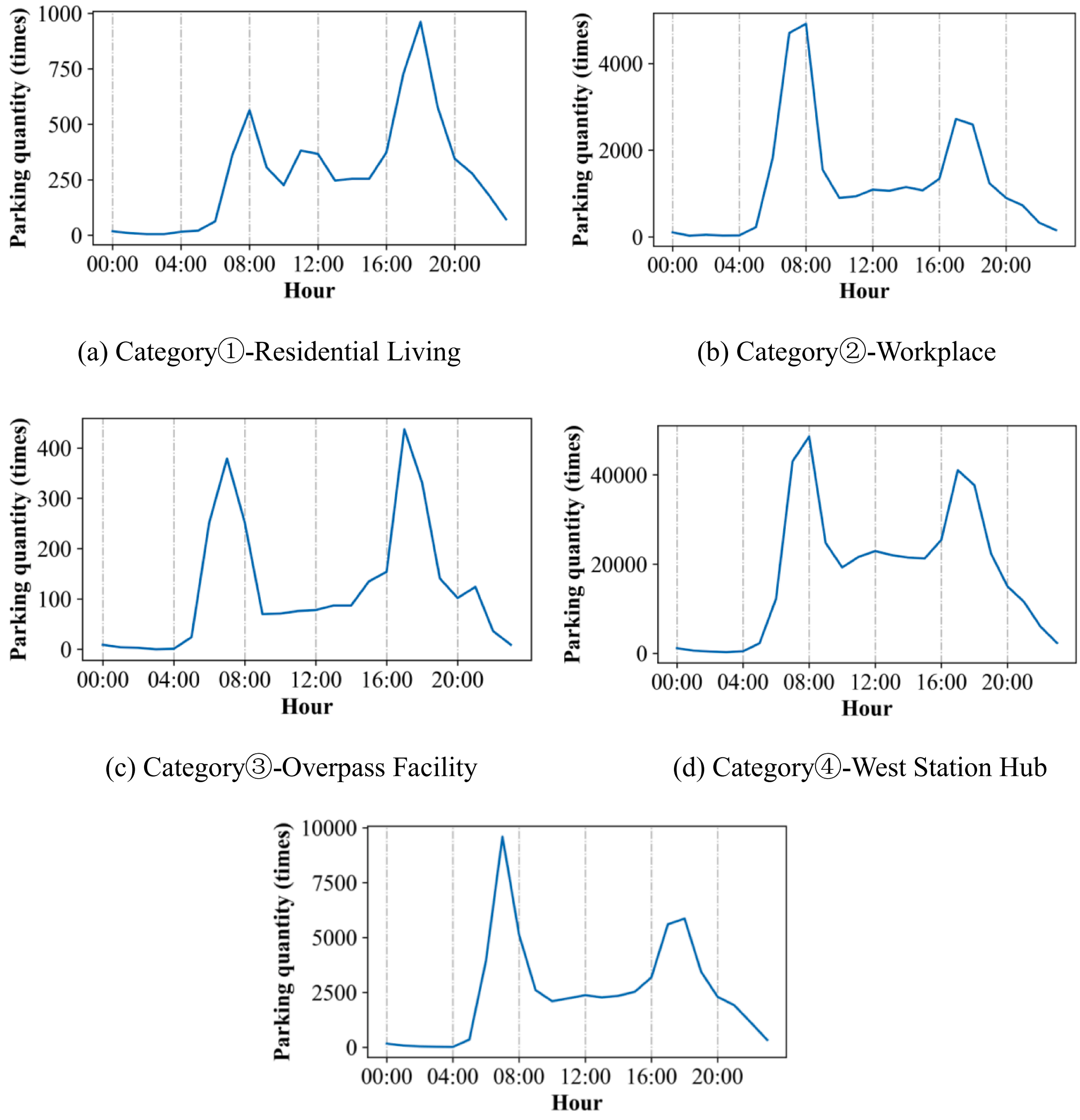
From the perspective of weather characteristics, the air quality index and average temperature are the top-ranking factors, which indicates that the day's air quality and outdoor temperature affect the user's riding mood. When air quality conditions are poorer and temperatures are higher, users tend to reduce their exposure to the outdoors and therefore do not spend as much effort on parking, which in turn affects inconsiderate parking behavior.

4.4.2. Marginal effects analysis

We further applied a partial dependence plot (PDP) to represent the nonlinear effect of influencing factors on inconsiderate parking. We also introduce individual conditional expectation (ICE) curves to detect heterogeneity effects due to interactions with other factors (Chen et al., 2021; Chen and Ye, 2021). Each thin line visualizes the dependence of predictions on features for each sample separately.

(1) Riding Characteristics

We focus on analyzing the nonlinear effect of riding distance on inconsiderate parking and present the results in Fig. 10. As riding distance increases, the probability of inconsiderate DBS parking first decreases and then increases, and is lowest when the riding



(a) Category①-Residential Living (b) Category②-Workplace

(c) Category③-Overpass Facility (d) Category④-West Station Hub

(e) Category⑤-Metro Station Hub

Fig. 8. Variations in daily parking for categories ①–⑤.

distance is about 1,500 m. When the riding distance exceeds 1,500 m, the probability of inconsiderate parking increases sharply. The marginal effect of riding distance on the probability of inconsiderate DBS parking is almost 0 when the riding distance exceeds 5,000 m.

(2) Built Environment

The influence of the number of catering service places (POI1) on inconsiderate DBS parking shows an M-shape. As the number of catering service places increases, the probability of inconsiderate DBS parking varies in an M-shape, then gradually increases to the horizontal line. As seen in Fig. 11(a), the probability of inconsiderate DBS parking is lowest when the number of catering service places near the parking POInt is 6. The probability of inconsiderate DBS parking is highest when the number of catering service places near the parking location is 2. A possible explanation is that when the density of nearby catering service places reaches a certain level (2–6), an optimal proportional distribution to reasonably set up bicycle parking areas exists and can guide considerate parking with maximum efficiency.

As the number of living service places (POI8) increases, the probability of inconsiderate DBS parking first decreases slightly and

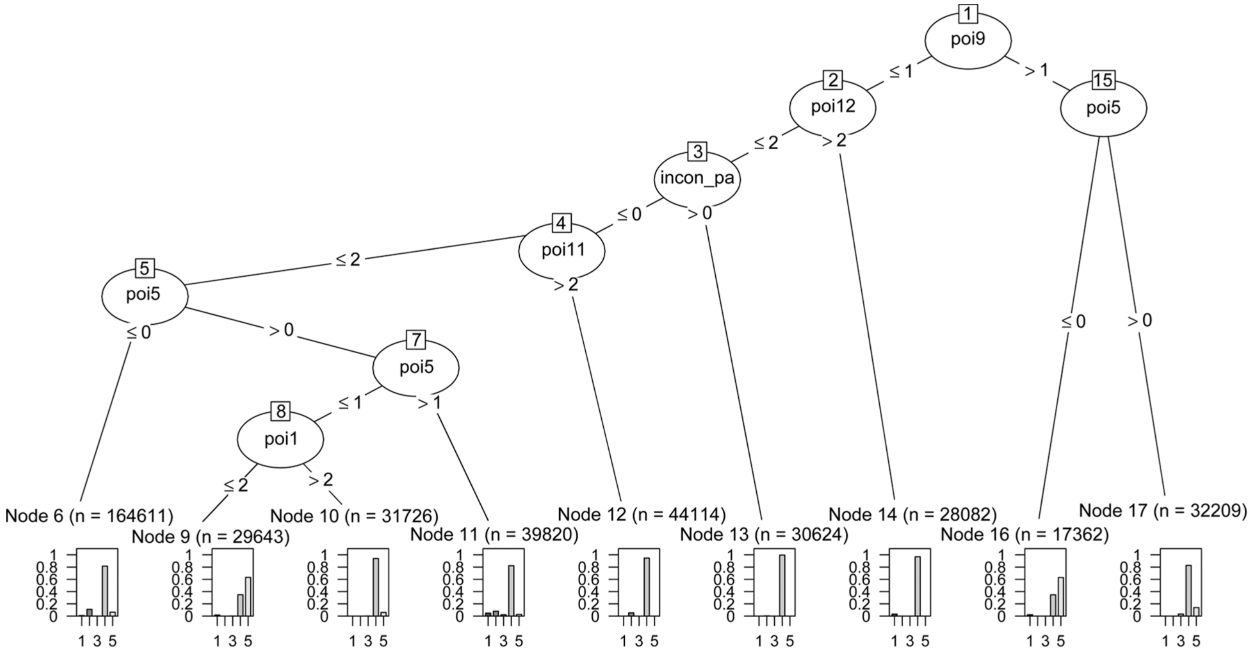


Fig. 9. Decision tree results.

Table 3
The contribution of impact categorical variables.

Variable	Contribution
Public facilities	100.00 %
Scientific and educational institutions	97.35 %
Sports and leisure places	96.40 %
Business residences	35.01 %
Government offices	29.95 %
Living service places	28.06 %
Financial and insurance institutions	25.95 %
Catering service places	24.64 %
Healthcare facilities	16.26 %
Whether inconsiderate parking	15.30 %
Companies	10.14 %
Transportation facilities	8.75 %
Hotels and hostels	2.58 %

then increases. When the number of living service places is less than 17, the probability of inconsiderate DBS parking remains stable. However, when the number exceeds 17, which implies a high-density area, the probability of inconsiderate DBS parking increases significantly.

The number of sports and leisure places (POI9) has a negative effect on inconsiderate DBS parking. Compared with the absence of sports and leisure places near the parking point (POI9 $= 1$), when there are sports and leisure places near the parking point (POI9 ≥ 1), the probability of inconsiderate DBS parking decreases from 10 % to about 5 %, which is a significant reduction. However, with the increase in the number of sports and leisure places, the marginal effect of sports and leisure facilities on the probability of inconsiderate DBS parking decreases to nearly 0.

The positive effect of the number of hotels and hostels (POI7) on the probability of inconsiderate DBS parking is effective under the threshold. When the number of hotels and hostels is less than 4, the higher the number of hotels and hostels near the parking point, the higher the probability of inconsiderate DBS parking. There are a high number of hotels and hostels near stations, attractions, and residential areas, and these areas are also high-risk areas for inconsiderate parking.

5. Discussion and targeted governance measures

5.1. Discussion

We analyzed the spatial and temporal characteristics of shared bike parking and inconsiderate parking using trip data from Mobike

Table 4
Importance ranking of variables under random forest.

Variable	Importance
Riding distance	0.24
Riding duration	0.09
Catering service places	0.08
Date of parking	0.06
Air quality index	0.06
Living service places	0.06
Average temperature	0.04
Sports and leisure places	0.04
Healthcare facilities	0.04
Scientific and educational institutions	0.03
Hotels and hostels	0.03
Business residences	0.03
Public facilities	0.02
Government offices	0.02
Cluster category	0.02
Parking time: 4:00–8:00	0.01
Parking time: 8:00–12:00	0.01
Parking time: 12:00–16:00	0.01
Parking time: 16:00–20:00	0.01
Mon	0.01
Tues	0.01
Wed	0.01
Thur	0.01
Weekend	0.01
Wind power	0.01
Sunny	0.01
Rainy	0.01
Companies	0.01
Transportation facilities	0.01
Financial and insurance institutions	0.01
Parking time: 0:00–4:00	0.00
OOB Score: 93.01 %	

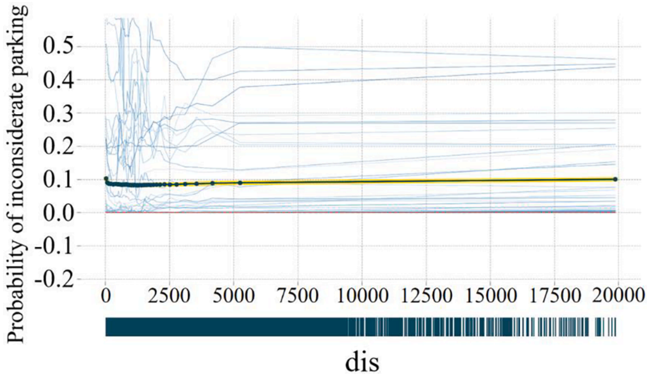
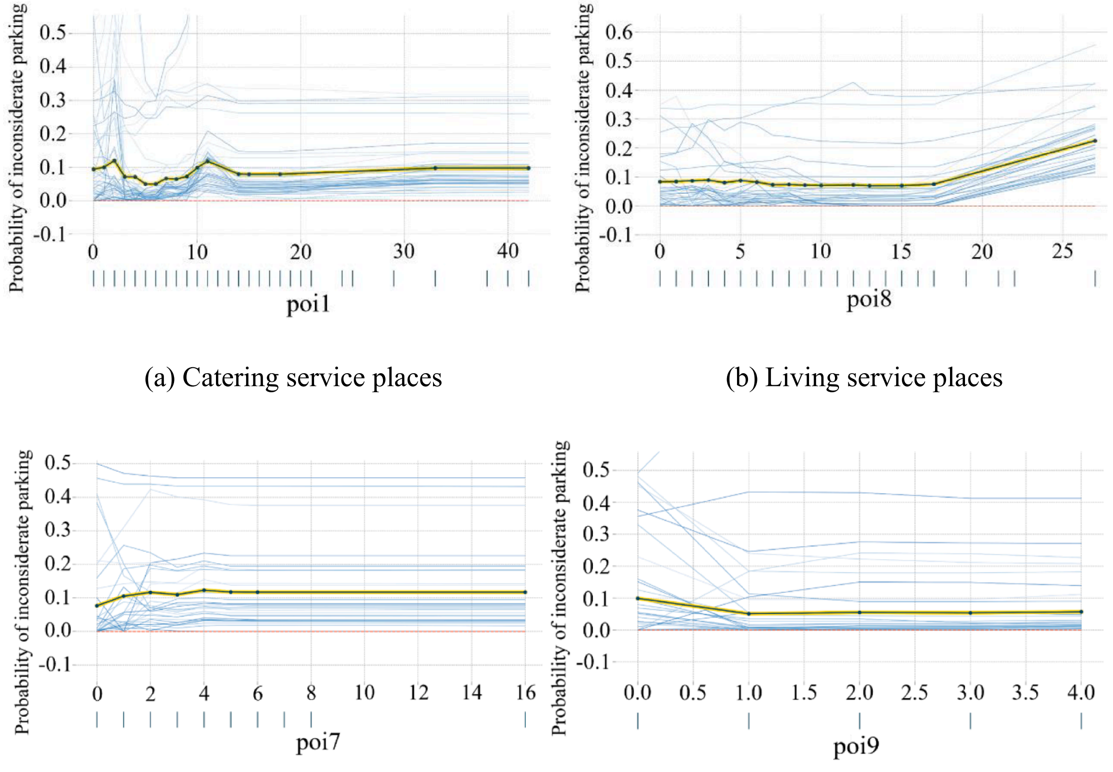


Fig. 10. Nonlinear effects of riding distance on inconsiderate parking Note: The yellow line indicates the partial dependence plot (PDP) and the thin lines in light green indicate individual conditional expectation (ICE). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

in 2018 and examined the causes of inconsiderate parking by combining riding characteristics data with built environment data and weather data as independent variables.

Based on the characteristics of the temporal distribution, both parking and inconsiderate parking have a dual-peak characteristic, with the daily morning peak occurring between 7: 00 and 9: 00 and the evening peak between 17: 00 and 19: 00. During the week, the highest volume of parking and inconsiderate parking occurs on Wednesdays and is relatively low on weekends. In terms of the rate of inconsiderate parking, the proportion of inconsiderate parking is higher in the early hours of the morning and on weekends, which indicates that moral restraint is weaker during these times.

Based on the characteristics of spatial distribution, hot spots for parking are mostly metro stations and large shopping malls, on both holidays and weekdays. More DBS are distributed around metro stations on weekdays, and more DBS are parked near shopping malls and supermarkets on holidays. This indicates that the main purpose of bike-sharing on weekdays is commuting and on holidays is entertainment.



(a) Catering service places (b) Living service places

(c) Sports and leisure places (d) Hotels and hostels

Fig. 11. Nonlinear effects of the built environment on inconsiderate parking.

Table 5
Suggestions for the targeted management of inconsiderate shared bike parking.

Dimension	Characteristic	Precise strategies	Conclusion		Specific recommendation
Temporal dimension	Peak features	Temporal dynamic scheduling	Morning and evening double peaks		Preparatory bikes dispatch
			Wednesday peak		Additional managers
			High rate of inconsiderate parking during times of weak supervision		Reinforce the intensity and frequency of reminders
Spatial dimension	Accumulation features	The precise layout of zones	Supermarkets and subway stations are hot areas		Decentralized and convenient parking place
Spatiotemporal interaction	Time zone characteristics	Time zone difference management	Residential Living: evening peak		Enhanced evening smart identification regulation
			Workplace: morning peak		Advance layout control
			Overpass Facility: morning and evening peak		Electronic eye monitoring
			West Station Hub: all-day peak		Improve the multilevel parking layout, strengthen fixed-point supervision
			Metro Station Hub: morning and evening peak		Provide recommended parking point
Mechanism analysis	Influence factors	Cause-assisted administration	Riding feature	Riding distance, riding duration	Send targeted reminders
			Built environment	Living service and hotels and hostels	Support centralized parking facilities
				Sports and leisure places or the number of catering service places	Reasonable layout of frequent entrances and exits
			Weather condition	Air quality, temperature	Adjust the scheduling scheme and provide cycling discounts in abnormal weather

Based on the characteristics of the spatiotemporal interaction, we clustered inconsiderate parking into 5 categories using the STING grid density clustering method. According to the built environment and temporal distribution characteristics in each category, the 5 categories were labelled Residential Living, Workplace, Overpass Facility, West Station Hub, and Metro Station Hub. Each category has different peak characteristics and inconsiderate parking patterns. The Residential Living category has a noon peak and a significant evening peak; the Workplace category has a more prominent morning peak; the Overpass Facility category has a distinct morning and evening double peak; the West Station Hub category has maintained a high level of parking and inconsiderate parking throughout the day, with fewer fluctuations in the "dual peaks"; and the Metro Station Hub category has a more distinct tidal wave of morning peak changes, so it must be divided into regions to derive precise and targeted management measures.

In terms of the influencing factors, we adopted a random forest to examine the factors that influence inconsiderate parking. Results show that from the perspective of riding characteristics, riding distance, parking time, riding duration, and riding date are the relatively important variables that influence parking; from the perspective of weather characteristics, the air quality index and average temperature influence inconsiderate parking; from the perspective of built environment characteristics, catering service places, living service places, and sports and leisure places influence inconsiderate parking, which indicates that the motivation for using shared bikes affects inconsiderate parking. Variables such as riding distance, catering service places, living service places, sports and leisure places, and hotels and hostels show nonlinear and threshold effects on inconsiderate DBS parking.

5.2. Targeted governance measures

Based on the results of our analysis of big data technology, we propose precise strategies to optimize the problem of shared bike parking. These strategies are designed to guide the government and diverse enterprises concerning long-term management mechanisms and improved scheduling schemes. We summarize the policy implications in Table 5 as follows.

(1) Identify the temporal peak characteristics of inconsiderate parking, develop dynamic dispatching measures, and accurately dispatch shared bikes to flexibly adapt to tidal commuting demand.

According to descriptive statistical analysis, DBS has pronounced double-peak parking in the morning and evening. Bike-sharing companies can carry out preparatory bike dispatch before the double-peak hours to improve the efficiency of allocation and utilization. Notably, the proportion of inconsiderate parking is relatively high at night and on weekends (since it is relatively unsupervised), and thus bike-sharing companies may increase the intensity and frequency of reminders or strengthen the adjustment of their credit rating system during these hours to address this problem. Additional management staff could also be deployed to arrange the layout of bike parking in advance of weekly peaks and dynamically adjust supply and demand to reduce the incidence of inconsiderate parking.

(2) Identify the spatial accumulation characteristics of inconsiderate parking demand and map precise layouts of DBS parking spaces concerning the built environment.

We suggest applying different parking schemes to different built environments, combining centralized with decentralized management, and adopting a three-dimensional approach to access or parking. We found that in addition to bus and metro stations, shopping malls and supermarkets are hot spots for inconsiderate parking, where parking demand is high and it is easy to form pile-up points. Therefore, we recommend establishing decentralized and convenient bicycle parking locations within 200 m of bus and metro stations and supermarkets. In addition, managers should focus on areas with high inconsiderate parking distribution, such as the West Station hub. Based on the findings of this study, an effective approach is to establish new parking spaces where inconsiderate parking accumulation points are most likely to form. Based on big data analysis, not only can the planning process be simplified, but the cycling environment can be improved and the network layout optimized by increasing the number of cycle paths and building a multilevel parking system.

(3) Classify the spatiotemporal interaction characteristics of parking behavior and implement differentiated management strategies by temporal region according to the distribution characteristics of each category.

For instance, the Residential Living category has a peak parking period from 17:00 to 19:00, with a correspondingly higher probability of inconsiderate parking in the evening. We recommend enhancing evening camera monitoring and smart identification supervision. The Workplace category has a higher density of parking in the morning, and we recommend that shared bikes be dispatched in advance of the morning peak. The built environment of the Overpass Facility category is mainly an important transport infrastructure, with high parking intensity during the morning and evening peaks, and can be appropriately equipped with electronic eye monitoring. The West Station Hub category has a high volume of parking and inconsiderate parking throughout the day. It will thus be necessary to improve the layout of the multilevel parking space for this area and strengthen fixed-point supervision and dispatching. For areas such as the Metro Station Hub category, which is dominated by public transport stations, the morning peak is more crowded than the evening peak, and therefore the intensity of inconsiderate parking is higher. It should be staffed for parking diversion during both the morning and evening peaks. We suggest providing recommended parking spots via the app's push notifications during the morning rush hour to avoid the formation of piles that can obstruct major entrances and transport hubs.

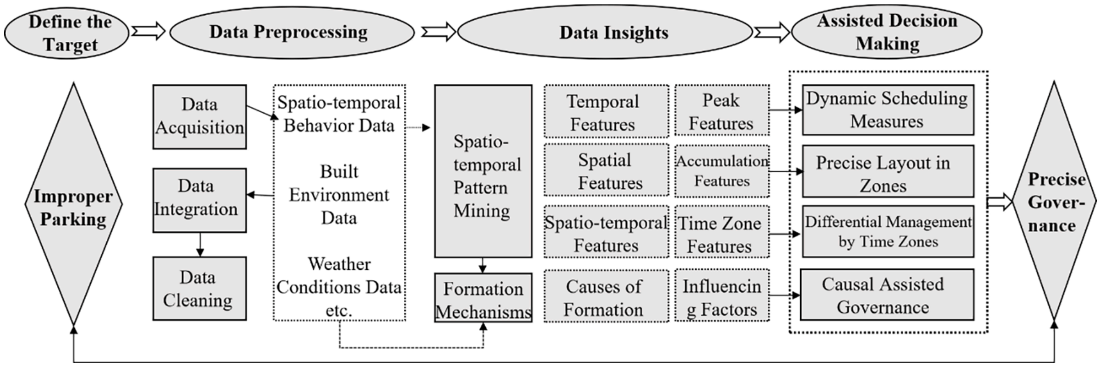


Fig. 12. The framework for the management of inconsiderate parking.

(4) Examine the mechanism of inconsiderate shared bike parking from the perspective of influence factors to enhance targeted management.

According to our investigation of the factors that influencing inconsiderate DBS parking, with respect to riding characteristics, riding distance and riding duration have a significant influence on inconsiderate parking. Our nonlinear analysis results show that when riding distance exceeds the 1,500 m threshold, the probability of inconsiderate parking increases sharply. Therefore, we recommend that bike-sharing companies send targeted "reminders" to users' mobile phones when the app finds that the user's riding distance exceeds 1,500 m.

In addition, in examining the temporal characteristics of inconsiderate parking, we found that the proportion of inconsiderate parking is higher at night and on weekends (unsupervised), so bike-sharing companies could offer some incentives during the identified periods. For example, discounts or credit could be offered for 10 consecutive instances of reasonable parking to encourage users to park their bikes properly.

Evidence also shows that weather conditions have a clear relationship with inconsiderate parking behavior, with the probability of inconsiderate parking rising when air quality is poor and temperatures are too high or too low. This suggests that users will neglect to choose suitable parking locations when riding in more extreme climatic conditions. Scheduling management could be reinforced in such weather by deploying additional managers to sort out placements and display weather conditions on the mobile phone screen to prompt users to follow parking norms. In addition, bike-sharing companies can provide incentives such as cycling discounts in extreme weather, low (high) temperature subsidies, bonus strategies for inconsiderately parked bikes, and so on, to boost the mood and further motivate assistance in scheduling and regulating parking (Gao et al., 2021).

From the perspective of the built environment, three types of the built environment (catering service places, living service places, and sports and leisure places) have a greater influence on inconsiderate parking. When the density of living service places and hotels and hostels near a parking point is high, the probability of inconsiderate parking is higher. We recommend establishing centralized bicycle parking facilities within 100 m of these areas and recommending suitable parking points via the app. When there are sports and leisure activities near the parking location or when the number of catering service places near the parking location is 2–6, the probability of inconsiderate parking is low. Therefore, we suggest arranging reasonable shared bike parking facilities in conjunction with regular entrances and exits.

5.3. Further discussion

The characteristics of inconsiderate parking are not only for the study area but also for the DBS market. Some of the spatio-temporal characteristics of DBS found in this paper are consistent with many cities (Ji et al., 2020; Liu et al., 2019; Zhang et al., 2017; Xing et al., 2020). This is due to the function of DBS: they are mainly used for recreation on weekends and for commuting on weekdays. Therefore, the peaks of usage and parking are consistent for different DBS operators and in different cities. And the spatial characteristics also show that they are mainly parked in commercial areas on weekdays and in recreational areas on holidays. This temporal-spatial characteristic of parking shows similar patterns across different regions.

Some findings provide in-depth implications for the management of inconsiderate parking of DBS which have the potential to be applied in other regions with similar built environments. This paper adopted machine learning approaches to capture the characteristics of inconsiderate parking, which is triggered by the inherent properties of different types of built environments. These correlation patterns can therefore be applied to urban areas or other cities with similar built environments. For example, our results indicate that there is less inconsiderate parking in the residential and flyover categories. More attention should be paid to urban transport hubs with high pedestrian traffic and complex environments. In terms of influencing factors, riding distance and riding time have a greater impact, and as bike-sharing companies can collect this information, companies need to take responsibility and use the advantage of the platform economy to intervene in user behaviour and guide behaviour. In terms of the built environment, while the density of the built environment may vary between cities and regions, the types are consistent. This paper finds that built environments associated with entertainment venues are likely to be associated with inconsiderate parking.

The different cities and regions may have different built environments, and influencing factors may vary widely. Therefore, this paper further provides a feasible framework for targeted governance of shared bicycles based on behavioral patterns. We proposed a management path of "define the target -data processing - data insights - decision support". Based on the accurate identification of inconsiderate parking, multi-source data related to parking behavior data can be collected, including high-frequency order info., built environment, weather conditions, etc. The spatial and temporal patterns and formation mechanisms of inconsiderate parking are analyzed according to the process shown in Fig. 12, and targeted intervention measures can be proposed accordingly. Even in different study areas and different cities, the framework of targeted governance of DBS inconsiderate parking based on the spatial and temporal heterogeneity of behavior and the heterogeneity of the built environment is transferable.

This framework takes full advantage of spatio-temporal big data to extract patterns and features, including temporal characteristics, spatial characteristics and spatio-temporal interaction characteristics (Qin and Liao, 2022). It also captures peak characteristics in time, identifies periods of high demand and high probability of parking, and then proposes relevant dynamic scheduling policies accordingly. Spatially, hot zones are identified and sub-regional infrastructure layout plans are proposed accordingly. Integrating spatial and temporal characteristics, the relevant characteristics of different types of areas and periods are explored and interactive management of time and area is proposed accordingly. From the perspective of influencing factors, the causes of the problem are explored and the impact of external and internal factors on inconsiderate parking is analysed. We summarize the path and framework for managing inconsiderate parking in Fig. 12.

In addition, whether the framework can be further extended to other micro-mobile transportation modes is also our concern. Although we have not further investigated the parking characteristics of other forms of micro-mobility such as scooters, the dockless, shared and smart characteristics of shared micro-mobility are consistent (Coretti Sanchez et al., 2022; Wang et al., 2021). Micro-mobility travel relies on the internet to generate massive amounts of behavioural big data. By exploring the relevant behavioural patterns and heterogeneous, nonlinear characteristics, suggestions for targeted governance are obtained. These consistent characteristics make the framework in Fig. 12 still relevant for the governance of other forms of micro-mobility and provide potentially useful implications for managing other micro-mobility modes.

6. Conclusion

To improve the management efficiency of inconsiderate DBS parking, it will be necessary to identify spatiotemporal patterns and the formation mechanisms of inconsiderate DBS parking to achieve effective targeted operation and management. This paper empirically analyzes the spatial and temporal distribution patterns of DBS parking and inconsiderate parking based on regional parking data from Mobike and multisource data by identifying coordinates data on prohibited parking areas through field measurements. We further empirically investigate the factors that affect inconsiderate parking based on parking characteristics, points of interest, and weather data using a random forest and examine the nonlinear and threshold effects of the factors that influence inconsiderate parking. Unlike previous studies that analyzed inconsiderate parking at a psychological level, this paper analyzed the spatial and temporal patterns of inconsiderate parking and the influence of the external environment based on riding data.

This study provides support for clarifying the decision logic of DBS inconsiderate parking governance and offers new insights for the management of inconsiderate parking empowered by big data. The paper's results show that there are considerable differences in the temporal and spatial characteristics of inconsiderate DBS parking. DBS parking patterns show significant heterogeneity in terms of the built environment and temporal attributes. This suggests that optimizing DBS parking and the management of inconsiderate parking requires targeted management strategies based on different spatiotemporal patterns. This paper examines the factors that influence inconsiderate DBS parking and offers parking planning and behavioral guidance from an external environment level. As a result of the nonlinear analysis of various factors, we have gained a deeper understanding of various attributes' degree of influence on the probability of inconsiderate parking.

The paper has several limitations, and future research can be expanded in these respects: (1) The determination of inconsiderate parking in this paper is based on prohibited parking zones measured in the field, so replicability is somewhat limited. However, advances in big data and internet technology offer the possibility of online identification of inconsiderate parking. (2) This paper used data from Mobike, a large bike-sharing company, for analysis; thus, the scope of the study is limited and applicability is somewhat restricted. In the next step, the study could be expanded to include an analysis of parking characteristics across an entire city or other characteristic areas. (3) Concerning examining the factors that influence inconsiderate parking, the variables studied in this paper are mainly from the big data perspective of revealed preferences. Inconsiderate parking is largely influenced by the individual heterogeneity of users and psychological factors, which we will analyze in future research through a combination of state preference and revealed preference data in the form of a questionnaire survey. (4) This paper only analyses the inconsiderate parking problem of DBS, and whether these conclusions and methods can be transferred to other forms of micro-mobility, such as dockless scooters, should be further explored in future research.

CRediT authorship contribution statement

Yacan Wang: Conceptualization, Supervision, Project administration, Funding acquisition, Investigation. **Jingjing Li:** Software, Methodology, Formal analysis, Data curation, Writing – original draft. **Duan Su:** Visualization, Investigation. **Huiyu Zhou:** Methodology, Validation, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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