Parking Pattern and Influencing Factors of Dockless Public Bicycle: Case Study from Nanshan Shenzhen

Zhaoyang Xie [1], Kun Liu [2*], Qingfeng Zhou [3]

[1]*Harbin Institute of Technology, Shenzhen*
[2] *Harbin Institute of Technology, Shenzhen e, liuk@hit.edu.cn*
3. [1]Harbin Institute of Technology, Shenzhen
** Corresponding Author*

Abstract: The last-mile problem has been the hot focus question in the field of urban planning for a long time. In recent years, booming dockless public bicycle system in China provides new solution of this problem. However, large number of dockless public bicycles have occupied large amount of public space and disturbed people's daily life. To support dockless bicycle system efficiently, it's urgent to understand the parking modes of dockless public bicycle and their impacts on public space use. Using big data from the OFO BSS in Shenzhen, demographic data, building environments and the location of points of interest. This study defines the "parking density" and "parking duration" of sharing bicycles to analyze the parking characteristics. We take Nanshan district in Shenzhen city as a representative case, and divides Nanshan area into a 500m*500m grid, counts the number of bicycles parked in each grid. The factors affect dockless public bicycles are grouped into four main categories: transportation, land-use/build environment, population-job and meteorological data. We summarized four parking modes and a logit regress model was applied to explore the relation between parking pattern and open space. Based on the results of the model, we discussed the management of public bicycles in Shenzhen and made some suggestions.

Keywords: Dockless bicycle sharing system; Parking mode; public space

1. Introduction

Public bike system (PBS) also called a bicycle sharing system (BSS), which was born in 1965 in Europe has been developed for three generations. The third-generation system included electronically-locking racks or bike locks, telecommunication systems, smart cards and fobs, mobile phone access, and onboard computers (Demaio, 2009). The concept of PBS/BSS is simple: A user arrives at a station, takes a bike, uses it for a while and then returns it to another station. It is economical, eco-friendly, healthy, ultra-low carbon emissions and more equitable, has increasingly received attention in the last decade and have rapidly emerged in many cities all over the world. A characteristic differentiating bike sharing systems from other non-motorized systems is that they do not necessitate ownership of bikes and therefore facilitate increased complementarity between biking and transit. Bicycle-sharing systems free the user from the need to secure their bicycles avoiding bicycle theft issues. At the same time, the decision to make a trip can be made in a short time frame providing an instantaneously accessible alternative for a one-way or a round trip. Generally, many studies referred to the docked system, which need several fixed stations with docks in each station used to store bicycles and finish rent and return operations. The dockless system, also considered as the fourth-generation system, based on the mobile app and GPS, which eliminates stations and docks. Passengers can easily pick up and drop off bikes anywhere using their cell phone.

This system is quite spread nowadays in China through enterprises as OFO and Mobike since early 2016. Majority of bike-sharing schemes contains fewer bicycles compared with a dockless sharing bicycle. Many available bicycles and no restrictions on parked locations may result in different characteristics of public bicycles using and their influencing factors from dock system. Dockless public bike system brings new experiences and conveniences as well as some problems: (1) the emergence of huge number of dockless public bicycles means that more parking space needs to be set up in the public space of the city. This is bringing challenges to urban planning and urban management. (2) meanwhile, the feature of "drop off bikes anywhere" will result in a lack of certain constraints on the user's parking behavior. The user's parking location may disturb or affect the daily activities of city residents such as parking bicycles on the pavement. (3) For areas where many bicycles are parked, if the demand and supply do not match, it will result in a waste of bicycle resources and urban space resources.

However, few studies focused on the dockless parking system which needed to be deeply discussed. This paper selected Shenzhen, one of Chinese fastest urbanizing city, as a representative Metropolis case, and explored dockless bicycles by OFO bike sharing system. OFO bicycle-sharing system was launched in Shenzhen in December 2016 with more than 2200,00 bicycles. This paper mainly studies the inactivity of the dockless public bike system. Four issues are discussed: (1) How to measure the parking of dockless public bicycles? (2) what are parking modes of dockless public bicycles? (3) What's the relationship between parking modes and built environment? (4) how to manage public space to support efficient dockless parking?

2. Literature review

2.1 The systems perspective of sharing bike research

Sharing bike involved in many areas of research and it is broadly based on two perspectives: user perspective and systems perspective (Faghih-Imani and Eluru, 2015). In this study, we only focus on systems perspective.

2.1.2 The systems perspective

System perspective research can be divided into three categories.

(1) **Based on the practical usage, a number of studies focus to deal with bike sharing rebalancing problem, using intelligent algorithms**. In bike sharing system, the lack of resources is one of the major issues: a user can arrive at a station that has no bike available or wants to return her bike at a station with no empty spot. Fricker and Gast (2016) propose a stochastic model of a homogeneous bike-sharing system to study the effect of users' random choices on the number of problematic stations and compute the rate at which bikes must be redistributed by trucks to ensure a given quality of service. You, Lee and Hsieh (2017) provide an integrated model for the problems of fleet sizing, empty-resource repositioning and vehicle routing for bike transfer in multiple-station systems. O'Mahony (2015) tackle rebalancing the system during rush-hour, developing novel methods for optimizing rebalancing resources and formulate an optimization problem whose goal is to produce a

series of truck routes to get the system as balanced as possible during the overnight shift. Chen, et al. (2015) address the layout planning of public bicycle system within the attracted scope of a metro station. and locations of service stations and the optimal route options for the implement of redistributing strategy. Lozano, et al. (2018) proposes a multi-agent model that provides visualization and prediction tools for bike sharing systems.

(2) **Explore the spatial and temporal patterns of bike use over the time of day, using data mining and visualization techniques.** Whereas the aim of clustering is to identify mobility patterns in BSS usage by partitioning the stations into different clusters having a similar usage. Wong and Cheng (2015) presents the insights of imbalanced public bicycle distributions through the analysis of spatiotemporal activity patterns of bike stations. the clustering algorithm is used to analyze how station activity patterns are geographically distributed in the city based on their usage patterns and explore how these activity patterns relate to underlying cultural and spatial characteristics of Taipei City. Temporal and spatiotemporal patterns among bike stations of Barcelona bike sharing system were explored by Froehlich et al.(2008). Numerous researches also used a hierarchical clustering method to generate clusters and investigate usage patterns geographically distributed in the city to understand the impact of the inhomogeneity of the city on the long-run activity of stations (Vogel and Mattfeld, 2011, Lathia, et al., 2012). Brien et al.(2014) proposed a classification of bike-shares, based on the geographical footprint and diurnal, day-of-week and spatial variations in occupancy rates. Etienne and Latifa (2014) present one such automatic algorithm based on a new statistical model which will automatically cluster BSS stations according to their usage profile. Zhou (2015) investigated the spatiotemporal biking pattern in Chicago by analyzing massive BSS data from July to December in 2013 and 2014， constructed bike flow similarity graph and used a fast greedy algorithm to detect spatial communities of biking flows.

(3)**Thirdly, study on demand estimation and corresponding methodology.** These studies examine the influence of BSS infrastructure, transportation network infrastructure, land use and urban form, meteorological data, and temporal characteristics on BSS usage. This is the most relevant reference for this research. Faghih-Imani et al.(2014) collect station-level occupancy data from two cities and transform station occupancy snapshot data into station level customer arrivals and departures to perform our analysis. develop a mixed linear model to estimate the influence of bicycle infrastructure, socio-demographic characteristics and land-use characteristics on customer arrivals and departures. In the work of Krykewycz, et al.(2010) various demographic, land use, and infrastructure factors understood to be favorable for bike share usage were spatially analyzed to define a primary market area. El-Assiet al.(2017) investigate the effects of weather, socio-economic and demographic factors, as well as land use and the built environment on bicycle share ridership, a regression analysis was performed on three different levels. Hampshire and Marla(2012) explaining the factors affecting the bike sharing trip generation and attraction. Using usage data from bike sharing systems in Barcelona and Seville, 9 census level demographic data, and the location of points of interest, employ a panel regression model to produce consistent estimates of trip generation and attraction factors in the presence of unobserved spatial and temporal variables. Zhang et al.(2017) employed a multiple linear regression model to examine the influence of built environment variables on trip demand as well as on the ratio of demand to supply at bike stations in China. Faghih-Imani et al.(2014) investigated factors affecting bicycle share demand at the station level using real-time ridership data. The results showed that stations close to major roads had lower trip activities compared to stations that were situated around minor roads and bicycle lanes. A number of land use and built environment variables, temporal characteristics and weather variables such as temperature were investigated. Maurer(2011) used a pair-wise suitability analysis to understand the effects of variables such as job density, household income, and alternative commuters on public bicycle share ridership to propose the locations of bicycle stations in Sacramento, California. Gebhart and Noland(2014) used real-time ridership data for Capital Bikeshare in Washington D.C. to investigate the impact of weather variables and proximity of bike share stations to metro stations on ridership levels. Buck and Buehler (2012) investigated the influence of bicycle infrastructure, population density, land use mix around stations, and the number of households without a car using bicycle share systems using ridership data from Capital Bikeshare. Wang et al.(2012) evaluated the effect of socio-demographic, land use, built environment and transportation infrastructure variables on bicycle share ridership. Rixey (2013) explored the influence of socio-demographic characteristics such as education, income, and employment and population density on monthly ridership data from three United States.

Most studies focused on the factors affecting the use of public bicycles and the scheduling methods between stations. Since the shared bicycle does not have a centralized station, the starting and ending position of the vehicle is only related to the user's personal travel destination, so the impact of the built-up area on the shared bicycle usage will change. In addition, because the shared bicycle does not have a fixed site, but is dispersed in the city, the network formed by it is extremely complicated; and its more fluid characteristics also makes it difficult to monitor the number of vehicles in real time. In addition, there are significant differences in the number of vehicles used between different regions. Based on the above characteristics of shared bicycles, the original site-based data analysis method and the small network-based global optimization scheduling strategy are difficult to apply to the current shared bicycle.

Therefore, combined with the current use of public bicycles without dock, this paper will focus on the relationship between the parking characteristics of the dockless public bicycles and the built environment.Explore the parking mode of dockless public bicycles under the influence of different built environment factors, and then coordinate the relationship between urban public space and dockless public bicycles, rationally plan bicycle parking facilities, and promote green travel to provide relevant suggestions.

3. Data sources and method

3.1 Data source

3.1.1 The data of bike status

OFO is one of the biggest companies operating dockless bike-sharing systems in China, with a market share of about 50%. OFO bike is equipped with GPS to provide useful, accurate trip data. OFO began operating in Shenzhen in December 2016 with more than 20,000 bicycles in September 2017.This study takes Nanshan district which is one of the city centers of Shenzhen as case study. Nanshan has a high accessible road traffic network with subway and bus system cover the whole area. The climate in Nanshan is also pleasant, so it is very suitable for short-distance travel by bicycle. In order to describe spatial distribution of the dockless public bicycle and compare the parking characteristics between different areas, this study divided Nanshan district into 500m*500m grids with a total of 823 grids.

Grids with an average 24-hour bike less than 10 were removed. Finally, 500 grids were taken into our analysis (Figure 1).

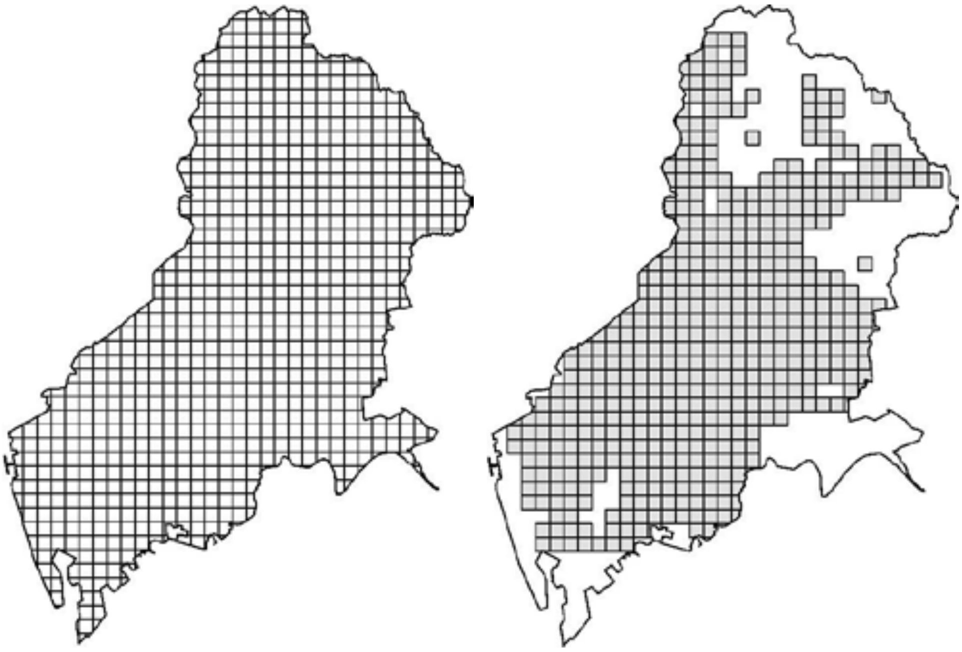


Figure1 the grids of Nanshan District

The raw data were obtained from the OFO website, which contained about 46.5 million pieces of messages including information of trip start time and date, trip end time and date, start location and end location This study scanned the working status of these bicycles every 5 minutes and got records the working day of the fourth week of September 2017. The data content includes the bicycle ID, the time and date when the bicycle starts to be used, and the bicycle position coordinates. There are about 57.6 million bicycle status records in a day.   We determined bicycle parking by identifying unmoved positions and corresponding duration during the day by bike's location and time stamp to explore parking mode.

Table 1 *The raw data of OFO using*

Time stamp	**Bike ID**	**GPS signal**	**X**	**Y**
2017-0321T00:13:21	7556118647	1(1-work,2-non-work)	113.884828	22.857536
2017-0321T00:13:21	7556073013	1(1-work,2-non-work)	113.884834	22.857274
…	…	…	…	…
2017-0321T00:27:44	7556146932	1	113.896694	22.458407

3.1.2 The factors of impacting bike parking

These factors are grouped into four main categories: transportation, land-use/build environment, population-job and meteorological data. Detailed indicators are shown in Table 2.

Table 2 The parking variables and influencing factors

Variable	Calculation	unit
Parking variables		
Parking density	Number of public bicycles parked in a grid at a time	num/ per gird
Parking duration	Average of the parking duration of all parked vehicles in a grid	minutes
Independent variables		
Density of fast way	Length of Expressway in a grid	km/km^2
Density of major& secondary road	Length of Major road and secondary road in a grid	km/km^2
Density of minor road	Length of Minor road in a grid	km/km^2
Bus stops	Number of bus stops in a grid	num/ per gird
Subway	Distance to the nearest subway	m
Population	Number of residents in a grid	1000/ per grid
Job	Number of Enterprise POI in a grid.	num/ 1 gird
Mix used	Information entropy	/
Residential land	Percentage of Residential land in a grid	/
Commercial land	Proportion of Commercial land in a grid	/
Educational Land	Proportion of Educational Land in a grid	/
Green Land	Percentage of Green Land in a grid	/
Building density	Number of building in a grid	num/ per gird
Service facility density	Number of shop and restaurant in a grid	num/ per gird
Altitude	Average altitude of a grid area	m

The parking density of a grid is the parking number of dockless public bicycle in a certain period. We first calculated parking number of each hour, then the average number of 24 hours is the parking density of a grid. The parking duration refers to the time interval value of a single dockless public bicycle from the time of stopping to the next use. The parking duration of a grid is the average of the parking duration of all parked vehicles in a certain period.

The land use mixing degree is to first calculate the area proportion of each type of land use in the grid, and then calculate by the following formula (1):

$$MixUsed = -\frac{\left(\sum_{i=1}^{N} p_i \ln p_i\right)}{\ln N} \qquad (1)$$

p_i——the percentage of i land type；

N——the number of all land types.

The data of subway comes from the website (http://www.szmc.net) of Shenzhen Metro Group Co., Ltd. The road net and bus data are provided by Shenzhen Urban Transport Planning Center. The information of population, job and land use is supplied by the Shenzhen Urban Planning Bureau and the Urban Planning and Design Institute of Shenzhen. We use points of interest (POI) data from BAIDU (see www.baidu.com).The terrain data of Shenzhen comes from google map.

3.2 Statistical analysis

First, we calculate the parking density and parking duration of each grid. According to these two attributes, we use the cross-classification method to divide the grid parking type. In this way, each grid corresponds to a parking mode, and then the built environment indicators of each grid are calculated. The multinomial Logit regression model is used to analyze the influencing factors of parking mode and the parking mode preferences in different built environments.

4. Results

4.1Statistical characteristics

4.1.1 Parking density

62 thousands dockless public bicycles had been parked in Nanshan district for more than 10 minutes, and on average, 49 thousand bicycles parked per hour, which occupied 7.3 ha public space. By grid analysis, the parking density was around 100 bicycles per grid per day, and the maximum number of bicycles in one grid was 575.

Figure 2 shows an uneven spatial distribution of parking density of dockless public bicycles in Nanshan. Obviously, the bicycles were unevenly distributed. The central area had a significant higher density than others because these are the main functional areas of people's daily life, such as living, employment, leisure, transportation, etc. The low-density areas were mainly close to less-developed area, mountain and other bicycle ban zones such as parks and waterfront.

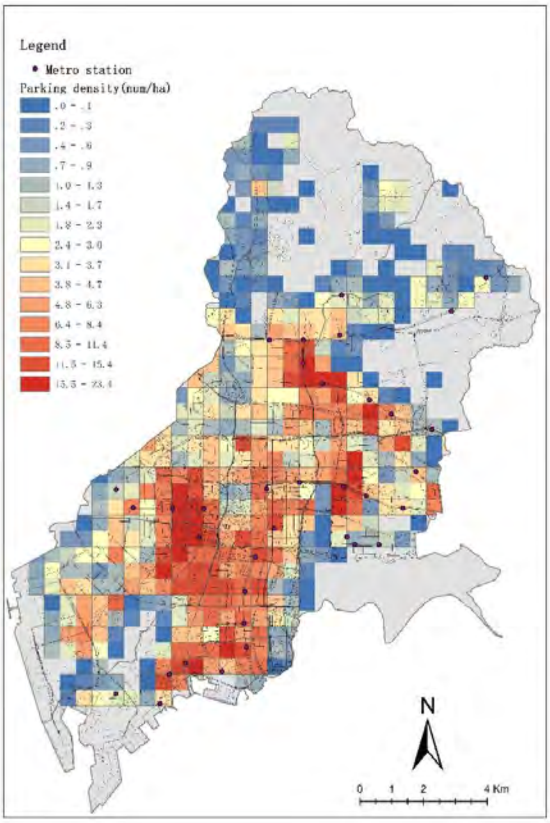


Figure 2 The spatial distribution of parking density of dockless public bicycles in Nanshan

3.1.2 Parking duration

The average parking duration of bicycles was 341 min per time, which meant bicycles were used around every 6 hours. The parking durations of around 10 thousand bicycles were more than 1420 min, which continuously occupied public space whole day. Figure 3 shows the spatial distribution of parking duration of dockless public bicycles in Nanshan. Grids in the center area of Nanshan had a significant shorter parking duration and peripheral grids had a longer parking duration. The short-term parking of grids was mainly in high-tech employment center, universities and commercial centers. These areas are mostly with good location, a large number of enterprises, well-constructed urban roads and mixed land use. In addition, the grid with subway station in has a high probability to be a short-term parking place. The grids with long-term parking were mostly in the suburb areas. The destinations of one-way riding such as Shenzhen-Hong Kong port area also caused long-term parking. By comparing the spatial distribution characteristics of parking density, it can be found that the area with a long parking period generally belongs to the area with a lower parking density.

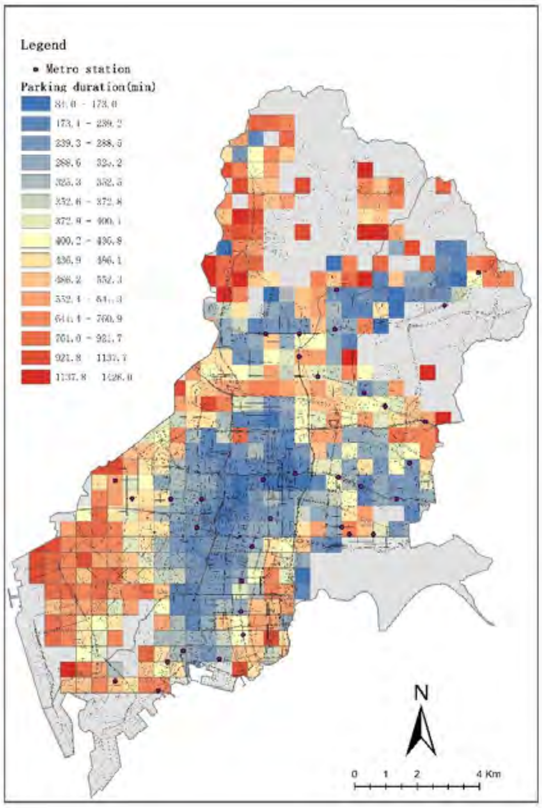


Figure 3 The spatial distribution of parking duration of dockless public bicycles in Nanshan

3.1.3 Parking patterns by Cross-classification

Figure 4 is a scatter plot of parking density and parking duration, in which X-axis is the parking density, and the origin is the average value of parking density and parking duration. Obviously, parking duration is negatively correlated with parking density. Four quadrants represented different parking characteristics of dockless public bicycles: （1） The grid in the first quadrant had high parking density and long-term parking and we called it **High-High(HH)** parking mode, which meant bicycles were static and dense stacked. （2） The grid in the second quadrant had low parking density and long-term parking. We named it **Low-High (LH)** parking mode, in which the bicycles were not many and inactive. (3) The grid in the third quadrant was the **Low-Low (LL**) parking mode which meant there were a few bicycles but efficiently used. (4) At last, the grid in the fourth quadrant with high parking density and short parking was **High-Low (HL)** parking mode, which was the most active mode.

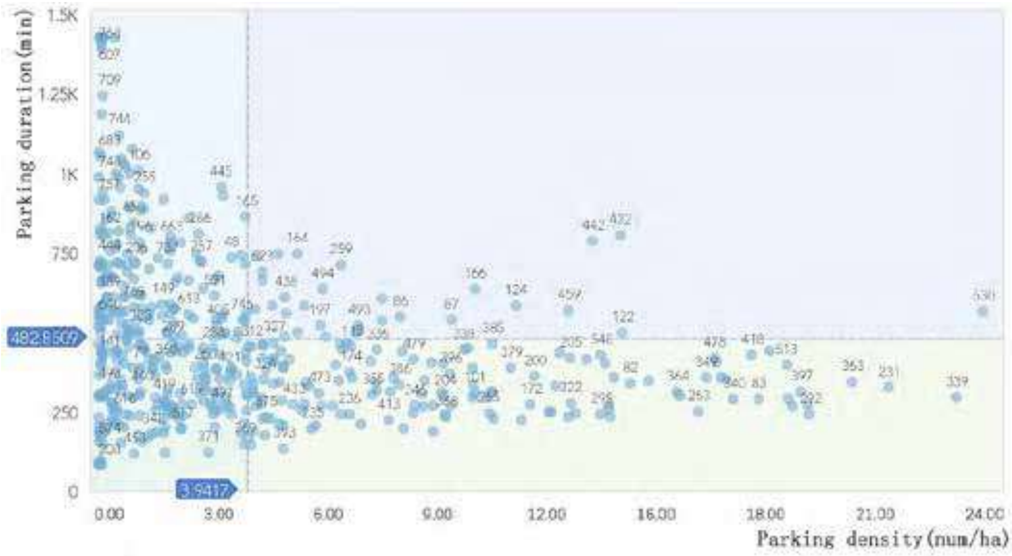
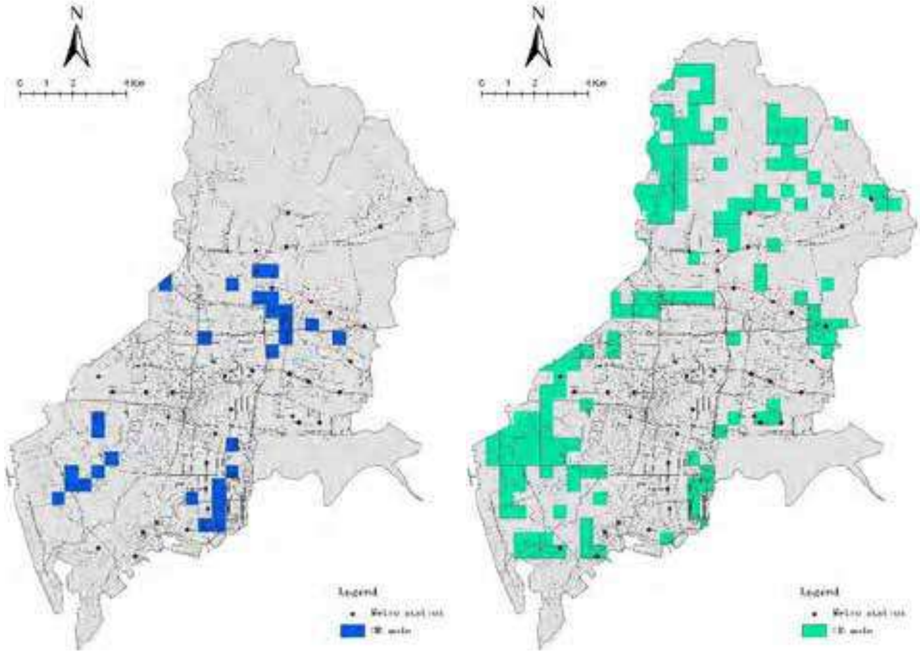


Figure 4 The scatter plot of parking density and parking duration

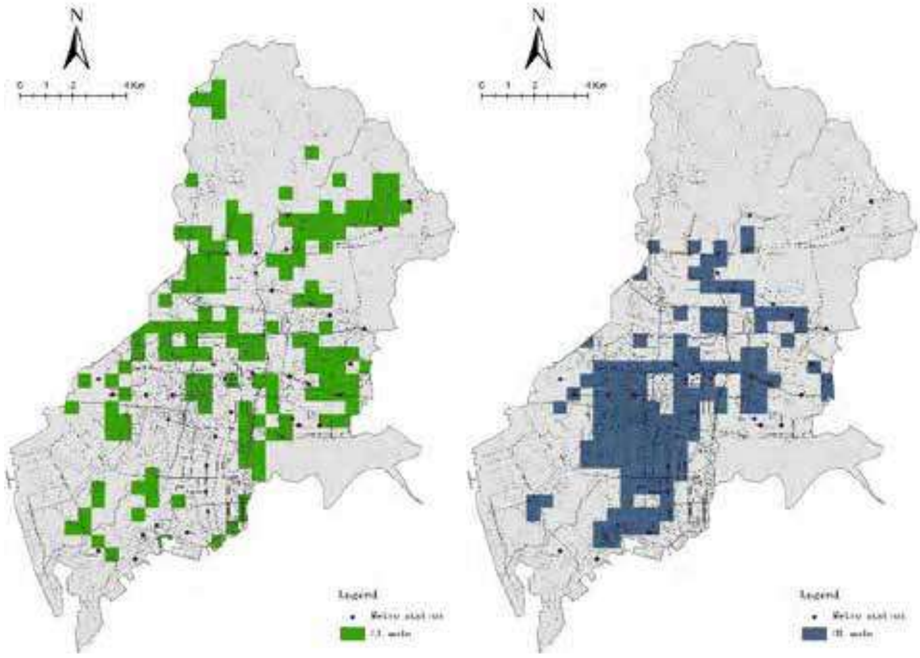
3.1.4 The spatial distributions of four parking modes

By categorizing the grids by 4 parking modes, the distribution of each parking mode were shown in Figure 5. Among all grids, HH mode accounted for 6%, LH mode had 34%, LL mode accounted for 32% and the left 28% was HL mode.

Table 3 shows the average value of built environment variables for each parking modes. Grids of HH mode had the highest density of fast way and grids of HL had the highest density of all other road types. LH mode grids had the poorest public transportation service (less bus stops and far away from metro station). HL mode was with the highest population and job density, and the LH mode was with the lowest ones. In terms of land use, HL mode had the highest mix use degree, residential land and proportion of commercial land. LL mode had the highest educational facilities and green land. The HL mode also had the highest service facility density followed by LL mode.



a High-High grids *b Low-High*



c Low-Low *d High-Low*

Figure 5 The spatial distribution of four dockless public bicycles parking mode in Nanshan

Table3 Statistical characteristics of built environment of four parking modes

Built environment variables	HH	LH	LL	HL
Density of fast way	32.91	14.25	20.06	22.97
Density of major & secondary road	46.10	15.49	27.22	51.01
Density of minor road	62.48	43.65	58.01	79.30

Bus stops	2.52	0.77	1.95	3.90
Subway	1222.15	2019.12	1226.13	672.47
Population	53.61	33.80	61.86	317.91
Job	0.48	0.34	1.08	2.80
Mix use	0.50	0.39	0.45	0.54
Residential land	0.02	0.02	0.02	0.07
Commercial land	0.03	0.02	0.05	0.06
Educational Land	0.02	0.01	0.09	0.05
Green Land	0.03	0.03	0.05	0.03
Building density	0.10	0.06	0.12	0.21
Service facility density	0.28	0.05	0.35	1.75
Altitude	12.95	35.64	28.02	16.23
Number of grids	31	167	162	140

4.2 The influencing factor of parking mode

A logistic regression model was applied to explore the built environment impacts on parking mode. The LH mode area had low artificial built environment and high altitude which was obviously far away from people's daily life. The number of dockless public bicycle in this area was small. Although the parking duration was long, this would not be a problem to occupy public place. We took LH as the compared group. The results are listed in table 4. The model's likelihood ratio is statistically significant at 0.01 level and the pseudo R square is 0.418.

Table4 Multinomial Logit Estimates Results of Built Environment Factors

	HH			LL			HL		
	B	Sig	Exp(B)	B	Sig	Exp(B)	B	Sig	Exp(B)
Intercept	-0.907	0.156		1.999	0.000		-0.007	0.990	
Density of fast way	**0.422**	**0.022**	1.525	0.242	0.093	1.274	**0.571**	**0.001**	1.770
Density of major & secondary road	**0.505**	**0.019**	1.657	0.239	0.165	1.270	**0.669**	**0.001**	1.953
Density of minor road	0.074	0.755	1.077	0.192	0.185	1.211	0.398	0.058	1.489
Bus stops	**0.606**	**0.041**	1.833	0.135	0.566	1.145	0.173	0.519	1.188
Subway	-0.572	0.067	0.564	**-0.605**	**0.000**	0.546	**-1.531**	**0.000**	0.216
Population	-0.573	0.405	0.564	0.054	0.883	1.055	**1.148**	**0.006**	3.152
Job	-0.112	0.892	0.894	**1.409**	**0.004**	4.093	**1.694**	**0.001**	5.441
Mix use	0.161	0.560	1.174	**-0.355**	**0.029**	0.701	0.066	0.800	1.068
Residential land	0.115	0.776	1.122	-0.381	0.128	0.683	-0.391	0.240	0.677
Commercial land	-0.198	0.561	0.820	0.310	0.059	1.363	0.215	0.298	1.240
Educational Land	0.832	0.187	2.299	**1.468**	**0.002**	4.339	**1.315**	**0.009**	3.724
Green Land	0.029	0.911	1.029	0.196	0.080	1.217	0.299	0.152	1.348
Building density	0.504	0.199	1.655	0.320	0.177	1.377	**0.850**	**0.014**	2.339
Service facility density	**2.462**	**0.033**	11.727	**2.428**	**0.016**	11.336	**2.836**	**0.006**	17.048
Altitude	**-1.851**	**0.002**	0.157	0.033	0.799	1.034	**-2.187**	**0.000**	0.112

（1）Results show that compared with LH parking mode, HH parking mode is with denser high-class roads (fast road, primary and secondary roads), probably because of spatial segregation of bike lanes by high-class roads. Grids with denser bus stops have positive impact on being a HH mode, since bike plus subway is not competitive than bus in these areas. Meanwhile, area with more shops and restaurants are the easier to be HH mode than LH mode. In addition, with the lower the altitude, public bicycles are easily stacked to increase the parking density and parking duration. Therefore, we can infer that it is easy to form a HH parking mode when those areas are separated, bus-oriented, lower and with lots of shops, where the attraction demands are **one-way demands**, .to restrain bicycle flows out of the areas. As a result, bicycles in this area stack and cause long-term parking, strongly occupied public space and disturbed people's outdoor activities.

（2）Close to subway station, dense job opportunities, lots of educational land and shops, less mixed land use indicate those special zones such as universities and independent high-tech parks, and form LL parking mode. These regions are normally independent managed, with big scale and closely interrelated, where the demands of dockless public bicycles are limited, clear, stable and continuous, therefore the use of dockless public bicycles is very efficient and the parking duration is short. The public bicycles in this area have less exchange with other areas. LL parking mode is self-sufficient, with the least occupation of public space comparing with other 3 modes.

（3）High-grade urban roads, closer to the subway station, high population density, high density of jobs, high density of shopping and restaurants, and relatively lower the altitude have a significant impact on the HL parking mode. Areas with the combination of the above characteristics will tend to be the core area of people's daily activities and have strong and aggregate demands to use bicycles. To meet the demands, bicycle operators often set up excessive bicycles to serve people at any time. Due to the large travel demand, the dockless public bicycles are used at high frequencies, resulting in a high density, low duration parking feature. At the same time, the bicycles in the area exchange frequently with the bicycles in the surrounding area. In HL mode areas, bicycles are most active, and besides parking space, the turnover space, bike lane and other facilities are urgently needed.

4.3 Suggestions for public space governance to adapt dockless public bicycles

Comparing the parking demand of public space, first, the two parking modes of LH and LL have little impacts on the occupation of public space. For the LH parking mode, a small number of public bicycles are parked in the area for a long time, which is not conducive to the maintenance of public bicycles. Bicycle maintenance and parking spots can be combined to design as part of a public space service facility. For area with LL parking mode, it is necessary to pay attention to changes in land use or transportation facilities in the area, which will cause changes in the demand for public bicycles. Some public space can be reserved as a potential bicycle parking slot. Secondly, HH parking mode and HL parking mode have high pressure on public open space. On the one hand, a multi-level parking facility system can be constructed, combining a centralized and decentralized layout. In areas where public open space is limited, multistory parking can be used. On the other hand, bicycles with less use is a waste of public open space and it is reasonable to control the scale of the dockless public bicycles. In addition, for the HH parking mode area, the considerable bike lane design is necessary to encourage bicycle flow and to overcoming those obstructions from slope and one-way destination.

Besides, the dispatch management of dockless public bicycle is an also important optional strategy for reducing public open space pressure. Dispatch management strategies can be divided into active dispatching and passive dispatching. Active dispatching encourages cyclists to ride public bicycles in the HH area to other areas in need by setting incentives for operators; and passive dispatching is to transport dockless public bicycles from HH area to the demand area by full-time dispatchers and vehicles. This involves vehicle route and bicycles redistribution problem.

In terms of urban spatial management strategy, some public open place should adopt a limited open management strategy for dockless public bicycles, allowing a certain number of dockless public bicycles to enter, which not only does not create pressure on the spatial environment in the region, but also meets people's cycling needs. In some important areas, such as the area within 10m around the entrance and exit of subway station, a no-parking area for public bicycles is set up to prevent public bicycles from occupying safe evacuation space.

5. Conclusions

This paper took Nanshan District in Shenzhen city as a representative case, to analyze the parking characteristics of dockless public bicycles by "parking density" and "parking duration".

For the "parking density" and "parking duration" of sharing bicycles in Nanshan, the short-term parking of grids are mainly high-tech employment centers, universities and commercial entertainment areas. The areas with long-term parking are mostly in the suburb areas close to mountain or construction site. the central area has a significant higher density than others. Based on cross classification, we presented four parking modes, and applied a logistic regression model to explore built environment impacts on parking modes.

The results show that spatial isolation, public transportation, urban centralization, functional zone and attitude all significantly influence the parking modes and cause uneven spatial distribution and uneven uses of dockless bicycles, and cause serious occupation of public space. To improve the efficiency of bicycle parking and reduce the useless occupation, considerable bike lane system to encourage bicycle’s flow, compact parking facilities to save space, dispatch management to improve efficiency, diverse policies to ease the burden of public space are all necessary strategies.

References

Buck, D., and R. Buehler. 2012. Bike Lanes and Other Determinants of Capital Bikeshare Trips. Transportation Research Board 91st Annual Meeting.

Chen, J., X. Chen, H. Jiang, S. Zhu, X. Li, and Z. Li. 2015. Determining the Optimal Layout Design for Public Bicycle System within the Attractive Scope of a Metro Station. Mathematical Problems in Engineering 2015:1-8.

Demaio P. 2009. Bike-sharing: History, Impacts, Models of Provision, and Future. Journal of Public Transportation, 12(4:41-56.

El-Assi, W., M. Salah Mahmoud, and K. Nurul Habib. 2017. Effects of built environment and weather on bike sharing demand: a station level analysis of commercial bike sharing in Toronto. Transportation 44 (3):589-613.

Etienne, C, M. and Latifa O. 2014. Model-Based Count Series Clustering for Bike Sharing System Usage Mining: A Case Study with the Velib System of Paris. Acm Transactions on Intelligent Systems & Technology 5 (3):1-21.

Faghih-Imani, A., N. Eluru, A. M. El-Geneidy, M. Rabbat, and U. Haq. 2014. How land-use and urban form impact bicycle flows: evidence from the bicycle-sharing system (BIXI) in Montreal. Journal of Transport Geography 41:306-314.

Faghih-Imani, A., and N. Eluru. 2015. Analysing bicycle-sharing system user destination choice preferences: Chicago's Divvy system. Journal of Transport Geography 44:53-64.

Fricker, C., and N. Gast. 2016. Incentives and redistribution in homogeneous bike-sharing systems with stations of finite capacity. EURO Journal on Transportation and Logistics 5 (3):261-291.

Froehlich, J., J. Neumann, and N. Oliver. 2008. Measuring the Pulse of the City through Shared Bicycle Programs. International Workshop on Urban, Community, and Social Applications of Networked Sensing Systems - UrbanSense08.

Gebhart, K., and R. B. Noland. 2014. The impact of weather conditions on bikeshare trips in Washington, DC. Transportation 41 (6):1205-1225.

Hampshire, R. C., and L. Marla. 2012. An Analysis of Bike Sharing Usage: Explaining Trip Generation and Attraction from Observed Demand. Transportation Research Board Annual Meeting.

Krykewycz, G. R., C. M. Puchalsky, J. Rocks, B. Bonnette, and F. Jaskiewicz. 2010. Defining a Primary Market and Estimating Demand for Major Bicycle-Sharing Program in Philadelphia, Pennsylvania. Transportation Research Record: Journal of the Transportation Research Board, No. 2143.DOI: 10.3141/2143-15.

Lathia, N., S. Ahmed, and L. Capra. 2012. Measuring the impact of opening the London shared bicycle scheme to casual users. Transportation Research Part C Emerging Technologies 22 (5):88-102.

Lozano, Á., J. De Paz, G. Villarrubia González, D. Iglesia, and J. Bajo. 2018. Multi-Agent System for Demand Prediction and Trip Visualization in Bike Sharing Systems. Applied Sciences 8 (1):67.

Maurer, L. K. 2011. Feasibility Study for a Bicycle Sharing Program in Sacramento, California. Transportation Research Board 91st Annual Meeting.

O'Mahony E , Shmoys D B . 2015. Data Analysis and Optimization for (Citi)Bike Sharing.Twenty-ninth Aaai Conference on Artificial Intelligence. AAAI Press.

O Brien, O., J. Cheshire, and M. Batty. 2014. Mining bicycle sharing data for generating insights into sustainable transport systems. Journal of Transport Geography 34:262-273.

Rixey, R. A. 2013. Station-Level Forecasting of Bike sharing Ridership. Transportation Research Record: Journal of the Transportation Research Board 2387 (1):46-55.

Vogel, P., T. Greiser, and D. C. Mattfeld. 2011. Understanding Bike-Sharing Systems using Data Mining: Exploring Activity Patterns. Procedia - Social and Behavioral Sciences 20:514-523.

Wang, X. L. G. S. 2012. Modeling Bike Share Station Activity: Effects of Nearby Businesses and Jobs on Trips to and from Stations. Journal of Urban Planning & Development, 142, Article ID: 04015001. https://doi.org/10.1061/(ASCE)UP.

Wong, J. T., and C. Y. Cheng. 2015. Exploring Activity Patterns of The Taipei Public Bike sharing System. Journal of the Eastern Asia Society for Transportation Studies 11:1012-1028.

You, P., P. Lee, and Y. Hsieh. 2017. An artificial intelligent approach to the bicycle repositioning problems. Engineering Computations 34 (1):145-163.

Zhang, Y., T. Thomas, M. Brussel, and M. van Maarseveen. 2017. Exploring the impact of built environment factors on the use of public bikes at bike stations: Case study in Zhongshan, China. Journal of Transport Geography 58:59-70.

Zhou, X. L. 2015. Understanding spatiotemporal patterns of biking behavior by analyzing massive bike sharing data in Chicago. PLoS One 10 (10):e137922.