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Research Article

Understanding the Operational Efficiency of Bicycle-Sharing Based on the Influencing Factor Analyses: A Case Study in Nanjing, China

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With the expansion of urban scale and the growth of urban population, the bicycle-sharing system has been greatly helping grease the wheels of convenience and diversity of citizens' travel. Nevertheless, there are a set of additional problems, including imbalance of supply and demand at rental stations and low utilization of system operation, which have disrupted the travel experience of consumers, the profitability of businesses, and the coordination of government. In this study, we take Nanjing as an example to measure the operating efficiency of bicycle-sharing by calculating the capacity utilization rate (CUR). Afterwards, based on the IC card data of bicycle-sharing users, we statistically analyzed the traffic inflow and outflow at rental stations. Besides, this paper discusses the factors influencing the use of bicycle-sharing, by introducing the method of sampling stepwise regression into the study of rental situation and geographical environment. The results are as follows: (1) demand for bicycle-sharing is higher on weekdays than on weekends, especially during the morning and evening rush hours. (2) The daily average capacity utilization rate of bicycle-sharing is less than 0.08, indicating that the system is not efficient enough. During morning and evening rush hours, only less than 10% of rental stations have high inflow and outflow, and there is an imbalance of inflow and outflow for the same rental station at different times of the day. (3) The stepwise regression results show that the inflow and outflow of bicycle-sharing rental stations are mainly affected by the distribution of traffic, education, entertainment, medical, and other functional zones near the stations. These findings could provide relevant government departments and enterprises with strategies and suggestions for the efficient and healthy operation of the urban bicycle-sharing system.

1. Introduction

As a part of public transportation, bicycle-sharing meets the traffic needs of urban life and provides a feasible way for short-distance commuting, which has a profound impact on urban transportation and residents' travel. That transportation mode first appeared in Europe and was introduced in China's big cities such as Beijing, Wuhan, and Hangzhou in 2007. In those cities, relevant government departments or enterprises have set up bicycle-sharing rental stations in populated areas, e.g., residential quarter, business zones, service, and transportation areas to provide commuting services for residents and charge consumers according to their travel time [1, 2]. Furthermore, due to the development of modern communication and Internet technology, the operation and management of bicycle-sharing have been gradually improved and widely promoted to other cities. For instance, a few years later, more than 200 cities in China, including Nanjing, Chengdu, and Chongqing, adopted this novel mode of transportation [2]. Indeed, bike-sharing is seen by travelers in China as an environmentally friendly, flexible, and inexpensive mode of public transportation that optimizes urban public transportation systems and contributes to the evolution to a low-carbon and green lifestyle.

Bicycle-sharing not only makes people's short-distance trip feasible but also improves the efficiency of the urban public transportation system. Studies show that bicycle-sharing could relieve the traffic pressure of buses [3]. In comparison with taxi, it enables people to reach their destinations faster in terms of short trip, especially in the densely-populated and road-clogged sections [4, 5]. However, with more and more public bikes on the road, bicycle-sharing have also given rise to some social problems like unreasonable distribution of rental stations in cities, lack of cycling safety protection, and incomplete supporting laws and policies [6, 7]. It is often difficult to lease or return the bicycle when there is a heavy traffic [8]. Despite the fact that the utilization rate of bicycle-sharing is relatively high during rush hours in the morning and evening, but it is lower overall, because there is a significant "tidal" phenomenon of bicycle-sharing using.

For the sake of solving these problems, some scholars studied the bicycle-sharing's travel mode from the perspective of travelers' behavior, such as the frequency changing of residents using bicycle-sharing, users' travel purpose, the spatiotemporal distribution of rental station [9], the renting tide ratio of rental stations, and the turnover rate of pile sites [10]. It is found that residents use bicycle-sharing twice a day on average, mainly for commuting and shopping, and the properties of land use would have a significant impact on the demand of rental stations [9]. At the same time, traffic travel was generally influenced by different factors, such as spatial, temporal, and environmental ones [11–13]. Some scholars also researched the demand law and the use of bicycle-sharing from the perspective of influential factors. For example, they used the graph convolutional neural network model to actively learn the relationship hidden in rental stations and accurately predict the hourly demand of each rental station in the network [14]. By combining the demand for bike-sharing trips with external factors that influence the use of bike-sharing, scientists could estimate the potential demand for bike-sharing at different spatial and temporal dimensions [15]. The demand of bicycle-sharing is affected by a series of external factors, including time periods (rush hours in the morning and evening, workdays or not) [16], traffic at around rental stations [17], weather and climate conditions [18], properties of land use in the vicinity [19, 20], geographical environment (such as terrain) [19], population density [20], and rental stations' locations [21] (such as the distance from the city center [20]).

The imbalance of supply and demand in bicycle-sharing market is also a common concern, which mainly expresses in the excessive redundancy of bicycle-sharing at rental stations [22], the mismatching of inflow and outflow [23], the excessive fluctuation of demand at rental stations in different time dimensions [24], etc. On the one hand, scholars solved the problem by optimizing the schedule of bicycle-sharing system [25, 26] or enhancing the accuracy of bicycle-sharing positioning [27, 28]. For example, they built a mixed integer linear programming (MILP) model with minimum total cost and optimized the search algorithm to realize the substitution and overall schedule of multitype bicycle-sharing at rental stations [29]. Or, they innovated the dynamic positioning method of bicycle-sharing and predicted the number of bicycle-sharing left and users arriving at rental stations and so on, in order to optimize the vehicle scheduling path and realize the optimal allocation of the system [30, 31]. On the other hand, some scholars also established a bicycle-sharing network model from the perspective of system to explore the network structure characteristics of bicycle-sharing [32, 33] and optimized the system's network flow from the perspective of structure to balance the supply and demand of bicycle-sharing [23, 34].

Previous researchers have studied the travel characteristics, network structure characteristics, and the imbalance of supply and demand of bicycle-sharing and made great achievements. However, there is still little research on the operational efficiency on bicycle-sharing, which is time-varying and affected by various factors. In this paper, the time-varying law of the operational efficiency of bicycle-sharing is calculated and analyzed based on the statistical analysis of users' travel characteristics. At the same time, a sampling regression model is proposed to quantify the key factors affecting the demand of bicycle-sharing, providing theoretical support for balancing the supply and demand and optimizing the management of urban bicycle-sharing market.

This study is organized as follows: in Section 2, the research data and methods are introduced. In Section 3, the analysis is provided in terms of the bicycle-sharing users' characteristics, the operational efficiency, and the impact of urban POI distribution on its demand. In the last section, we summarize and highlight our key findings and further provide policy advise to relevant government and businesses.

2. Data and Methodology

2.1. Data. The research data obtained from Nanjing Bicycle-sharing Co. Ltd. include two parts: one is the lease and return records of bicycle-sharing in Nanjing from March 1, 2016, to March 31, 2016, each of which contains six fields: users' account, users' ID number, the lease station's number, lease time, the return station's number, and return time, as shown in Table 1; the other is the bicycle-sharing rental stations' information (a total of 641 rental stations), containing six fields: area name, the rental station's number, the rental station's name, rental station address, longitude, and latitude, as shown in Table 2.

After data cleaning, outliers and irrational data are removed. Among them, outliers refer to the data with missing ID number or abnormal date of birth; irrational data refer to the data that the return time earlier than the lease time. The study area of this paper is six urban areas of Nanjing, China, including Gulou District, Jianye District, Xuanwu District, Yuhua District, Qinhuai District, and Qixia District, and the data with rental stations outside the six urban areas are deleted. Finally, 2,705,161 valid records are collected.

Table 1: Data fields and descriptions of bicycle-sharing user's leasing and returning.

Data field	Example	Data field	Example
ID_FACE	NJHX00168946	LEASE_TIME	2016/3/9 17 : 38 : 15
CERT_ID	32010519870328XXXX	RT_NID	12161
LEASE_NID	11016	RT_TIME	2016/3/9 17 : 58 : 13

Table 2: Data fields and descriptions of bicycle-sharing rental stations.

Data field	Example	Data field	Example
Administrative district	Gulou district	LEASE_Address	Xikang road
LEASE_NID	011016	Longitude	118.7704
LEASE_Name	East gate of hohai university	Latitude	32.0611

2.2. Methodology

2.2.1. Measuring the Capacity Utilization Rate. Capacity utilization rate is an important indicator reflecting the operational demand and efficiency of bicycle-sharing. In essence, the operational efficiency of urban bicycle-sharing is the reflection of scale and technical efficiency, that is, the service level of bicycle-sharing demand can be satisfied under the condition that the service capacity of bicycle-sharing is determined. In other words, with the same investment of bicycle-sharing, the higher the satisfaction degree of bicycle-sharing demand is, the higher the operational efficiency will be; otherwise, the lower the operational efficiency will be. Capacity utilization rate of bicycle-sharing directly affects the utilization of public traffic resources and plans, operation, and management of the bicycle-sharing system, which is used to measure the operational efficiency of bicycle-sharing [35]. The capacity utilization rate (f^h) is calculated as per the following equation:

$$f^h = \sum \frac{(t_i/T_i)}{N} = \sum \frac{f_i^h}{N}, \tag{1}$$

where t_i is the time period that the i-th bicycle-sharing is used, that is, the time interval from leasing to returning; T_i is the service time of the i-th bicycle-sharing, including the load time plus idle time; N is the number of bicycle-sharing; and f_i^h is the capacity utilization rate of the i-th bicycle-sharing.

When the contribution weight of each bicycle-sharing to the capacity utilization rate is the same, we can calculate the average capacity utilization rate (f^h) using equation (1). When the contribution weight is different, we use equation (2) to calculate the weighted average capacity utilization rate (F^h) as follows:

$$F^h = \frac{\sum t_i}{\sum T_i} = \sum w_i f_i^h, \tag{2}$$

where w_i is the weight, $w_i = (T_i/\sum T_i)$. In this study, $f^h = F^h$ because T_i of each bicycle-sharing is equal. The larger the value of F^h, the longer the cumulative time for bicycle-sharing to be used and the shorter the idle time, indicating that bicycle-sharing can meet more travel demands and has a higher operational efficiency; otherwise, the operational efficiency is lower.

2.2.2. Multifactor Influencing Model of Bicycle-Sharing. Next, after calculating the travel demand, we build a variable selection model based on Spike-slab sparse function and stepwise regression [36, 37] to study the relationship between the travel demand of bicycle-sharing and the properties of urban land use in different districts, which is mainly divided into two parts:

First, the travel demand of bicycle-sharing rental stations (including the inflow and outflow of bicycle-sharing) is influenced by the properties of land use (POI distribution) around the rental stations [16]. We count the number of different functional zones in a circular buffer zone with a radius of one kilometer centered on the bicycle-sharing rental station, such as supermarkets, banks, and bus stations, according to the POI industry classification of Baidu Map and the geographic position (GPS) of rental stations. We take 17 functional zones divided by Baidu Map as the first-level indicators in the process of constructing the model. Then, we match the functional zones using keywords and count the distribution of the second-level functional zones (122 in total) around the bicycle-sharing rental stations. The classification of functional zones is shown in the Table 3.

We record the observations of the number of 122 second-level functional zones at different bicycle-sharing rental stations as a matrix ($X = (x_{ij})$). Meanwhile, we calculate the daily average demand (daily inflow and daily outflow) of bicycle-sharing at each rental station and named y_i, where $i = 1, 2, \ldots, 641$ refers to bicycle-sharing rental stations, and $j = 1, 2, \ldots, 122$ refers to the second-level functional zones (POI). The functional relationship between the daily average demand of bicycle-sharing at each rental station (dependent variable) and the distribution of properties of land use in the area (i.e., the distribution of functional zones and independent variable) is shown in equation (3) as follows:

$$y_i = \alpha + \beta_1 x_{i,1} + \beta_2 x_{i,2} + \cdots + \beta_{122} x_{i,122} + \varepsilon_i, \tag{3}$$

where $i = 1, 2, \ldots, 641$, α is the intercept term, ε is the residual term, and β_j is the regression coefficient of the j-th variable in the regression equation. For convenience, we will consider this model as inflow model and outflow model in the following description if y_i refers to daily inflow and outflow of bicycle-sharing at rental stations, respectively.

Second, we build a variable selection model based on Spike-slab sparse function and stepwise regression to solve

Table 3: Indicators of bicycle-sharing using.

First-level indicator	Second-level indicator
Enterprise	Factory mine, company, gardening, park
Shopping	Convenience store, supermarket, shopping mall, market, home appliance and digital, home building materials, shop
Traffic	Subway station, airport, service area, port, bus station, railway station, gas station, bridge, toll station, parking lot, coach station
Education	Adult education, college and university, science museum, research institution, overseas study agency, training institution, parent-child education, special education school, library, primary school, kindergarten, middle school
Finance	ATM, pawnshop, investment and finance management, credit union, bank
Hotel	Apartment hotel, express hotel, star hotel
Beauty	Hairdressing, manicure, beauty, body care
Tourist attraction	Museum, zoo, scenic spot, garden, Church, aquarium, cultural relic and historic site, amusement park, arboretum
Catering	Teahouse, cake and dessert, bar, coffee house, foreign restaurant, snack, Chinese restaurant
Auto service	Car inspection field, car beauty, auto parts, car repair, car sales, car rental
Real estate	Offices, dormitory, uptown
Life service	Newsstand, funeral service, lottery sales outlet, pet service, real estate agency, WC, public service, household service, ticket office, communications office, graphic printing shop, maintenance point, logistics company, laundry, post-office, photo studio
Cultural medium	Radio and television, art gallery, cultural center, journalism publication, art troupe, exhibition hall
Entertainment	KTV, cinema, resort, troupe, theater, farmhouse, internet cafe, bath and massage, leisure square, play place
Medical	Emergency center, CDC, nursing home, physical examination organization, drugstore, clinic, special hospital, general hospital
Exercise	Extreme sports site, fitness center, sports stadium
Government agency	Party group, welfare institution, government, public security agency, administrative unit, foreign-related institution, political education institution, central agency

equation (3). Ordinary OLS cannot estimate the influence coefficients of various independent variables on the dependent variable accurately, because equation (3) has many independent variables and there is multicollinearity among the variables. At the same time, we are inclined to keep factors as many as possible in the model unless the variable does not affect the demand of bicycle-sharing. The solution steps are as follows:

Step 1: obtain a sample of independent variable (X) by random sampling based on the Spike-slab sparse function, denoted as X_γ

Step 2: construct a stepwise regression model, using X_γ to regress the dependent variable (y), and get the regression results at the specified significance level (the significance level in this paper is 0.05);

Step 3: repeat Step 1 and Step 2 enough times and average all regression results that pass the test to obtain the estimated values of all parameters in equation (3).

Here, are the specific steps. First, we record the coefficients of independent variable (X) as a column vector ($\beta = (\beta_j)$). We build $\gamma = (\gamma_j)$ according to β, where $\gamma_j = 0$ if $\beta_j = 0$; otherwise $\gamma_j = 1$ if $\beta_j \neq 0$. We usually can define γ based on the Bernoulli distribution, just as shown in equation (4) as follows:

$$\gamma \sim p_j^{\gamma_j}\left(1 - p_j\right)^{1-\gamma_j}, \quad j = 1, 2, \ldots, 122, \tag{4}$$

where p_j can be set a prior subjectively. For example, we can define $p_j = m/n$ when we would like the expected number of independent variables to be m (in this paper $m = 45$) for each stepwise regression model, where n is the total number of independent variables, that is 122. We obtain a priori γ by sampling according to equation (4). Then, we select the corresponding variable (x_j) with $\beta_j \neq 0$ according to $\gamma_j = 1$ and record it as a set (X_γ), which is the independent variable sample of the current stepwise regression.

Besides, we build a stepwise regression model and estimate the values of the parameters in model ($y = f(X_\gamma)$) to obtain the estimated values of the regression coefficients (β and α) corresponding to the current X_γ. The stepwise regression method can ensure that the variables retained in the model are independent variables that have a significant effect on the dependent variables and eliminate multicollinearity.

Finally, we repeat sampling enough times (such as 10,000 times) to ensure model convergence. We record the regression parameters of the i-th stepwise regression as $\varphi^{(i)} = (\alpha, \beta)^{(i)}$, and then we can obtain a series of fitting results ($\varphi^{(i)}$). We calculate the mean of all regression coefficients and use it as the final estimated coefficients of independent variables, that is, $\overline{\varphi} = \sum_{i=1}^{N} (\varphi^{(i)}/N)$. Therefore, the model of the relationship between the inflow and outflow of bicycle-sharing at rental station (i) and the properties of land use of rental station (i) is shown in equation (5) as follows:

$$\widehat{y}_i = \overline{\alpha} + \overline{\beta}_1 x_{i,1} + \overline{\beta}_2 x_{i,2} + \cdots + \overline{\beta}_{122} x_{i,122}. \tag{5}$$

3. Results

3.1. Overview. We describe the age and duration distribution of bicycle-sharing users in each administrative district as shown in Figure 1. From the age distribution of users, there is no significant difference in different administrative districts. The users are mostly between 25 and 55 years old, among whom 25–40 years old account for the highest

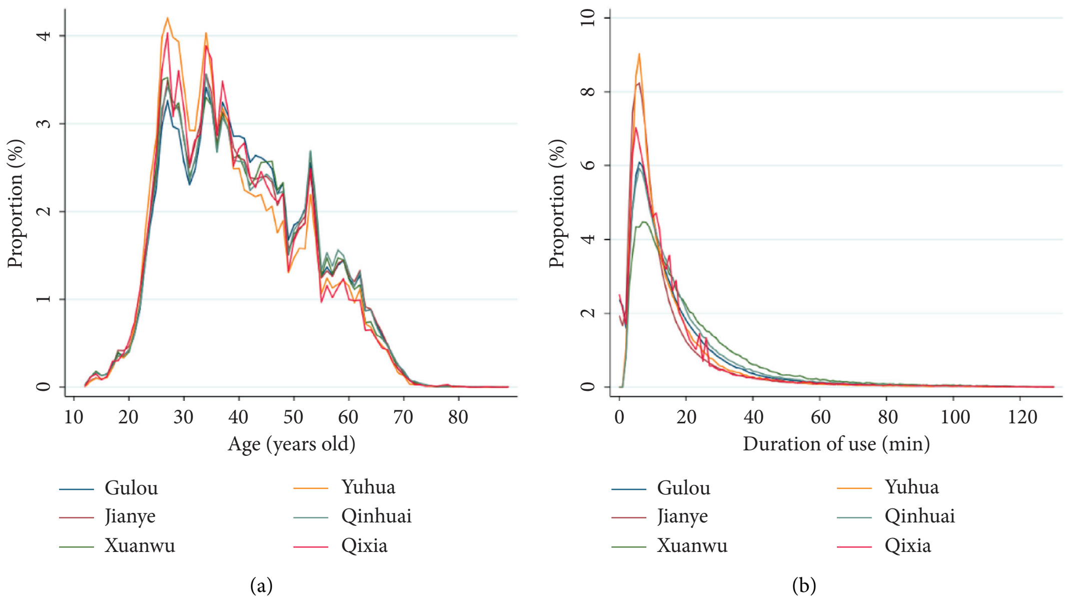


Figure 1: Distribution of (a) age and (b) use duration of bicycle-sharing users.

proportion. It can be seen that the main bicycle-sharing users are office workers (25–55 years old), while teenagers and the elderly use less. From the duration of users, it is roughly the same in different administrative districts. The time in each trip mainly lasts for 0–20 minutes. With the increase of the use duration, the proportion decreases gradually. For example, 57.5% of users in Jianye District spend less than 10 minutes on bicycle-sharing. People tend to use bicycle-sharing for short trips, which has more advantages in urban short trips of residents.

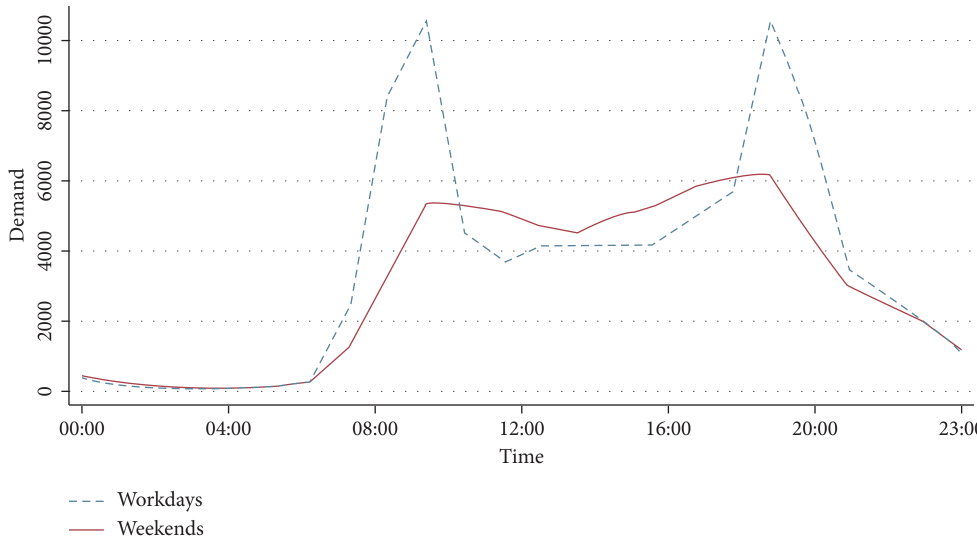
Figure 2 shows the daily variation tendency of people using bicycle-sharing to travel on workdays and weekends. On the whole, as shown in Figure 2(a), people are affected by on and off duty on workdays, for which the demand of bicycle-sharing is higher during rush hours in the morning and evening and shows obvious travel peaks. In contrast, on weekends, travel peaks are delayed and not obvious during the daytime (compared with peak hours in the morning and evening on workdays). Compared with workdays, its travel demand is higher during off-peak hours (mainly refers to 10 : 00–17 : 00). This is because on workdays, people mostly work and rarely travel during this time. On weekends, people spend more time on outdoor activities such as shopping and entertainment, leading to a greater demand for bicycle-sharing. From 22 : 00 to 6 : 00 the next day, people travel less; thus, there is relatively low demand for bicycle-sharing.

The daily variation tendency of bicycle-sharing travel demand in the six major urban areas of Nanjing is roughly the same, but there is a difference in total demand, as shown in Figure 2(b). For example, there are 176 bicycle-sharing rental stations in Jianye District and 192 in Gulou District, where people have a greater demand for bicycle-sharing. There are 61 bicycle-sharing rental stations in Xuanwu District and 41 in Qixia District, where people have a relatively low demand for bicycle-sharing.

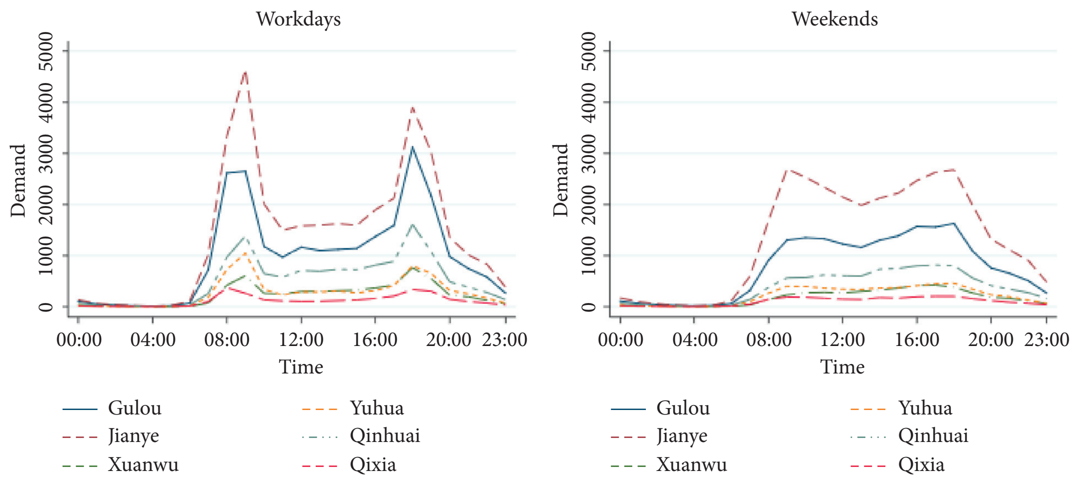
We count the inflow and outflow of bicycle-sharing rental stations during rush hours in the morning (7 : 00–10 : 00) and evening (17 : 00–19 : 00). The results are shown in Table 4 and Figure 3. During rush hours in the morning and evening, the total outflow of rental stations is greater than the total inflow. The proportion of rental stations where the inflow is greater than or equal to the outflow is not significantly different from that of rental stations where the outflow is greater than the inflow, and the latter is slightly higher. Only 5.15% of inflow and outflow of the rental stations is relatively high during rush hours in the morning (the sum of the inflow and outflow is greater than 150), and there is only 6.86% during rush hours in the evening. For the same rental station, there is a difference in the inflow and outflow of almost all stations. It can be seen that there is an imbalance of supply and demand for bicycle-sharing at rental stations, which will also make bicycle-sharing system inefficient.

3.2. Daily Variation Tendency of Capacity Utilization Rate. The capacity utilization rate of bicycle-sharing reflects its operational efficiency, which is not only related to the number of bicycle-sharing at rental stations but also significantly related to the population density around the rental stations and the travel environment (such as temperature). We calculate the average daily capacity utilization rate of bicycle-sharing in the six major urban areas of Nanjing from March 1 to March 31 using equation (1), and the results are shown in Figure 4. On the whole, the average daily capacity utilization rate of bicycle-sharing in all urban areas is roughly the same and is relatively low overall. This indicates to a certain extent that the cumulative using time of bicycle-sharing is short, most shared bicycles are not being used for a long time, and the operational efficiency of the system is low.

Specifically, the six urban areas are ranked in descending order of the average capacity utilization rate of bicycle-



(a)



(b)

Figure 2: Daily variation tendency of bicycle-sharing travel demand in (a) different time periods and (b) different administrative districts.

Table 4: Statistical analysis of rental stations' inflow and outflow during rush hours.

Period	Total inflow	Total outflow	Proportion of rental stations where inflow ≥ outflow (%)	Proportion of rental stations where outflow > inflow (%)
Morning peak	18232	19777	44.15	55.85
Evening peak	21995	23436	49.30	50.70

sharing: Jianye District, Qinhuai District, Gulou District, Xuanwu District, Yuhua District, and Qixia District. In particular, the average daily capacity utilization rate of bicycle-sharing declined rapidly on March 8th, which is related to the weather conditions (as shown by the dotted line in Figure 4). It can also be seen from Figure 4 that the temperature change in Nanjing in March is roughly the same as the average daily capacity utilization rate change of bicycle-sharing. When the weather gets warmer, people travel more and bicycle-sharing demand increases; when the weather gets colder, people travel less and bicycle-sharing demand decreases, which prove that the travel by bicycle-sharing are affected by weather conditions. People will reduce outdoor activities or travel by a better closed means of transportation instead of by bicycle-sharing due to the bad weather.

The number of rental stations and population density in the six major urban areas will also affect the capacity utilization rate of bicycle-sharing. Table 5 shows the correlation between the capacity utilization rate and average temperature, number of rental stations, and population density. It can be seen from Table 5 that the number of rental stations and population density are positively correlated with the average capacity utilization rate. In other words, if the

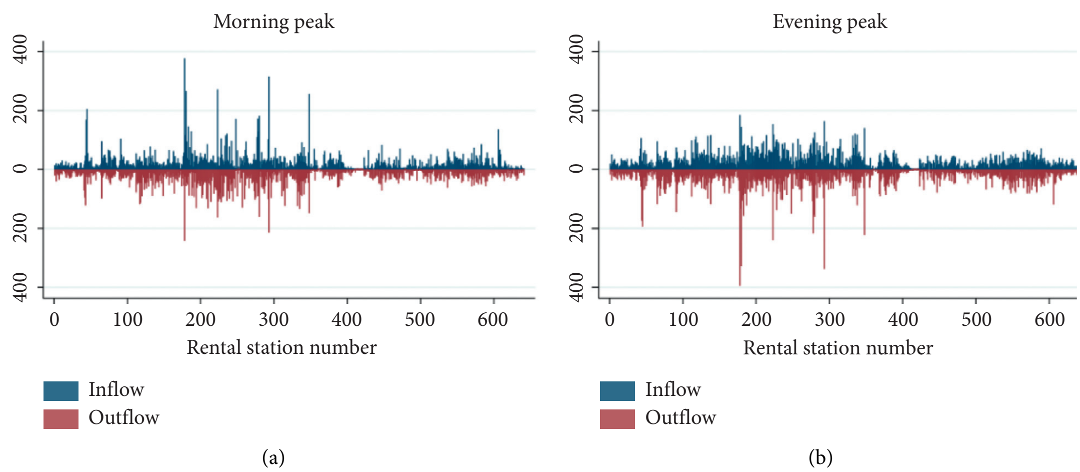


FIGURE 3: Inflow and outflow of rental stations during rush hours in the (a) morning and (b) evening.

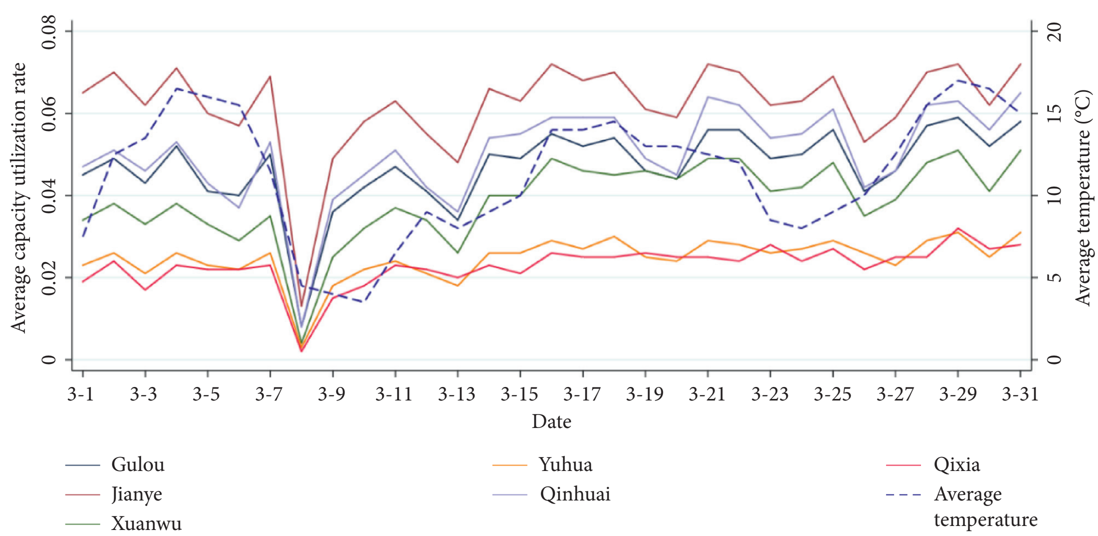


FIGURE 4: Daily variation tendency of capacity utilization rate of bicycle-sharing.

TABLE 5: Correlation analysis between the capacity utilization rate and factors.

Correlative factor	Average temperature	The number of rental stations	Population density
Pearson correlation coefficient	0.555**	0.787**	0.514**
P value (two-sided test)	0.001	0.000	0.004

Note. **indicates a correlation at the significance level of 0.01.

number of rental stations is increased in the current situation, the convenience of leasing and returning bicycle-sharing will be improved, and people will increase the use of bicycle-sharing, which can increase the average capacity utilization rate of bicycle-sharing. At the same time, if the population density around the rental stations is increased, the number of bicycle-sharing users and the average capacity utilization rate of bicycle-sharing will also increase.

Figure 5 shows the daily variation tendency of the average capacity utilization rate of bicycle-sharing in various administrative districts of Nanjing. On the whole, the average capacity utilization rate can be shown obviously in morning peak (7 : 00–10 : 00), midday peak (13 : 00–15 : 00), and evening peak (17 : 00–19 : 00), which reaches the highest point at 9 : 00, 14 : 00, and 18 : 00, respectively. During rush hours in the morning and evening, urban traffic volume increases so that road congestion is serious. People tend to ride bicycle-sharing to go to the bus stations or subway stations which makes the capacity utilization rate of bicycle-sharing relatively high during commuting hours in the morning and evening. During the midday peak, especially between 13 : 00 and 14 : 00, some office workers go out to work, which leads to an increase of traffic volume and use of bicycle-

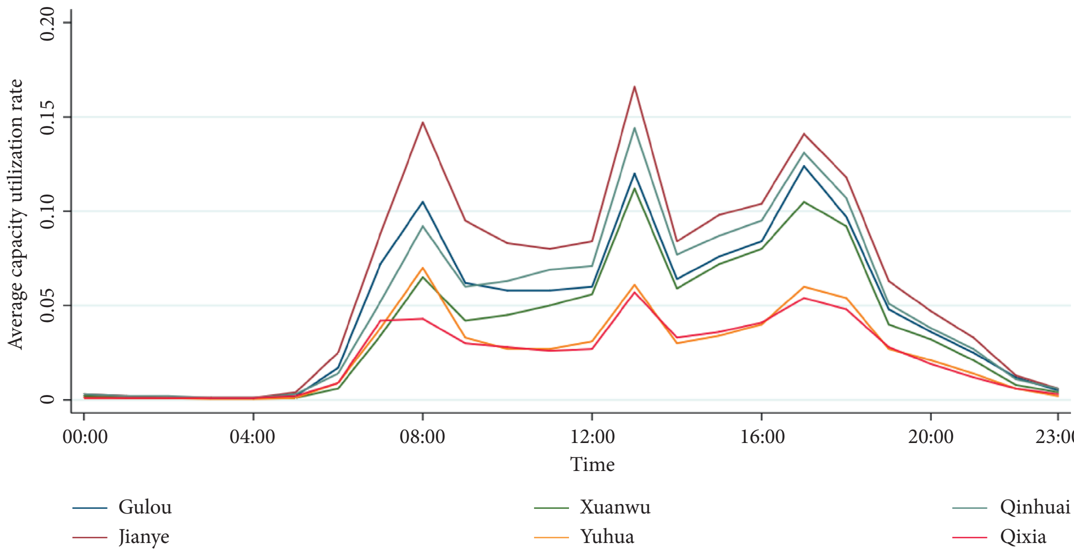


Figure 5: Average capacity utilization rate of bicycle-sharing in different time periods in different urban areas.

sharing. From 23 : 00 to 6 : 00, the next day, people hardly travel by bicycle-sharing, and the average capacity utilization rate tends to zero.

3.3. The Impact of Urban POI Distribution on the Demand of Bicycle-Sharing. We should determine the number of independent variables (m) in each stepwise regression equation firstly when solving equation (3). On the one hand, with the increase of the number of independent variables (m), the regression model's goodness of fit (R^2) has an increasing trend, as shown in Table 6. But, the time complexity of the variable selection model will increase rapidly, and the multicollinearity of the independent variables will also become serious. Therefore, we subjectively set the number of sampled independent variables to 45 in each stepwise regression based on these considerations. We estimate equation (3) using the daily inflow and outflow data of bicycle-sharing rental stations, respectively. The goodness of fit (R^2) for inflow model and outflow model should be 0.318 and 0.306, respectively (Table 6). The error term fluctuates around 0, resulting in passing the ADF test (Table 7). Figures 6(a) and 6(b) compare the difference between the daily inflow and daily outflow observations and the estimates obtained by inflow model and outflow model for all bicycle-sharing rental stations, respectively. It can be seen that the properties of land use around the rental stations can be partially explained by the inflow and outflow of bicycle-sharing, and the model fits relatively well.

The estimated parameters of the model are shown in the Tables 8 and 9. In fact, most estimates of the coefficients are relatively small, indicating that most functional zones have a weak impact on the inflow and outflow of bicycle-sharing rental stations. Table 10 lists the top 10 functional zones that have the most positive or negative impact on the inflow and outflow of bicycle-sharing rental stations (the absolute value of variable coefficient is the largest). Table 11 lists the top 10 functional zones that have the least positive or negative

Table 6: The number of randomly selected variables (k) and the goodness of fit (R2) of regression.

k	20	25	30	35	40	45
R^2 of inflow model	0.210	0.240	0.265	0.285	0.303	0.318
R^2 of outflow model	0.204	0.232	0.256	0.276	0.292	0.306

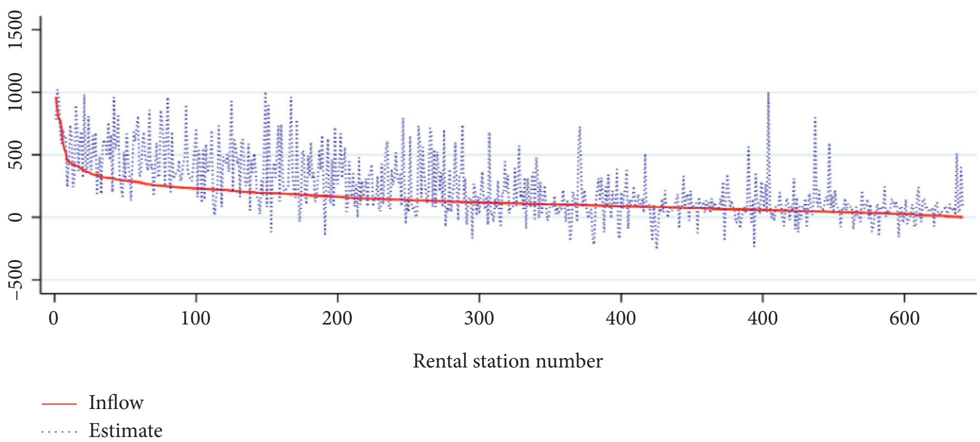
impact on the inflow and outflow of bicycle-sharing rental stations (the absolute value of variable coefficient is the smallest).

It can be seen from Table 10 that the functional zones which have a significant impact on the inflow and outflow of bicycle-sharing rental stations are exactly the same. For the same functional zone, the influence difference in the inflow and outflow is small. People choose different trip modes for different trip purposes. The first-level indicators with the significant impact are traffic, education, entertainment, exercise, medical, tourist attraction, and enterprise. The study found that the functional zones with a large demand of bicycle-sharing have the following characteristics: higher population density and mobility, difficulties in parking, and all closely related to residents' lives. However, in the same functional zone, the impact of different facilities on the inflow and outflow of bicycle-sharing may vary greatly. For example, in the traffic functional zone, the number of service areas has a high positive impact on the inflow and outflow of bicycle-sharing (the coefficient value is positive), while the number of coach stations has a negative impact on it (the coefficient value is negative).

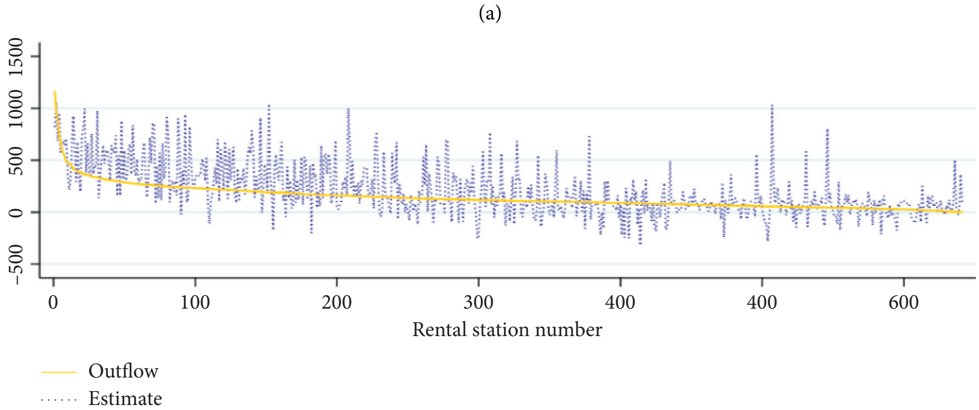
From the functional zones that have a small impact on the inflow and outflow of bicycle-sharing at rental stations (Table 11), the first-level indicators with few impacts are mainly life service, autoservice, government agency, shopping, and hotel. These functional zones are mainly service-oriented. Although they are closely related to residents' lives, the population density is small and there are generally no serious parking problems, which lead to the low demand of bicycle-sharing. These functional zones have few impacts on

Table 7: ADF test results of the error term.

Model	Test statistic	1% critical value	5% critical value	P value
Inflow model	−22.785	−3.430	−2.860	0.000
Outflow model	−22.414	−3.430	−2.860	0.000



(a)



(b)

Figure 6: Comparison between estimated value of the model and real value.

Table 8: Parameters and coefficients' estimated values in inflow model.

Parameter	Estimated value	Parameter	Estimated value	Parameter	Estimated value
α_1	83.3969	β_{41}	-6.9867	β_{82}	0.0000
β_1	−2.7587	β_{42}	4.9349	β_{83}	−7.1934
β_2	2.2415	β_{43}	−9.2338	β_{84}	6.9266
β_3	19.2002	β_{44}	7.1613	β_{85}	7.7667
β_4	−5.8607	β_{45}	6.2249	β_{86}	−11.6402
β_5	7.0240	β_{46}	7.4451	β_{87}	−8.1153
β_6	−5.3885	β_{47}	−3.2830	β_{88}	12.2151
β_7	6.3915	β_{48}	−3.9637	β_{89}	7.7834
β_8	8.9447	β_{49}	−3.3035	β_{90}	6.9951
β_9	3.6900	β_{50}	6.6822	β_{91}	−9.3924
β_{10}	−2.0702	β_{51}	13.0168	β_{92}	9.0235
β_{11}	−3.7502	β_{52}	−23.3411	β_{93}	3.6491
β_{12}	13.6733	β_{53}	−5.1993	β_{94}	−8.0170
β_{13}	6.4144	β_{54}	10.5969	β_{95}	−11.4879
β_{14}	149.9000	β_{55}	5.8249	β_{96}	45.6391
β_{15}	−13.2663	β_{56}	−7.9995	β_{97}	−7.6196
β_{16}	−3.3590	β_{57}	2.3723	β_{98}	3.9504

Table 8: Continued.

Parameter	Estimated value	Parameter	Estimated value	Parameter	Estimated value
β_{17}	2.8811	β_{58}	−6.6928	β_{99}	−3.8184
β_{18}	−9.4576	β_{59}	5.3987	β_{100}	8.0614
β_{19}	4.1217	β_{60}	4.1922	β_{101}	−5.3234
β_{20}	0.0000	β_{61}	3.2082	β_{102}	−7.6699
β_{21}	−3.2024	β_{62}	4.9134	β_{103}	−5.8581
β_{22}	−33.6326	β_{63}	−8.4073	β_{104}	−10.0074
β_{23}	13.1721	β_{64}	15.8291	β_{105}	−8.4513
β_{24}	7.2430	β_{65}	−7.5476	β_{106}	27.2642
β_{25}	21.4611	β_{66}	0.2386	β_{107}	13.8721
β_{26}	−4.1276	β_{67}	−4.1264	β_{108}	−6.2522
β_{27}	37.6117	β_{68}	8.5244	β_{109}	2.7554
β_{28}	−3.5742	β_{69}	5.4584	β_{110}	8.4834
β_{29}	−11.5428	β_{70}	−5.0782	β_{111}	−9.8788
β_{30}	−46.8318	β_{71}	−3.0379	β_{112}	35.5544
β_{31}	0.9829	β_{72}	−10.1715	β_{113}	9.7980
β_{32}	9.3570	β_{73}	8.9434	β_{114}	−1.2067
β_{33}	7.7032	β_{74}	−3.0838	β_{115}	−6.3799
β_{34}	−3.2671	β_{75}	−3.3837	β_{116}	4.3948
β_{35}	−5.1777	β_{76}	2.1052	β_{117}	7.2570
β_{36}	−8.6607	β_{77}	−3.8903	β_{118}	−1.8437
β_{37}	7.8410	β_{78}	−9.8123	β_{119}	1.2370
β_{38}	−8.3185	β_{79}	18.4531	β_{120}	−14.0662
β_{39}	3.8894	β_{80}	−11.1164	β_{121}	9.0092
β_{40}	−3.2873	β_{81}	5.0392	β_{122}	−6.2830

Table 9: Parameters and coefficients' estimated values in the outflow model.

Parameter	Estimated value	Parameter	Estimated value	Parameter	Estimated value
α_2	82.0370	θ_{41}	−7.3218	θ_{82}	0.0000
θ_1	−2.7247	θ_{42}	1.9573	θ_{83}	−7.5080
θ_2	−0.1385	θ_{43}	−9.5385	θ_{84}	7.0023
θ_3	19.8124	θ_{44}	7.4760	θ_{85}	8.4361
θ_4	−6.0150	θ_{45}	6.3188	θ_{86}	−11.7815
θ_5	6.9068	θ_{46}	8.2213	θ_{87}	−8.3869
θ_6	−4.5390	θ_{47}	−2.5987	θ_{88}	12.1632
θ_7	6.8820	θ_{48}	−4.1913	θ_{89}	7.9017
θ_8	8.9013	θ_{49}	−3.2394	θ_{90}	7.3889
θ_9	3.5766	θ_{50}	6.9138	θ_{91}	−9.1555
θ_{10}	−1.9898	θ_{51}	12.8864	θ_{92}	7.3187
θ_{11}	−4.3748	θ_{52}	−24.1010	θ_{93}	3.6142
θ_{12}	13.2462	θ_{53}	−5.1009	θ_{94}	−8.1516
θ_{13}	7.1805	θ_{54}	11.0108	θ_{95}	−12.0123
θ_{14}	149.6667	θ_{55}	9.8946	θ_{96}	45.9434
θ_{15}	−12.9182	θ_{56}	−8.2992	θ_{97}	−8.7558
θ_{16}	−3.3860	θ_{57}	2.2150	θ_{98}	3.6624
θ_{17}	2.9523	θ_{58}	−6.9695	θ_{99}	−8.0618
θ_{18}	−9.3741	θ_{59}	5.4592	θ_{100}	8.5201
θ_{19}	3.9422	θ_{60}	4.3497	θ_{101}	−5.5351
θ_{20}	0.0000	θ_{61}	2.8405	θ_{102}	−8.1175
θ_{21}	−3.1948	θ_{62}	5.0488	θ_{103}	−6.3701
θ_{22}	−33.9958	θ_{63}	−11.0726	θ_{104}	−15.0849
θ_{23}	12.6726	θ_{64}	16.2320	θ_{105}	−8.6648
θ_{24}	7.6257	θ_{65}	−7.7795	θ_{106}	28.3063
θ_{25}	24.1864	θ_{66}	−2.5659	θ_{107}	13.8782
θ_{26}	−4.4776	θ_{67}	−4.3022	θ_{108}	−6.3529
θ_{27}	37.9816	θ_{68}	8.8685	θ_{109}	4.0970
θ_{28}	−3.9973	θ_{69}	5.6673	θ_{110}	8.6896
θ_{29}	−12.3609	θ_{70}	−5.1174	θ_{111}	−10.6633
θ_{30}	−48.0445	θ_{71}	−1.9990	θ_{112}	37.8580

Table 9: Continued.

Parameter	Estimated value	Parameter	Estimated value	Parameter	Estimated value
θ_{31}	1.4996	θ_{72}	−10.7866	θ_{113}	10.2339
θ_{32}	9.4674	θ_{73}	9.0976	θ_{114}	−0.3291
θ_{33}	7.7704	θ_{74}	−3.5439	θ_{115}	−6.6536
θ_{34}	−5.8020	θ_{75}	−4.5094	θ_{116}	2.5143
θ_{35}	−5.2800	θ_{76}	−0.6945	θ_{117}	7.5772
θ_{36}	−8.1847	θ_{77}	−3.8980	θ_{118}	−2.5149
θ_{37}	8.0315	θ_{78}	−10.0159	θ_{119}	2.8593
θ_{38}	−8.4529	θ_{79}	18.8821	θ_{120}	−13.8277
θ_{39}	4.0684	θ_{80}	−11.0471	θ_{121}	9.8436
θ_{40}	−2.6815	θ_{81}	5.1629	θ_{122}	−6.4383

Table 10: Top 10 variables with the largest absolute value of coefficient in model.

Inflow model			Outflow model		
First-level indicator	Second-level indicator	Coefficient value	First-level indicator	Second-level indicator	Coefficient value
Traffic	Service area	150	Traffic	Service area	150
	Coach station	−34		Coach station	−34
Education	Special education school	−47	Education	Special education school	−48
	Overseas study agency	38		Overseas study agency	38
	Science museum	21		Science museum	24
Entertainment	Resort	46	Entertainment	Resort	46
Exercise	Extreme sports site	36	Exercise	Extreme sports site	38
Medical	Nursing home	27	Medical	Nursing home	28
Tourist attraction	Aquarium	-23	Tourist attraction	Aquarium	-24
Enterprise	Gardening	19	Enterprise	Gardening	20

Table 11: Top 10 variables with the smallest absolute value of coefficient in model.

Inflow model			Outflow model		
First-level indicator	Second-level indicator	Coefficient value	First-level indicator	Second-level indicator	Coefficient value
Life service	Graphic printing shop	0	Life service	Graphic printing shop	0
	Real estate agency	2		Real estate agency	−1
Traffic	Toll station	0	Traffic	Toll station	0
Auto service	Car repair	0	Enterprise	Company	0
Education	Library	1	Exercise	Sports stadium	0
Exercise	Sports stadium	−1	Education	Library	1
Government agency	Administrative unit	1	Hotel	Star hotel	2
	Public security agency	−2	Shopping	Home building materials	−2
Shopping	Home building materials	−2	Real estate	Uptown	−2
Enterprise	Company	2	Catering	Cake and dessert	2

the inflow and outflow of bicycle-sharing, but the same facilities have significantly different effects on the inflow and outflow of bicycle-sharing. For example, the number of real estate agencies in the life service functional zone has a positive impact on the inflow of bicycle-sharing (the coefficient value is positive) and has a negative impact on the outflow (the coefficient value is negative).

Then, we discuss the top 10 functional zones that have the most positive and negative impacts on the inflow and outflow of bicycle-sharing rental stations during rush hours in the morning and evening, as shown in Tables 12 and 13.

It can be seen from Tables 12 and 13 that the functional zones that have a significant effect on the inflow of bicycle-sharing at rental stations during rush hours in the morning are consistent with the functional zones that have a significant effect on the outflow of bicycle-sharing at rental stations during rush hours in the evening. On the contrary, the functional zones of the outflow during rush hours in the morning are consistent with that of the inflow during rush hours in the evening. At the same time, we notice that the functional zones regarding education, traffic, medical, tourist attraction, and entertainment are also the ones that have a significant impact on the bicycle-sharing demand model. The impact of different facilities on the inflow and outflow of bicycle-sharing may vary greatly. For example, during rush hours in the evening, in the education functional zone, the number of overseas study agencies has a positive impact on the inflow and outflow of bicycle-sharing (the coefficient value is positive), while the number of special education schools has a negative impact on it (the coefficient

Table 12: Top 10 variables of the largest absolute value of coefficient in model during rush hours in the morning.

Inflow model			Outflow model		
First-level indicator	Second-level indicator	Coefficient value	First-level indicator	Second-level indicator	Coefficient value
Government agency	Central agency	15	Entertainment	Resort	13
Education	Special education school	−14	Education	Special education school	−12
	Overseas study agency	9		Overseas study agency	10
	Science museum	7	Traffic	Coach station	−9
Traffic	Coach station	−10	Government agency	Central agency	−8
Medical	Nursing home	8	Tourist attraction	Arboretum	−7
	Emergency center	−6		Aquarium	−6
Tourist attraction	Arboretum	8	Medical	Nursing home	7
	Aquarium	−7		Emergency center	−5
Entertainment	Farmhouse	−6	Life service	Household service	5

Table 13: Top 10 variables of the largest absolute value of coefficient in model during rush hours in the evening.

Inflow model			Outflow model		
First-level indicator	Second-level indicator	Coefficient value	First-level indicator	Second-level indicator	Coefficient value
Traffic	Service area	34	Government agency	Central agency	16
	Coach station	−−8	Education	Special education school	−15
Entertainment	Resort	12		Overseas study agency	11
Education	Special education school	−11		Science museum	8
	Overseas study agency	10	Entertainment	Resort	14
Medical	Nursing home	6		Farmhouse	−6
Tourist attraction	Aquarium	−5	Traffic	Coach station	−10
	Arboretum	−5	Tourist attraction	Arboretum	9
Life service	Household service	5		Aquarium	−7
Enterprise	Gardening	4	Medical	Nursing home	8

value is negative). However, in the same first-level functional zone, the impact of its facilities on the inflow and outflow of bicycle-sharing may be different. For example, the number of arboretums in the functional zone of tourist attraction during rush hours in the morning has a positive impact on the inflow of bicycle-sharing (the coefficient value is positive) and a negative impact on the outflow (the coefficient value is negative). Therefore, we can make a preliminary prediction of the inflow and outflow of bicycle-sharing at rental stations with the distribution of functional zones around the stations, so as to realize a reasonable dispatch of vehicles among the rental stations.

4. Conclusions

In this paper, we analyze the usage status and user group characteristics of urban bicycle-sharing statistically and describe the daily variation tendency of the capacity utilization rate of bicycle-sharing by using the data of the Nanjing bicycle-sharing system in March 2016. Then, we establish the variable selection model based on the Spike-slab sparse function and stepwise regression and investigate the influence of urban land use properties (POI distribution) on the demand of bicycle-sharing. The conclusions are as follows:

Bicycle-sharing is mainly used by office workers for short trips. Users are aged between 25 and 55, and the travel time is concentrated between 0 and 20 minutes. The total demand of bicycle-sharing for users during rush hours on the workday morning and evening is higher than that on weekends significantly. Compared with workdays, there are more travel demands during nonpeak hours (10 : 00–17 : 00) at weekends. The overall capacity utilization rate of bicycle-sharing is relatively low, and most of bicycle-sharing have been idle for a long time, which indicate that the system is inefficient. The capacity utilization rate of bicycle-sharing is affected by factors such as the number of rental stations, population density, and travel environment (air temperature). When the population around the rental stations or the number of stations is larger, the capacity utilization rate of bicycle-sharing will be higher, which will help improve the operational efficiency. But for now, it seems that only less than 10% of the bicycle-sharing rental stations have relatively high inflow and outflow during rush hours in the morning and evening. Moreover, the difference between the inflow and outflow at the same rental station is large during rush hours in the morning and evening, which will lead to an imbalance between supply and demand and the low operational efficiency of the bicycle-sharing system.

In this paper, we explore the impact of urban land use properties on the inflow and outflow of bicycle-sharing at rental stations and find that functional zones such as traffic, education, entertainment, exercise, and medical zones around the rental stations have a significant impact on the demand of bicycle-sharing for users, while life service, auto service, government agency, shopping, and hotel zones have a relatively weak impact. In particular, the inflow and outflow of rental stations during rush hours in the morning and evening are mainly affected by the functional zones such as government agency, education, traffic, medical, tourist attraction, and entertainment zones near the stations. Therefore, when adding new bicycle-sharing rental stations, we not only consider the geographical distribution of rental stations but also focus on those functional zone facilities that have a significant positive impact on bicycle-sharing demand, such as service area, resort, and overseas study agency, in order to meet the trip demand of the people in the vicinity and improve operational efficiency.

Understanding the existing deficiencies and reasons of bicycle-sharing system has a great guiding significance to improve its operational efficiency. We should alleviate the imbalance of supply and demand of bicycle-sharing rental stations, increase the capacity utilization rate, and schedule bicycle-sharing among different rental stations reasonably. On the one hand, the relevant departments should predict the inflow and outflow of rental stations and schedule the vehicles at rental stations reasonably in accordance with the distribution of functional zones around the stations and the variation tendency of people's demand of bicycle-sharing in different time periods. On the other hand, the relevant institutions or enterprises should perfect policy guidance and strengthen the quality promotion and safety guarantee of cyclists, to provide greater convenience for users and to promote the sustainable development of the urban bicycle-sharing system.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

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