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## A case study in Nanjing, China

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# Comparison of usage regularity and its determinants between docked and dockless bike-sharing systems: a case study in Nanjing, China

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## Abstract

Bike-sharing systems have rapidly expanded around the world. Previous studies found that docked and dockless bike-sharing systems are different in terms of user demand and travel characteristics. However, their usage regularity and its determinants have not been fully understood. This research aims to fill this gap by exploring smart card data of a docked bike-sharing scheme and GPS trajectory data of a dockless bike-sharing scheme in Nanjing, China, over the same period. Both docked and dockless bike-sharing users can be classified into regular users and occasional users according to their usage frequency. Two systems are cross-compared regarding their travel characteristics. Then, binary logistic models are applied to reveal the impacts of travel characteristics and built environment factors on the regularity of bike-sharing usage. Results show that for both bike-sharing systems, regular users and occasional users share similar riding time and distance, while significant differences in the spatio-temporal distribution between docked and dockless bike-sharing systems are observed. The regression model results show that the "Trips during morning and afternoon peak hours" are positively associated with the regularity of both docked and dockless bike-sharing usage. However, the "Riding distance" variable is negatively associated with the usage regularity of both systems. Built environment factors including working point of interest (POI), residential POI, and transit POI promote the usage regularity of both bike-sharing systems. Finally, policy implications are proposed, such as increasing the density of docking stations in suburban areas and developing high-quality parking area for dockless bike-sharing around public transport stations. This study can help operators or governments to launch or improve the service of bike-sharing systems.

**Keywords:** Docked bike-sharing, Dockless bike-sharing, Regularity, Spatio-temporal pattern, Smart card data, GPS trajectory data

## 1. Introduction

The heavy reliance on the automobile has caused several problems, such as traffic congestion, air pollution, respiratory health issues, and climate change (Park and Sohn, 2017; Shelat et al., 2018). As a short-term bike rental service, bike-sharing has become a common travel mode in many cities around the world during the last decade (Liu et al., 2018; Zhang et al., 2015). It is regarded not only as an economical, flexible, convenient, and sustainable travel mode, but also as a method to mitigate problems, such as air pollution and traffic congestion. It promotes a healthy lifestyle and can support multimodal transport connections (Maizlish et al., 2013; Yang et al., 2016). By October 2019, more than 2080 bike-sharing schemes are already in operation and 360 others are under construction in more than 50 countries (Meddin and DeMaio, 2019).

Currently, the bike-sharing systems operated worldwide can be divided into two categories: docked bike-sharing and dockless bike-sharing (Liu et al., 2018). For the docked bike-sharing system, users have to rent bikes from designated docking stations and then return them to available lockers in docking stations (Hsu et al., 2018). The dockless bike-sharing system has two prevalent models for bicycle parking. One is the physical or geo-fencing designated parking areas provided in public space with or without bike racks (Zhang et al., 2019). The second model has quite different features. Shared bikes could be scattered almost everywhere as long as the place is accessible to all users (Pal et al., 2017; Tian et al., 2018). The co-existence of these systems presents new opportunities for sustainable transportation in cities all over the world, both serving door-to-door trips and first/last mile transit trips (Brand et al., 2017; Sanmay et al., 2018).

Usage regularity is usually considered from the perspective of trip-making behavior of individuals – refer to as how often travelers would use a specific service in a spatio-temporal context (Mcleod et al., 2017). A better understanding of travel patterns and regularity will enable service providers to evaluate the services they offer, to adjust marketing strategies, to retain loyal customers and to improve overall transit performance (Ma et al., 2013). A good understanding of the unusual loyalty of some riders can help transport agencies to determine where and when they should provide discounts to retain these loyal passengers and attract potential passengers (Martin et al., 2012). Based on identified travel patterns and usage regularity, transport authorities can better understand how passengers' behaviors are likely to change in response to a new fare structure. Then they can design a fare policy that attracts more users and creates more revenue (Martin et al., 2012).

Previous literature has explored the usage regularity and the corresponding determinants of bike sharing systems. However, so far, the main focus has been lying on docked bike sharing systems (Tang et al., 2010; Zoubir et al., 2017). Although Kiana et al. (2019) concluded that it was necessary to understand the behavior of users for each of these systems for better planning, operation, and management of the systems, none of previous studies has compared the usage regularity of docked and dockless bike sharing systems in a same study. To fill this gap, this paper compares the usage regularity of two systems by applying the smart card data and GPS data of a same period from a model city in China. The main contributions of this paper are twofold: (1) the difference in usage regularity between two bike sharing systems, including riding distance, riding time, and spatial-temporal usage patterns are revealed; (2) binary logistic models are established to measure how travel behavior and built environment factors influence the usage regularity of the two systems. This study is one of the pioneers to address the similarities and differences in travel patterns among regular and occasional users of two systems. Results of this research can help operators of docked and dockless bike sharing systems to improve their operations and service. Also, the findings of this paper may inspire cities to launch and manage bike sharing programs.

The remainder of this paper is organized as follows. The next section provides an overview on comparative analysis of docked and dockless bike-sharing, influential factors of cycling regularity and influential factors of the usage of bike-sharing systems. Section 3 describes the study area, data sets, variables, and modeling approach used for the analysis. Research results are then presented in Section 4,

followed by conclusions and policy implications.

## 2. Literature Review

### 2.1. Comparative analysis of docked and dockless bike-sharing

Docked bike-sharing has been prevalent for more than twenty years while dockless bike-sharing system emerged and expanded rapidly since 2017 (Hirsch et al., 2019). The docked and dockless bike-sharing systems are quite different in terms of user demand and travel characteristics (Li et al., 2019). Several studies have analyzed the difference of travel patterns between the users of docked and dockless bike-sharing systems. Chen et al. (2018) concluded that most users of the two systems traveled less than 3 km in China. In addition, their use frequency decreased along with longer travel distance. Based on an up-to-date empirical analysis, Gu and Kim (2019) discussed recent development of bike-sharing in China. They suggested that cities with low cycling rate and high motor vehicle usage rate should implement docked bike-sharing. As a sustainable and green public service, bike-sharing is cost-efficient and well regulated. Ma et al (2019) discovered that, users of the docked bike-sharing system traveled longer both in distance and in time than dockless bike-sharing users. However, the usage frequency and hourly usage volume of the former system are higher than those of the latter. Regarding influential factors on user demand, Chen et al. (2018) analyzed the survey data and used ordinal logistic regression for both systems. They concluded that travel distance had a significantly positive correlation with the usage of docked shared bikes instead of with dockless sharing bikes. Through a survey study in Nanjing, China, Ma et al (2019) established a mode choice model and revealed that high-income travelers and those who were highly sensitive to discounts, internet technology and online payment service were more likely to use dockless bike-sharing.

### 2.2. Influential factors of cycling regularity

Due to the lack of existing studies on dockless bike-sharing, this section focuses on the usage frequency of general bikes. Sherwin et al. (2014) interviewed 61 individuals in England and divided the respondents into non-regular cyclists and regular cyclists to explore qualitatively how social influence affected the decision to cycle. The availability of bicycles through social networks is found to be important for new regular cyclists. Using online survey data of the users from Shanghai Minhang bike-sharing system, Tang et al. (2017) classified respondents into daily users and non-daily users according to their average usage frequency and they explored the factors that influence usage frequency. The results indicated that users who used a docked bike for daily shopping and public services were more likely to use the bike-sharing system. Sardianou and Nioza (2015) conducted a survey and presented insights into the profile of cycling frequency based on the estimation of binary logistic regression models. They found that women were more likely to be regular eco-cyclists than men, which was consistent with the finding of Damant-Sirois et al.(2015). Manaugh et al. (2017) examined several factors influencing the cycling frequency in a campus in Montreal, Canada and they found that the availability of cycle paths was strongly associated with a higher cycling frequency.

### 2.3. Factors influencing bike-sharing system usage

#### 2.3.1. Docked bike-sharing system

Researchers have identified many determinants on docked bike-sharing usage. They found that personal and socio-demographic characteristics significantly influence the use of docked bike-sharing system. In areas where bike-sharing programs are implemented, bike-sharing users are more likely to be male (Tu et al., 2019), younger (Fishman et al., 2013), well-educated (Ricci, 2015), and with higher income (Fishman et al., 2014). In China, the automobile ownership of bike-sharing users is higher than that of non-users (Tang et al., 2010). Bike-sharing stations that are located in areas with higher population density and job density (Faghih-Imani et al., 2014) tend to introduce a higher ridership. Additionally,

docked bike-sharing usage is associated with built environment characteristics and transportation infrastructure. Increased use of docked bike-sharing is positively associated with bike-sharing infrastructure (e.g. the density and capacity of docking stations) (Wang and Akar, 2019; Xu et al., 2019), cycling infrastructure (e.g. bike lane and paths) (Cervero et al., 2009), accessibility of bike-sharing stations (Rixey, 2012), proximity to central business districts (CBD) (El-Assi et al., 2017), street density (González et al., 2016), degrees of mixed land uses (Wang and Akar, 2019), and the density of restaurants and residential point of interest (POI) surrounding bike stations (FaghihImani and Eluru, 2015; Ogilvie and Goodman, 2012). Different studies have different views on the effect of the density of commercial companies, schools, and recreational POI on docked bike-sharing usage (Faghih-Imani et al., 2017; Feiyang et al., 2018; Noland et al., 2016; Wang and Akar, 2019). The views on the relationship between bike-sharing usage and public transport facilities are also mixed. Some studies pointed out that the proximity of bike-sharing stations to public transport facilities boosted bike-sharing usage (Faghih-Imani et al., 2014; González et al., 2016; Noland et al., 2016). In contrast, other studies reported that such proximity reduced bike-sharing usage (Campbell and Brakewood, 2017; Zhao, 2013). Additionally, weather conditions significantly influence docked bike sharing usage (El-Assi et al., 2017). Gebhart and Noland (2014) observed that cold temperatures, rain, snow and high humidity levels reduced docked bike-sharing trips.

#### 2.3.2. Dockless bike-sharing system

It is quite difficult to access dockless bike-sharing trip data due to privacy issues and business secrets. The number of studies on the dockless bike-sharing system is therefore limited (Zhang et al., 2019). Recently, Shen et al. (2018) investigated the impact of bike fleet size, built environment characteristics, accessibility to public transportation, bicycle infrastructure, and weather conditions on the usage of dockless bike-sharing. They found that high land use mixtures, easy access to public transportation, more supportive cycling facilities, and free-ride promotions were positively associated with the usage of dockless bikes. They also revealed that rainfall and high temperatures reduced the usage of dockless bike-sharing. Tu et al. (2019) applied a generalized additive mixed model to identify the factors associated with the usage of dockless bike-sharing. They found that floor area ratio, percentages of residential, industrial, and green space, the degrees of mixed land use, and the densities of primary and secondary roads were positively associated with the usage of dockless bike-sharing. In contrast, the density of intersections was negatively associated with such usage. They also found that females and children were less likely to ride dockless shared bikes. Li et al. (2018) conducted a survey and explored the factors affecting the usage of the dockless bike-sharing. They found that the higher-educated and high-income users prefer to use dockless bike-sharing. Ma et al. (2019) examined the influence of the docked bike-sharing fleets and built environment factors on the demand for dockless shared bikes. They found that docked bike-sharing fleets and the density of Entertainment POI were positively associated with the usage of dockless shared bikes, whereas the density of bus/metro stations were negatively associated with such usage.

### 2.4. Research gaps

Although aforementioned studies discussed the usage patterns and the conresponding determinants of both bike-sharing systems, none has compared the usage regularity of the two systems. Additionally, survey data are often used to identify regular bike-sharing users and non-regular bike-sharing users. This method often results in insufficient sample size and fails to analyze the dynamic variation of the spatio-temporal patterns of regular and non-regular bike-sharing usage. Compared with traditionally collected survey data, smart card data and GPS data additionally record the day-to-day variability of a cyclist's travel pattern. They can be used to identify cyclists and detect the spatial and temporal regularity of bike-sharing usage over a continuous long period of time (Schneider et al., 2013). As of now, the differences in travel patterns between regular users and occasional users in response to docked and dockless bike-sharing systems are unknown to us. The effects of travel characteristics and built

environment factors on the usage regularity of docked and dockless bike-sharing are also to be discovered. To address these issues, this study explores the travel pattern difference by mining the smart card data of docked bike-sharing and GPS data of dockless bike-sharing. Binary logistic models are established to quantify the effects of various travel characteristics and built environment factors on the usage regularity of different bike-sharing systems.

## 3. Study area, data and methods

### 3.1. Study area

As the capital of Jiangsu province and a core city of Yangtze River Delta economic zone, Nanjing has long been ranked as the second largest commercial center in the East China region, following Shanghai. With a total population of 8.33 million, the city covers an area of 6, 587 km$^2$. Multiple travel modes, including private car, local bus, subway, taxi, private bikes, docked bike-sharing, dockless bike-sharing and walking, are available in this city. In order to ease traffic pressure and bring citizens great convenience, Nanjing launched docked and dockless bike-sharing programs in January, 2013 and January, 2017 respectively. As of 2017, Nanjing has approximately 60,000 docked shared bikes and 450,000 dockless shared bikes. In this paper, five urban districts (Xuanwu, Qinhuai, Gulou, Jianye and Yuhua), where both docked and dockless bike-sharing systems are well developed, are selected as the study area, as shown in Fig. 1 below.

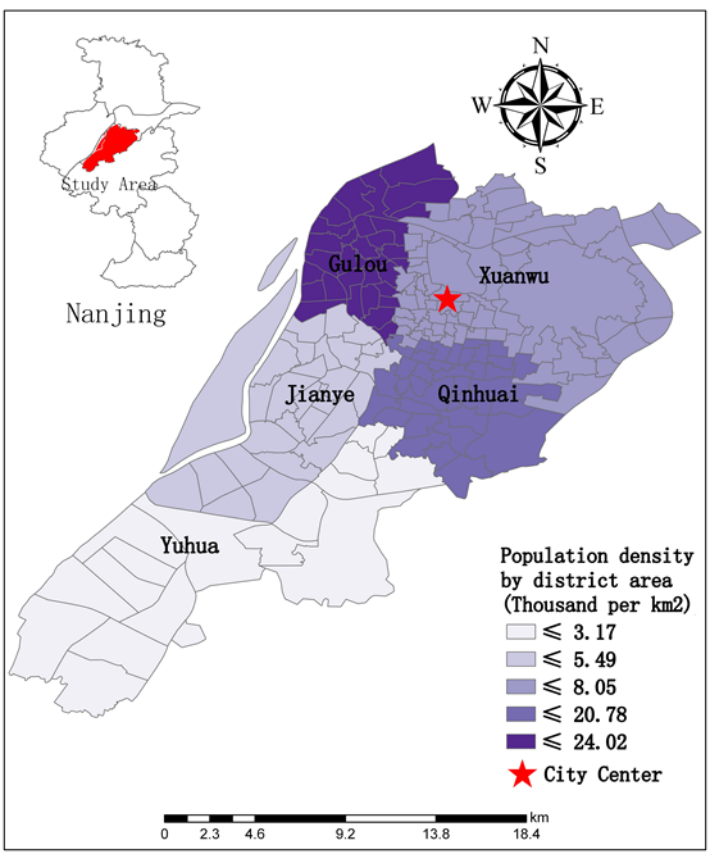



**Fig. 1.** Map of study area.

### 3.2. Data

The data used in this paper includes one week of smart card data of docked bike-sharing and GPS

trajectory data of dockless bike-sharing from September 18th to 24th, 2017 provided by Mobike company and Nanjing Public Bicycle Company, respectively. Table 1 and Table 2 show the typical sequence of docked and dockless transaction records. For each trip, available attributes include user ID, starting timestamps, starting longitude, starting latitude, ending timestamps, ending longitude, ending latitude. A brief description of each variable is included in the original database (see Table 1 and Table 2)

**Table 1** A sequence of docked bike-sharing transaction records

| User ID | Starting Timestamps | Starting Longitude | Starting Altitude | Ending Timestamps | Ending Longitude | Ending Altitude |
|---|---|---|---|---|---|---|
| Njhx00037… | 2017/9/18 18:25:17 | 118.729 | 32.051 | 2017/9/18 18:33:16 | 118.747 | 32.018 |
| Nj1110000… | 2017/9/18 18:25:23 | 118.776 | 32.037 | 2017/9/18 18:45:58 | 118.769 | 32.038 |
| Nj1110000… | 2017/9/18 18:26:04 | 118.779 | 32.064 | 2017/9/18 18:48:32 | 118.773 | 32.067 |
| Njhx00037… | 2017/9/18 18:26:25 | 118.790 | 32.043 | 2017/9/18 18:29:18 | 118.790 | 32.043 |
| Njhx00121… | 2017/9/18 18:26:28 | 118.772 | 32.114 | 2017/9/18 18:39:00 | 118.744 | 32.093 |

Note: User ID are not fully presented in this table to ensure privacy of bike-sharing users

**Table 2** A sequence of dockless bike-sharing transaction records

| User ID | Starting Timestamps | Starting Longitude | Starting Altitude | Ending Timestamps | Ending Longitude | Ending Altitude |
|---|---|---|---|---|---|---|
| 45e985b3d… | 2017/9/18 18:25:02 | 118.805 | 32.051 | 2017/9/18 19:18:16 | 118.821 | 32.062 |
| C2d73ddc9… | 2017/9/18 18:25:10 | 118.733 | 31.987 | 2017/9/18 18:32:08 | 118.730 | 31.992 |
| 0e11477c7… | 2017/9/18 18:25:16 | 118.743 | 32.093 | 2017/9/18 18:30:44 | 118.742 | 32.086 |
| D50596c0f… | 2017/9/18 18:25:33 | 118.750 | 32.065 | 2017/9/18 18:28:12 | 118.748 | 32.068 |
| 4581a379e… | 2017/9/18 18:25:34 | 118.734 | 32.151 | 2017/9/18 18:32:08 | 118.726 | 32.149 |

Note: User ID are not fully presented in this table to ensure privacy of bike-sharing users

At data pre-processing stage, both docked and dockless bike-sharing trips with the following properties have been removed:

- Trips either started or ended outside the study area;
- Distance: Trips shorter than 100 meters or longer than 5 km, as suggested by Shen et al. (2018);
- Duration: Trips lasting less than 30s or longer than 2 hours, as suggested by Pal et al.(2017) ;
- Completeness: Trips without complete journey details.

Thus, we have obtained valid trip records of 674,390 for docked bike-sharing and 2,559,176 for dockless bike-sharing.

## 3.3. Data analysis method

### 3.3.1. Classification of bike-sharing users

Following the method of Ortegatong et al. (2013), we define regular users as those who use bike-sharing more than 4 days in a week, and occasional users as those who use bike-sharing less than 4 days a week. Both docked and dockless bike-sharing users are classified into the two groups. For docked bike-sharing, there are 421,874 regular users (62%) and 252,516 occasional users (38%). For dockless bike-sharing, there are 1,643,623 regular users (64%) and 915,553 occasional users (32%). The number of regular users is larger than that of occasional users for two systems, which indicates bike-sharing is an important daily travel mode.

### 3.3.2. Binary logistic model

In order to explore the determinants on the usage regularity of both docked and dockless bike-sharing systems, binary logistic models are established. In this study, the dependent variable *y* for the type of bike-sharing user is binary: 0= occasional user (OU), 1= regular user (RU). Mathematically, OU and RU are the two alternatives in the binary choice set of each individual (Ben-Akiva and Bierlaire, 1999):

$$\mathrm{U}_{in} = \mathrm{V}_{in} + \varepsilon_{in} \tag{1}$$

$$\mathrm{V}_{in} = \sum_{i=1}^{k} \beta_{\mathrm{i}} \mathrm{x}_{\mathrm{i}} \tag{2}$$

where:

$U_{in}$—the utility of the alternative $i$ (either OU or RU) to the $n^{th}$ individual;

$V_{in}$ —the deterministic or observable portion of the utility estimated to the $n^{th}$ individual;

$\varepsilon_{in}$—the error of the portion of the utility unknown to the $n^{th}$ individual;

$x_i$ — a vector of independents variables, including travel characteristics and built environment factors;

$\beta_i$ — a vector of estimated coefficients.

When ε is independent and identically (i.i.d.) Gumbel distributed, the probability that the $n^{th}$ individual will be a regular user can be written as Ben-Akiva and Bierlaire (1999):

$$P_{RUn} = \frac{1}{1+e^{-V_n}} = \frac{e^{V_{RUn}}}{e^{V_{RUn}}+e^{V_{OUn}}} \quad (3)$$

The odds ratio (OR) is a measure of effect size and describes the strength of association, indicating for example to what extent the odds of being a regular user are increased or decreased if the independent variable is increased by one unit (Maroof, 2012). An OR greater than one indicates that the concerned independent variable leads to a higher likelihood of using docked and dockless bike-sharing, and vice versa.

Table 3 below summarizes the variables included in the models. Dependent variable is set as user type and independent variables can be divided into travel characteristics and built environment factors. We consider two independent binary logit models for each of the bike-sharing systems. Particularly, POI data is extracted from Baidu Map, which is a prevailing web mapping service in China (Baidu Map, 2019). In addition, the POI types of bike-sharing trips are determined by the method of Zhang et al.(2017). Particularly, if a bike-sharing trip is near (in front of the entrance of) a workplace, residential community, public transit stations entertainment places and other POIs, then the trip is included in "trips recorded at working/residential/ transit/ entertainment/ other POIs" respectively. "Distance to CBD" represents the distance between trip ending location and CBD.

**Table 3** Descriptions of variables.

| Variable Name | Variable Description | Docked system | Dockless system |
|---|---|---|---|
| | | Mean | Mean |
| **Dependent variables** | | | |
| User type | For docked bike-sharing:<br>Being a regular user=1, Being an occasional user =0;<br>For dockless bike-sharing:<br>Being a regular user=1, Being an occasional user =0 | | |
| **Travel characteristics** | | | |
| Riding distance | The average riding distance of trips (meter) | 689.08 | 505.55 |
| Riding time | The average riding time of trips (second) | 466.55 | 321.13 |
| Trips during morning peak hours | The number of trips recorded during morning peak hours (7:00-9:00) | 1.05 | 0.99 |
| Trips during afternoon peak hours | The number of trips recorded during afternoon peak hours (17:00-19:00) | 0.85 | 0.98 |
| Trips during off-peak hours | The number of trips recorded during off-peak hours | 2.50 | 3.18 |
| Trips on workdays | The number of trips recorded on workdays | 3.68 | 4.18 |
| Trips on weekends | The number of trips recorded on weekends | 0.72 | 0.97 |
| **Built environment factors** | | | |
| Working POI | The number of trips recorded at working POI | 1.34 | 1.29 |
| Residential POI | The number of trips recorded at residential POI | 0.61 | 0.79 |
| Transit POI | The number of trips recorded at transit POI | 0.01 | 0.03 |

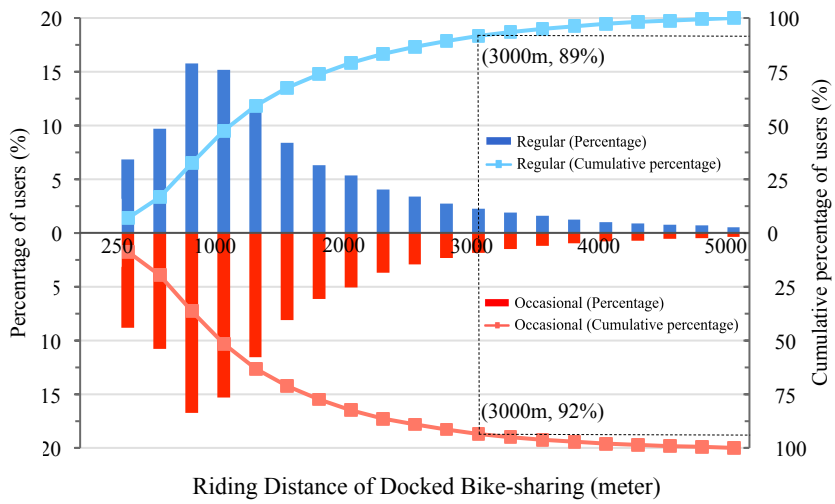
| | | | |
|---|---|---|---|
| Entertainment POI | The number of trips recorded at entertainment POI | 1.19 | 1.61 |
| Other POIs | The number of trips recorded at other POIs | 1.24 | 1.43 |
| Distance to CBD | The average distance from departure location to CBD (meter) | 6332.10 | 6294.82 |

## 4. Results and Discussion

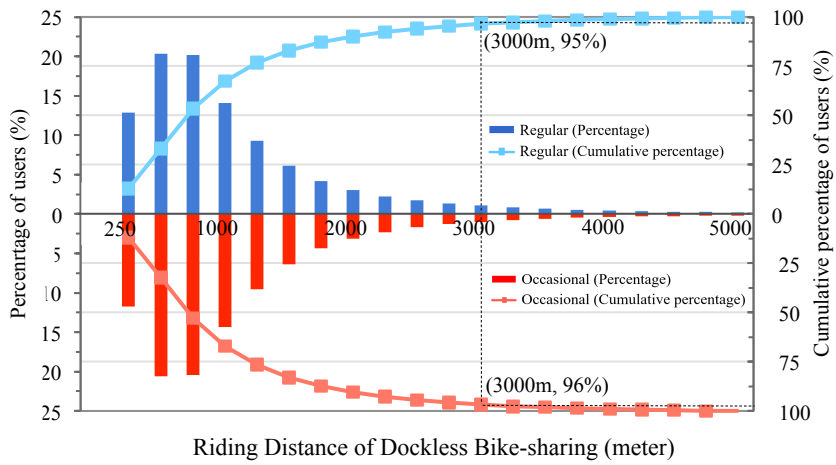
### 4.1. Comparison of travel patterns

#### 4.1.1. Riding distance

Fig. 2 below visualizes the distribution of four user groups' riding distance. The four groups include regular users of docked bike-sharing, occasional users of docked bike-sharing, regular users of dockless bike-sharing, and occasional users of dockless bike-sharing. Regular and occasional users of both bike-sharing systems share similar distributions. For the docked bike-sharing system, both regular and occasional users are most likely to ride within 500-1000m. For the dockless bike-sharing system, both regular and occasional users are most likely to ride within 250-750m. As the cumulative probability curve indicates, 89% of regular docked bike-sharing users and 92% of occasional users finish their trips within 3km (See Fig. 2(a)). For the dockless bike-sharing system, 95% of regular users and 96% of occasional users travel within 3 km (See Fig. 2(b)). In general, docked bike-sharing users ride a longer distance than dockless bike-sharing users, which is in line with the results of Gu et al. (2019) and Ma (2019b). This may be because, people can easily find dockless shared bikes and do not have to dock bikes at a fixed station, which makes it more convenient to ride a dockless shared bike when the travel distance is shorter. Thus, we suggest that more docking stations for docked bike sharing system should be built to shorten the distance between each station and to attract more users.




(a) Docked bike-sharing

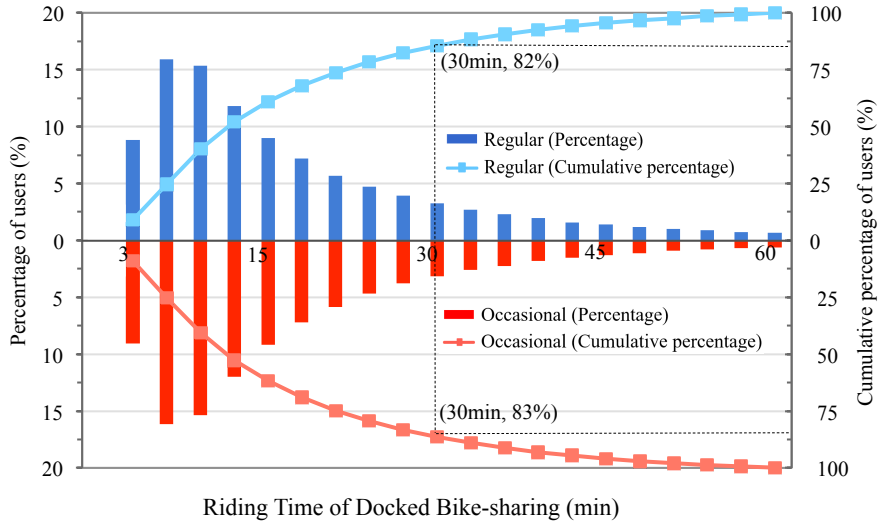



(b) Dockless bike-sharing

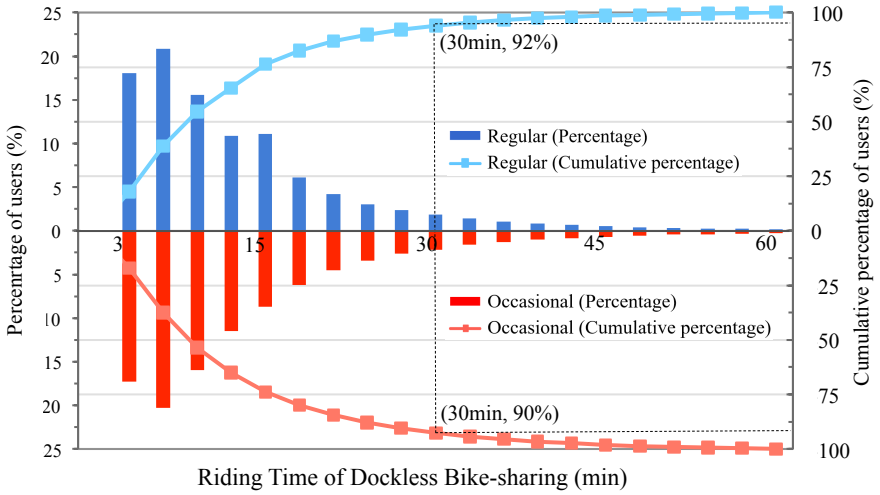
**Fig. 2.** The distribution of the riding distances of (a) docked and (b) dockless bike-sharing.

4.1.2. Riding time

Fig. 3 below compares the riding time distribution. There is no significant difference between regular and occasional users of each system. The most popular riding time for both docked and dockless users is 3-6 min; while the second most popular riding time is 6-9 min for docked users and within 3 min for dockless users. As the cumulative probability curve indicates, 82% of docked bike-sharing regular users and 83% of occasional users travel within 30 min (Fig. 3(a)). For dockless bike-sharing, 92% of regular users and 90% of occasional users finish their rides within 30 min respectively (Fig. 3(b)). It can be concluded that, compared with docked bike-sharing users, dockless bike-sharing users are more likely to finish their rides within 30 minutes. For dockless bike-sharing usage, the charge is 1 RMB (US$ 0.15) within half an hour, whereas for docked bike-sharing usage, the first two hours of riding is free. In order to increase the turnover rate of the docked bike-sharing system, it is suggested that the free rental time of docked bike-sharing should be shortened from 120 min to 30-60 min.




(a) Docked bike-sharing.



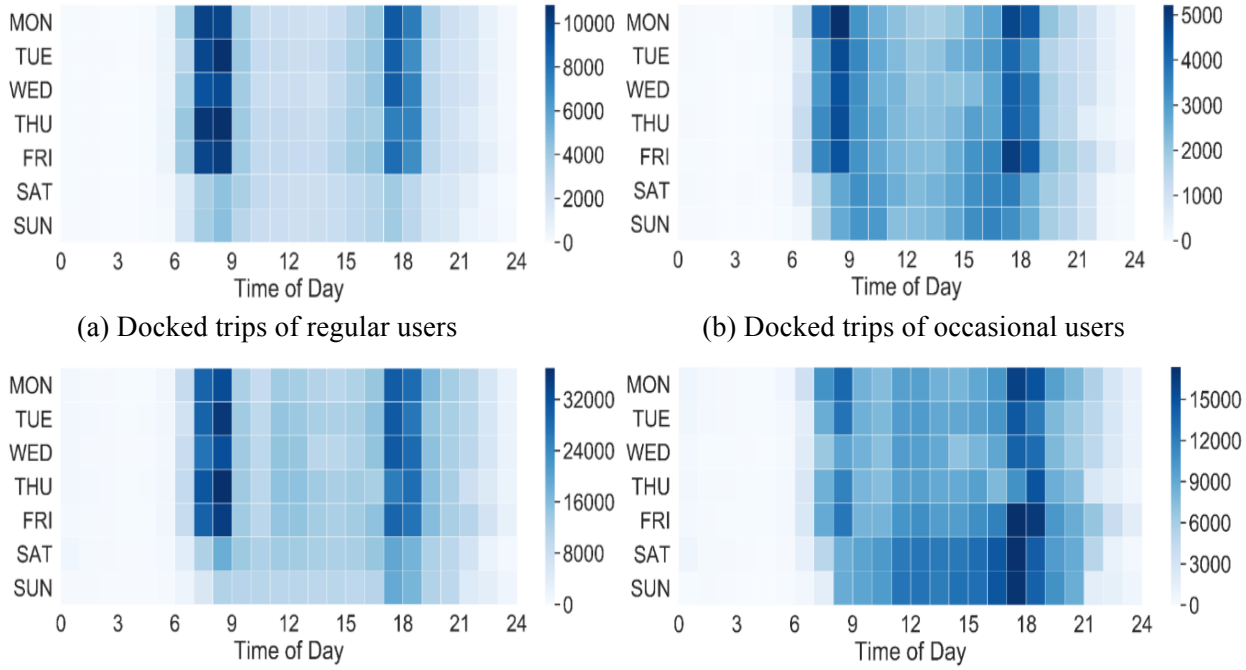

(b) Dockless bike-sharing.

**Fig. 3.** The distribution of the riding time of (a) docked and (b) dockless bike-sharing.

4.1.3 Temporal patterns

Fig. 4 below compares the temporal patterns of docked bike-sharing and dockless bike-sharing. Darker color in the figure indicates a higher usage volume of shared bikes. It can be seen that the number of maximum hourly trips of docked bike-sharing is significantly lower than that of dockless bike-sharing. This is reasonable because in Nanjing, the total number of docked shared bikes (about 60,000) is significantly lower than that of dockless shared bikes (about 450,000), as mentioned in the study area section.

Fig. 4 (a) and (c) show obvious morning peak hours (7:00-9:00) and afternoon peak hours (17:00-19:00) on workdays for regular users of both systems. In addition, more shared bikes are used during morning peak hours than the afternoon peak hours. However, there is no obvious peak hour for occasional users, as shown in Fig. 4 (b) and (d). This is because regular users travel mainly for commuting while occasional users travel for more diversified purposes, such as for shopping and leisure (Raux et al., 2017). In addition, for docked regular users, the peak hour starts at 6:00 am, which is earlier than that of dockless regular users. This is mainly because those who live far from workplaces prefer docked shared bike due to its longer free-of-charge cycling time than dockless bike-sharing. For both regular users and occasional users of dockless bike-sharing, a small peak of usage is observed between 11:00 and 13:00 during workdays, which is consistent with the finding of Chen et al. (2019). This may be because some people ride for lunch near their homes or workplaces. However, docked bike-sharing cycling has no such characteristics, which may be because docked bike-sharing stations are generally a little far away from residential places and working sites. Particularly, Fig. 4 (b) and (d) show a more frequent usage by occasional users during off-peak hours on workdays and weekends. This finding indicates a high proportion of occasional users travel for recreation purposes during those time periods, supporting the earlier finding of Song et al. (2017) that users with low bike usage frequency cycle often for leisure.




(a) Docked trips of regular users (b) Docked trips of occasional users

(c) Dockless trips of regular users (d) Dockless trips of occasional users

**Fig. 4.** Temporal distribution of the bike-sharing usage by four types of users.
Note: As the usage volume of dockless bike-sharing is much higher than docked bike-sharing, the Legend is not unified.

4.1.4. Spatial patterns

Spatial distribution of bike-sharing usage is visualized based on traffic analysis zone (TAZ). In general, Fig. 5 and Fig. 6 below illustrate the spatial distribution of both docked and dockless bike-sharing usage during morning and afternoon peak hours.

*4.1.4.1. Docked bike-sharing*

Docked bike-sharing usage mainly concentrates in Hexi New Town area A, especially for regular users during the morning peak (see Fig. 5 (a)). This is reasonable because Hexi New Town is a newly built area with well-constructed bike infrastructure and public transport system. Ji et al. (2017) have shown consistent evidence that the daily average usage of docked bike-sharing in Hexi New Town area is significantly higher than that in any other districts. We suggest that docked bike-sharing facilities should be improved in other areas, especially in suburban areas, to solve the "first/last mile" problem. Additionally, in southern suburban area B, regular users of docked bike-sharing are more likely to use shared bikes during morning peak hours rather than during afternoon peak hours. The reason is that during afternoon peak hours, people usually have longer free time and travel for multi-purpose, such as for leisure and social activities.

| | Morning peak | Evening peak |
|---|---|---|

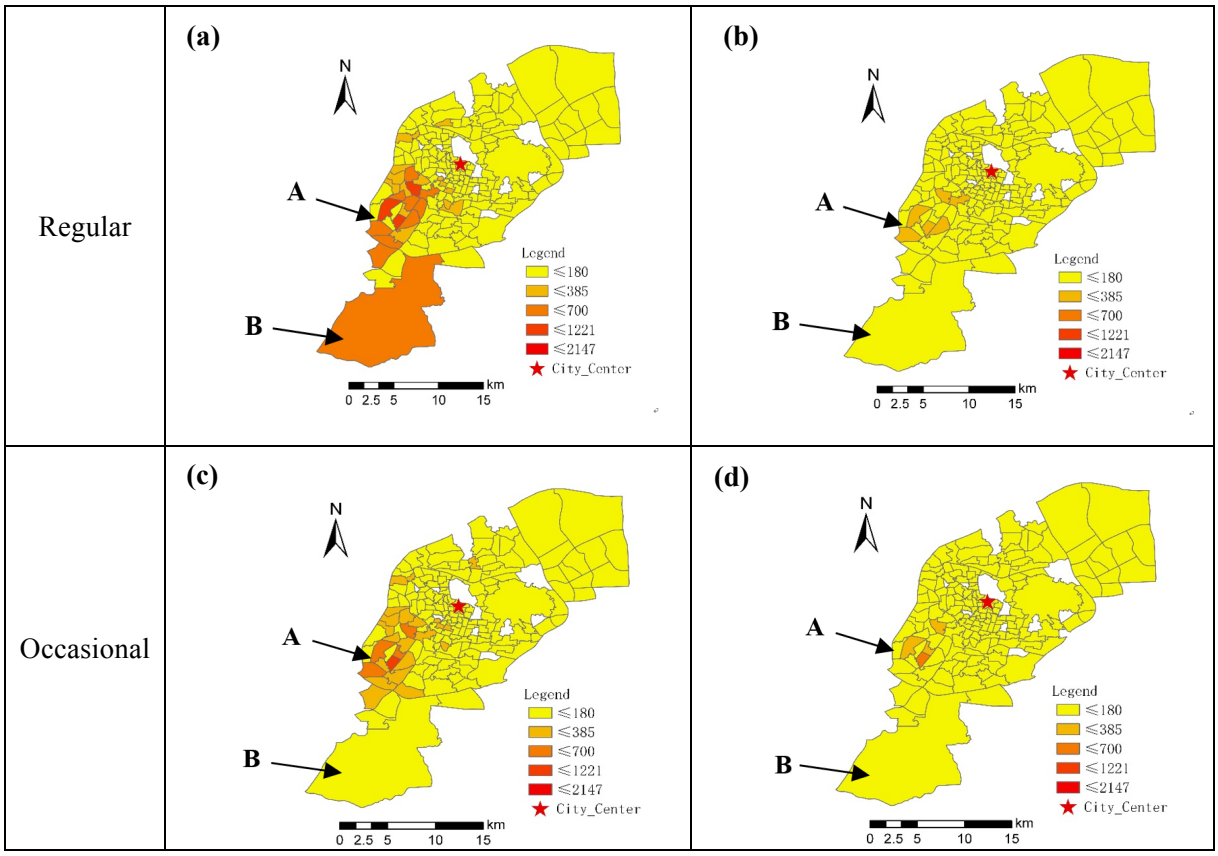



**Fig. 5.** Spatial distribution of the average docked bike-sharing usage during peak hours by four types of users.

*4.1.4.2. Dockless bike-sharing*

It can be seen from Fig. 6 below that, unlike the concentrated distribution of docked bike-sharing in Hexi New Town area A, dockless bike-sharing is distributed throughout the study area, especially in the core urban area C and northern suburban area D. In the core urban area C, the usage of dockless bike-sharing is higher than that of docked bike-sharing. This is mainly because the traffic here is congested and people are unwilling to look for docking stations for docked shared bikes. Instead, they prefer dockless sharing bikes. In northern suburban area D, docked bike-sharing usage always remains at a low level and is significantly lower than dockless bike-sharing usage. The main reason is that the docked bike-sharing facilities in this area is insufficiently, failing to attract potential users. Particularly, in Zhongshan scenic area E, the supply of both kinds of bike-sharing is few due to the challenging topography. The dockless bike-sharing usage by regular users (Fig. 6 (a) and (b)) is higher than that by occasional users (Fig. 6 (c) and (d)). It can be explained that some commuters who work in this area use dockless bike-sharing because of free registration and station flexibility. Occasional users of both systems travel less in this area, mainly because they do not travel for sightseeing.

| | Morning peak | Evening peak |
|---|---|---|

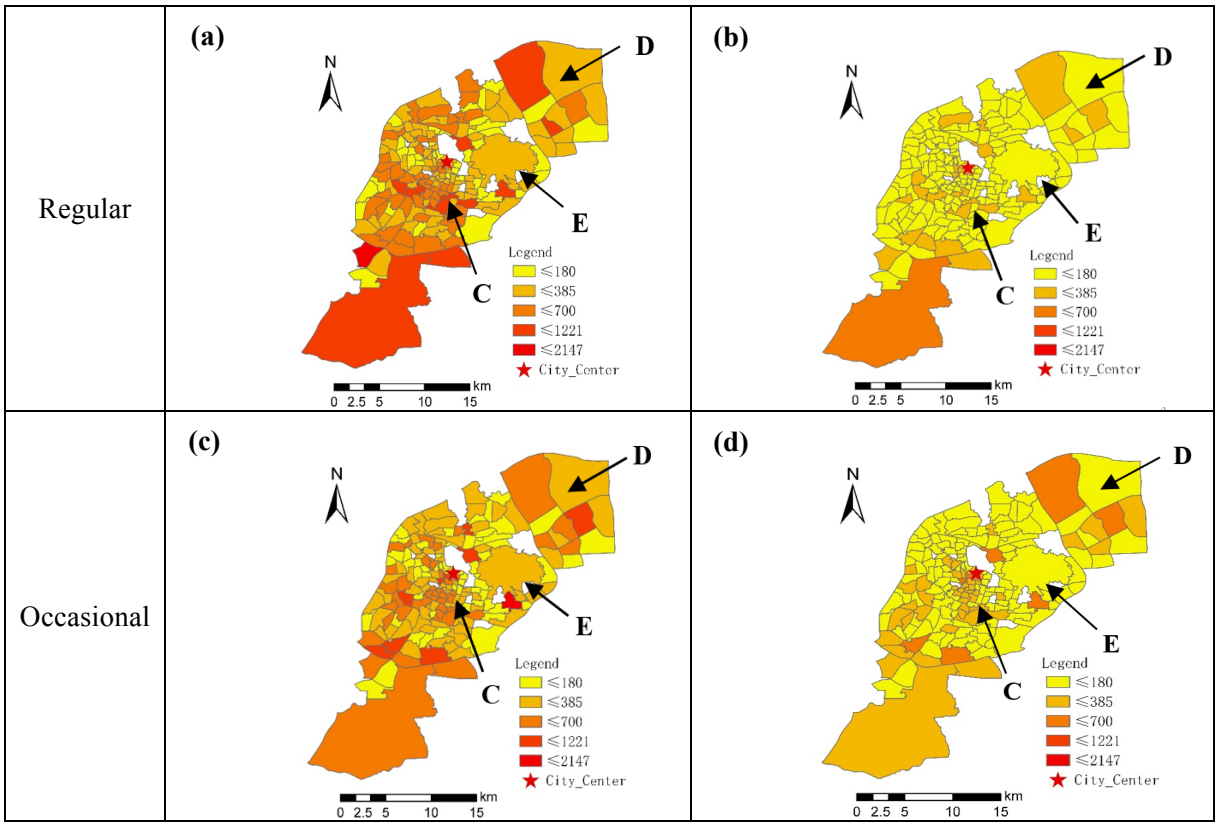



**Fig. 6.** Spatial distribution of the average dockless bike-sharing usage during peak hours by four types of users.

Generally, it can be revealed that the average hourly usage of docked bike-sharing is less than that of dockless bike-sharing, because of a larger supply of dockless shared bikes. Additionally, regular users of both systems are more likely to use bike-sharing than occasional users during morning and afternoon peak hours, which indicates that regular users are more likely to travel for commuting. Considering traffic congestion and limited travel time during the morning peak hours, regular users find it more convenient to travel by bike-sharing (or integrated with public transit). This finding is consistent with the study of Ma et al. (2018) that the proportion of commuting trips is relatively high among all trips during peak hours.

### 4.2. Model Estimation and Discussion

To test co-linearity between independent variables, variance inflation factors (VIF) were examined. All variables' VIFs were less than five, which indicates that the estimation model did not have a multicollinearity issue (Wang et al., 2017). Two binary logistic models are established, with "being an occasional user" as reference categories (see in Table 2). Models are stepwise adjusted by adding the travel characteristics variables first and then by adding the built environment variables. Only the variables with acceptable statistical significance ($p < 0.05$) are kept in subsequent model runs (Riggs, 2015). The final models are depicted in Table 4, only with the variables that are significant at 95% interval. The Pseudo $R^2$ values of the two models are 0.7126 and 0.6806 for docked and dockless bike-sharing respectively, which indicates a good model fit.

**Table 4** The results of model estimation.

| | **Docked bike-sharing system** | | | **Dockless bike-sharing system** | | |
|---|---|---|---|---|---|---|
| | **Coef.** | **OR** | **P>\|z\|** | **Coef.** | **OR** | **P>\|z\|** |

| | | | | | | |
|---|---|---|---|---|---|---|
| **Travel characteristics factors** | | | | | | |
| Riding distance | -0.0005 | 0.9995 | 0.000*** | -0.0006 | 0.9994 | 0.000*** |
| Trips in morning peak | 0.4805 | 1.6169 | 0.000*** | 0.4751 | 1.6082 | 0.000*** |
| Trips in afternoon peak | 0.4879 | 1.6289 | 0.000*** | 0.3224 | 1.3804 | 0.000*** |
| **Built environment factors** | | | | | | |
| Working POI | 0.1994 | 1.2206 | 0.000*** | 0.1838 | 1.2018 | 0.000*** |
| Residential POI | 0.2027 | 1.2247 | 0.000*** | 0.2241 | 1.2512 | 0.000*** |
| Transit POI | 0.2666 | 1.3055 | 0.000*** | 0.0698 | 1.0723 | 0.040** |
| Distance to CBD | —— | —— | —— | 9.62E-06 | 1.0003 | 0.000*** |
| **Constant** | -6.1868 | 0.0021 | 0.000*** | -4.4348 | 0.0119 | 0.000*** |
| | N =147,838 | | | N=496,598 | | |
| | Pseudo $R^2$=0.7126 | | | Pseudo $R^2$=0.6806 | | |

Note: ** Statistically significant at 5% level (p<0.05); *** Statistically significant at 1% level (p<0.01).

The study results share some similarities with other findings from previous work. For instance, As the riding distance increases, both docked and dockless bike-sharing users are less likely to be regular users. This finding supports previous studies of Heinen et al. (2013) , Zahabi et al. (2016) and Cervero et al. (2009) where it was found that shorter-time travelers are more inclined to be regular bike-sharing users. The OR of docked and dockless bike-sharing are 0.9995 and 0.9994 respectively, which indicates that when riding distance decreases by one unit, the odds of being a regular user increases by 0.9995 and 0.9994 times of the original value.

Moreover, some of the findings are consistent with other researches in terms of the effects of time variables ("Trips during morning peak hours" and "Trips during afternoon peak hours") on the regularity of bike-sharing usage. "Trips during morning peak hours" and "Trips during afternoon peak hours" promote travelers to use docked and dockless bike-sharing regularly. As Zahabi et al. (2016) indicated, compared with occasional users, regular users are more likely to travel to work during peak hours. Besides, the OR of "Trips during afternoon peak hours" of docked bike-sharing is larger than that of dockless bike-sharing (1.6289>1.3804). This result suggests that "Trips during afternoon peak hours" affects more the regularity of docked bike-sharing usage. The operation of redistributing shared bikes across the network using a fleet of vehicle(s) is known as bike-sharing rebalancing. Static rebalancing usually happened at night, when intervention by bike-sharing users is negligible. If user intervention is considered, it is regarded as dynamic rebalancing (Pal and Zhang, 2017).Both docked and dockless bike-sharing run static rebalancing for the morning bike-sharing service. As for dynamic rebalancing system, docked bike-sharing is much better than dockless one. As a result, dockless bike-sharing faces more serious rebalancing problems in the afternoon and regular dockless bike-sharing users would reduce their reliance on it. We suggest that dockless bike-sharing companies should strengthen the dynamic rebalancing to provide dockless bike-sharing with more available bikes, especially during peak hours and around public transit stations. Meanwhile, for dockless bike-sharing, the OR of "Trips during morning peak hours" is larger than that of "Trips during afternoon peak hours" (1.6082>1.3804). This finding reveals that the variable "Trips during morning peak hours" promotes dockless bike-sharing usage more than "Trips during afternoon peak hours" does. Bike-sharing trips recorded during morning and afternoon peak hours are mainly for commuting (Cai et al., 2019). Specifically, users prefer to use bike-sharing in morning peak hours than in afternoon peak hours. This is reasonable because people tend to have more time after work and tend to travel for multi-purpose rather than commuting.

As to POI-related variables, the coefficients of working POI, residential POI and transit POI are all positive, indicating positive effects on the regularity of bike-sharing usage. These results are consistent with the findings of Shaheen (2010) that many commuters borrow shared bikes near home to go to work in the morning and return in the afternoon and that regular bike-sharing users are more likely to use

bike-sharing near their work place than general population. Meanwhile, Damant-Sirois et al. (2015) found that regular bike-sharing users are more willing to use bike-sharing around transit stations. An obvious OR difference of "Transit POI" is observed between docked bike-sharing and dockless bike-sharing (1.3055>0.0698). This suggests that "Transit POI" influences more the regularity of docked bike-sharing usage than that of dockless one. This is reasonable because docked bike-sharing stations are available around most transit stations. Well-developed parking facilities at transit stations would attract more regular users of docked bike-sharing. We suggest that more parking areas for dockless bike-sharing should also be constructed around the public transit stations.

The positive coefficient of "Distance to CBD" (9.62E-06) of dockless bike-sharing suggests that travelers are more likely to be regular users with "Distance to CBD" increasing. However, this variable has little effect on docked bike-sharing due to insufficient docked bike-sharing supply in suburban areas. Docking stations of docked bike-sharing systems are sparsely distributed in suburban areas, so people prefer to use dockless bike-sharing integrated with other travel modes.

## 5. Conclusions and Recommendations

This paper compares travel characteristics of users between docked and dockless bike-sharing systems, and compares the factors that influence the usage regularity of these two systems. The findings have several important policy implications, especially for cities where government agencies have heavily invested in both docked and dockless bike-sharing to develop urban transportation systems. By mining the historical trip data, usage patterns including riding time, riding distance, temporal pattern and spatial pattern are compared between regular users and occasional users of both systems. Results show that for both docked and dockless bike-sharing, there is no obvious difference in riding time and riding distance between regular users and occasional users. However, docked bike-sharing users are more likely to travel further and longer than dockless bike-sharing users. Bike-sharing usage reaches the peak during the morning peak hours (7:00-9:00) and the afternoon peak hours (17:00-19:00) on workdays regardless of whether users are regular or not. After that, significant differences in the spatial distribution between docked bike-sharing and dockless bike-sharing are revealed. Then, binary logistic models are applied to reveal the effects of travel characteristics and of built environment factors on the regularity of bike-sharing usage. The analysis identifies that except the variable "Riding distance", variables including "Trips during morning and afternoon peak hours" and "Working/ Residential/Transit POI" all positively affect the usage regularity of both docked and dockless bike-sharing. In addition, "Distance to CBD" only has a slightly positive effect on the regularity of dockless bike-sharing usage.

According to the results, several suggestions are proposed to improve the service of docked and dockless bike-sharing and to attract more potential regular users. (1) For both docked and dockless bike-sharing users, the shorter distance they ride, the easier they become regular users. Therefore, it is suggested that more docking stations be built to attract more docked bike-sharing users, especially in the suburban areas. (2) The static rebalancing of the dockless bike-sharing system makes regular users hard to find bikes when needed. It is suggested that dynamic rebalancing mechanisms be strengthened to provide users with real-time information of the bikes, especially around public transit stations. Additionally, dockless sharing bike companies could encourage users to participate in the rebalancing process through incentive policies. (3) As working POI, residential POI and transit POI all positively influence the regularity of bike-sharing usage, it is suggested that more docked and dockless bikes should be moved closer to those POI sites to attract more regular users. (4) This study reveals that well-developed parking facilities for docked bike-sharing systems at transit stations promote users to ride regularly. However, the current parking policy in the study area is unfavourable to dockless bike-sharing systems. Decent parking areas should also be constructed for dockless bike-sharing (e.g., comparable-quality parking facilities at public transit stations if space is available.) so the dockless bike-sharing service can be better integrated with public transit modes.

There are several limitations to our study. First, since the data used for this paper only covers one-week, deeper comparative analysis with a higher time dimension (e.g., months, seasons, and years) can be conducted if the data are collected over a longer period. Second, this paper only uses Nanjing as a

case study. It may also be useful to obtain smart card data and GPS data of bike-sharing systems from other cities to examine bike-sharing regularity usage patterns in other contexts, which could provide some comparisons. Third, this paper only considers travel characteristics and built environment factors when establishing the models. Attributes including socio-demographic and weather variables are also worth exploring. Moreover, further research could compare the usage patterns across docked, dockless and electric bike-sharing systems to obtain a more complete picture.

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