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Impact of Built Environment on Bike Sharing Diurnal Variation Characteristics: A Case Study in Xiamen

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Abstract: The impact mechanism of built environment on bike sharing is the basis of analyzing the spatial differences of bike sharing travel behavior and formulating regional management strategies. However, the research on the characteristics of diurnal variation of bike sharing travel volume is relatively insufficient. Most existing research use short-term data of several days, and lack of research on the long-term effects of spatial heterogeneity. Based on the bike sharing data of Xiamen for nearly three months in 2018, this paper conducts regional research and establishes an index system describing the long-term fluctuation of bike sharing daily travel volume. Five regional bike sharing travel modes are divided, and the impact of regional built environment on the diurnal variation of bike sharing daily travel volume is discussed. The results show that the built environment will affect the daily travel volume of regional bike sharing and its long-term fluctuation. Population, traffic accessibility, and the number of POI will positively affect the daily travel volume of regional bike sharing, while the POI category, the connection with rail transit and the land use diversity will have different effects on the fluctuation characteristics of daily travel volume. The daily travel volume variation tends to be uniform as the land use diversity increases. Targeted management strategies in different areas can be developed accordingly. **DOI:** 10.13813/j.cn11-5141/u.2021.0029-en

Keywords: transportation planning; bike sharing; daily volume; diurnal variation characteristics; built environment; Xiamen

0 Introduction

The launch of the bike sharing service by Ofo (a Beijing-based bike sharing company) in June 2015 marked the beginning of dockless bike sharing. Bike sharing ushered in explosive growth in 2017: the number of bike sharing users exceeded 70 million [1] by May 2017. In 2018, bike sharing companies continued to merge and the bidding policies were introduced. Under this background, along with the increase in fees and restrictions on bike sharing operations, users with weak demand for bike sharing gradually stopped using the service and bike sharing started to cool off. In the first quarter of 2019, the number of bike sharing users was 40.5 million, a decrease of 24.4% [2]. The daily turnover rate in major cities was only 1 to 2 times per bike[3] [4]. Since the outbreak of COVID-19 in 2020, public transportation has been severely restricted and bike sharing usage has begun to increase. The data from bike sharing platforms, such as Hellobike, Meituan Bike and Qingju Bike, show that bike sharing volume has a significant increase since work resumption. Although the evolution of bike sharing is tortuous, the usage and popularization of bike sharing undoubtedly stimulated the demand for cycling and promoted the development of the non-motorized transportation system. As a new, green, and environment-friendly individual travel mode, bike sharing could potentially become one of the main non-motorized travel modes. The study of bike sharing has also become a hot topic in urban traffic research.

Most existing studies on the travel characteristics of bike sharing use the data of one or several days to analyze the temporal and spatial characteristics of bike sharing travel behavior. In terms of temporal characteristics, a study of European and American cities found that the usage of public bicycles had morning and evening commute peaks on weekdays and evening peaks on weekends [5]. Fu and Juan confirmed that bike sharing travel had a clear temporal pattern by using one week's Mobike data for Shanghai [6]. In terms of spatial characteristics, Lyu and Pan studied one month of Mobike data for Shanghai, and found that bike sharing activities mainly occurred around urban public

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activity centers, and shared bikes were mostly parked near rail transit stations [7]. Deng, Xie and Huang analyzed 15-day's Mobike usage data collected from the built areas of Beijing, and classified bike sharing activities into five types according to their spatial characteristics [8]. A study based on weekday and weekend bike sharing data for Nanjing showed that the spatial agglomeration characteristics of bike sharing were significantly different on weekdays and on weekends, as well as in morning and evening peaks and other time periods [9]. Another study analyzed five weekdays of bike sharing travel data for Nanjing, and summarized four temporal modes and two spatial modes of bike sharing usage [10]. These studies indicated that bike sharing showed certain temporal and spatial distribution patterns, which are worthy of further research. Considering the long-term fluctuation of the travel volume of bike sharing and the significant difference in different periods, Lyu and Pan [7] analyzed the bike sharing data for one month, but did not pay attention to the long-term fluctuation characteristics. Studying the long-term fluctuation of bike sharing travel volume has more practical significance for arranging the operation of bike sharing and guiding the construction of relevant facilities.

The policy-making of bike sharing needs to study not only the variation in travel volume, but also the differences between different areas to support the strategy of management by area. Many studies on bike sharing found that there were obvious differences in travel volume in different urban areas [11]. Existing studies have confirmed that the built environment could affect travel volume of bike sharing [12] [13]. However, as a long-term environmental variable, the impact of the built environment on bike sharing travel volume should also be studied from a long-term perspective. Such studies are important for the formulation of management strategies for bike sharing. They can not only reflect the long-term impact of the built environment on bike sharing travel volume but also analyze the spatial difference of travel volume variation. Targeted management strategies according to the built environment of different areas and long-term travel characteristics of bike sharing align with the requirements of urban elaborated governance. For example, some cities have adopted different bike sharing policies for urban central areas and peripheral areas, and many communities and business districts have their own management measures for bike sharing.

The study of bike sharing daily volume and its long-term variation patterns in different areas is helpful in understanding each area's bike sharing travel intensity and its diurnal variation, which in turn will help the development of management measures by area. This paper analyzes nearly three months of bike sharing data for Xiamen and studies the daily volume and diurnal variation characteristics of bike sharing in different areas. The paper also summarizes the indicators to describe the long-term bike sharing travel characteristics and discusses the impact of the built environment on bike sharing travel volume and its diurnal variation characteristics. The research results from this paper can be used to guide the development of bike sharing management measures by area.

1 Research background

1.1 Data processing

The data studied in this paper were 11 weeks of bike sharing data collected from March 5 to May 20, 2018 in Xiamen. They cover all four bike sharing companies in Xiamen during this period: Mobike, Ofo, Hellobike, and Jiujiu Bike. The transaction data of each bike sharing trip (Table 1) were obtained by processing the status data (unlocked/locked) of shared bikes. The transaction data are cleaned as follows.

1) Removing erroneous data

The following transaction data were deleted: transactions with locations outside of Xiamen; duplicate transactions that occurred at the same time; transactions with abnormal riding time (more than 2 hours or less than 2 minutes); transactions with abnormal riding distance (less than 200 meters); and transactions with abnormal riding speed (average speed more than 20 km $\cdot$ h^{-1}).

2) Processing of missing values

Two to six hours of data were missing on 4 days among the 11 weeks. The interpolation method is used to supplement data for data integrity. The missing data of three workdays on April 24, April 25 and May 2 were supplemented with the average values of two adjacent weekdays over the same hours. The missing data of the holiday on May 1 were supplemented with the average values of the five-day holiday over the same hours.

After data cleaning, 12.45 million transaction records were obtained for further research.

Table 1 Original data and order data

Data processing stages	Variable	Description
Original data (unlocked/locked status data) before data processing	id	Record ID
	UpdateTime	Update time
	CompanyId	Company ID
	BicycleId	Bicycle ID
	Loc	Location
	LockStatus	Status of the shared bike (unlocked/locked)
Transaction data after data processing	Oid	Order ID
	T	Time when the shared bike is unlocked at the beginning of the order
	Lon	Longitude where the shared bike is unlocked at the beginning of the order
	Lat	Latitude where the shared bike is unlocked at the beginning of the order
	Tb	Time when the shared bike is locked at the end of the order
	Lonb	Longitude where the shared bike is locked at the end of the order
	Latb	Latitude where the shared bike is locked at the end of the order

1.2 Spatial unit

The grid method is used to divide the region to study spatial differences. The grid size is generally 100 m, 500 m, 1 km and so on, depending on the research needs. According to the Origin-Destination (OD) distance distribution of bike sharing trips in Xiamen, the peak OD distance is about 500 m, and the number of bike sharing trips decreases with an increase in OD distance when the OD distance is more than 500 m (Fig. 1). Therefore, an area of 500 m×500 m is selected as the base spatial unit in this research so that it can cover as many bike sharing trips as possible (the total bike sharing volume of a spatial unit is the sum of the number of bike sharing trips that originate and end in this unit). Only the spatial units with an average daily bike sharing volume above 100 are selected for study in this research.

2 Variation characteristics of bike sharing daily travel volume

2.1 Indicators to describe variation characteristics of bike sharing daily travel volume

The index system should include the scale and the fluctuation of the bike sharing daily travel volume during the studied period so that the variation characteristics of the bike sharing daily travel volume in the 423 spatial units can be fully described. The scale can be expressed as the average daily travel volume. On the other hand, the fluctuation characteristics need to be expressed by paying attention to the difference in the daily travel volume between workdays and nonwork days and the changes between adjacent workdays (Fig. 2), which can be used to provide guidance for operations and parking facilities during different time periods.

Therefore, the following indicators are developed in this research (Table 2).

1) Average daily travel volume

This indicator is used to describe the long-term bike sharing travel intensity for a spatial unit. The bike sharing travel volume in a spatial unit fluctuates within a certain range when no new bikes are introduced. The average daily travel volume is calculated as $V=\overline{Volum_n}$ where $Volum_n$ is the number of bike sharing trips on day n.

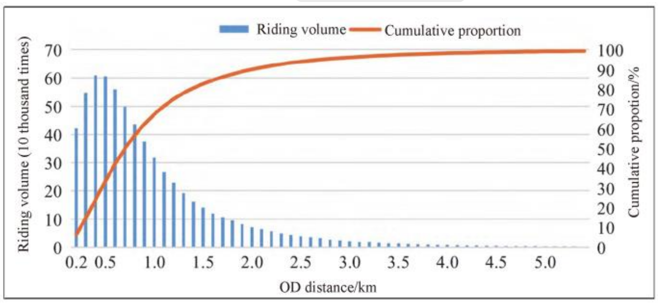


Fig. 1 OD distance distribution of bike sharing travel

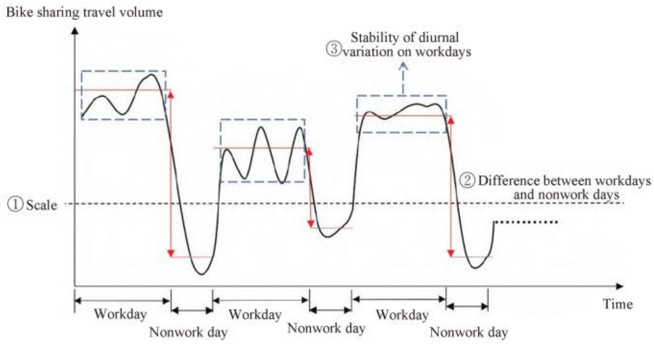


Fig. 2 Changes in daily travel volume of shared bikes

Table 2 Indicators of daily travel volume of regional bike sharing

Indicator name	Variable, abbreviation	Description	Indication
Average daily travel volume	$Volum$, V	Average daily volume of bike sharing trips	Long-term trip intensity
Maximum ratio of daily travel volume on workdays	$Max\ Ratio\_Working\ day$, MR_W	The maximum ratio of weekly average of daily travel volume on workdays to that on nonwork days	The maximum difference between workdays and nonwork days
Maximum ratio of daily travel volume on nonwork days	$Max\ Ratio\_non-Working\ day$, MR_NW	The maximum ratio of weekly average of daily travel volume on nonwork days to that on workdays	
Maximum variation rate of daily travel volume on workdays	$Max\ Variation$, MV	The maximum variation rate of daily travel volume on workdays	Stability of variation

The left-skewed distribution of the average daily travel volume in Fig. 3a shows most of the spatial units have bike sharing usage lower than the average level, and only a few spatial units have higher usage levels.

2) Maximum ratio of daily travel volume on workdays and on nonwork days

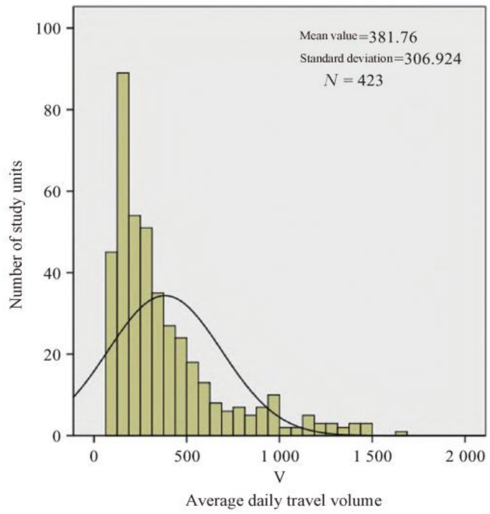
These two indicators are used to describe the difference between workdays and nonwork days. Many studies have confirmed that there is a significant difference in travel demand between workdays and nonwork days.

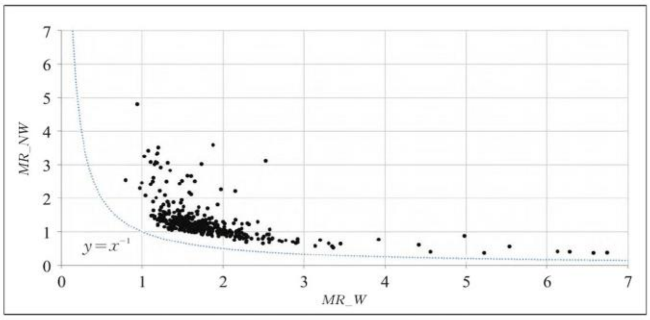
Referring to the method of using the peak-to-valley ratio to reflect the degree of traffic congestion in the study of traffic index [14], this paper calculates the ratio of travel volume on workdays (nonwork days) of a week. The ratio is calculated as dividing the average daily travel volume on workdays (nonwork days) in a week by the average daily travel volume on nonwork days (workdays) in the same week. The maximum ratio of the 11 weeks indicates the maximum difference in the bike sharing travel volume between workdays (nonwork days) and nonwork days (workdays) in a spatial unit. The calculation formulas are as follows:

$$MR\_W=MAX\{Ratio_{wm}\},\ Ratio_{wm}=\frac{\overline{Volum_{wm}}}{\overline{Volum_{nwm}}},$$

$$MR\_NW=MAX\{Ratio_{nwm}\},\ Ratio_{nwm}=\frac{\overline{Volum_{nwm}}}{\overline{Volum_{wm}}},$$

where $Volum_{wm}$ and $Volum_{nwm}$ are the average travel volume on workdays and nonwork days in week m; and $Ratio_{wm}$ and $Ratio_{nwm}$ are the ratios of workdays and nonwork days in week *m*.





b Joint distribution of maximum ratio of daily travel volume on workdays and on nonwork days

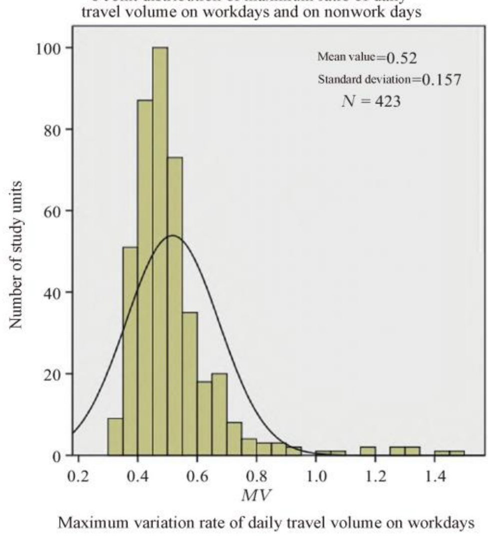


Fig. 3 Numerical distribution of each index

If MR__W and MR__NW are reciprocal to each other, $Ratio_{wm}$ and $Ratio_{nwm}$ are constant, which indicates that the bike sharing trips in a spatial unit follow a cyclical pattern and the bike sharing on weekdays and on nonwork days are relatively stable. The joint distribution of MR__W and MR__NW in Fig. 3b shows most data points fall far from the curve of y=1/x. This figure indicates that the bike sharing on weekdays and on nonwork days in the spatial units represented by these data points are unstable and it is necessary to consider the corresponding allocation and parking issues.

3) Maximum variation rate of daily travel volume on workdays

This indicator is used to describe the stability of daily travel volume on workdays. The variation rate of a workday is calculated as its difference from its previous workday in the same week divided by the travel volume of its previous workday. The variation rates are then ranked from high to low, and it was found that the top five variation rates (top 10%–15%) in different spatial units show significant differences (Fig. 4). Therefore, the average of the top five variation rates is taken as the maximum variation rate, which conforms to the normal-like distribution (Fig. 3C). The calculation formulas are as follows:

$$Variation_{m_i} = \frac{\left|Volum_{m_i} - Volum_{m_{i-1}}\right|}{Volum_{m_{i-1}}},$$

$$MV = \frac{Variation_{(1)} + \cdots + Variation_{(5)}}{5},$$

where, $Variation_{mi}$ is the variation rate of the ith workday of week m; $Volum_{mi}$ is the travel volume on the ith workday of week m with m=1, 2,..., 11, i=2, 3, 4, 5; $Variation_{(n)}$ is the nth largest value after the variation rates are ranked from high to low.

2.2 Bike sharing travel modes based on clustering

The indicators defined in Section 2.1 were standardized, and K-means clustering was conducted for the 423 spatial units, which were classified into the following modes based on the clustering results (Table 3).

1) Workday mode. The spatial units in the workday mode have bike sharing travel mainly occurring on workdays, and their workday travel volume is relatively stable. They can be further divided into three types: the periodic type, the high-intensity type, and the normal type. The spatial units of the periodic type, accounting for only 2.4%, are spatial units that show obvious periodic patterns in the variation of their daily travel volume. Their bike sharing travel statuses are basically the same every week. The spatial units of the high-intensity type and the normal type do not show obvious periodic patterns and they account for 14.2% and 63.6% respectively. These numbers indicate that bike sharing trips in most areas occur mainly on workdays, and only a few of them show some regularity.

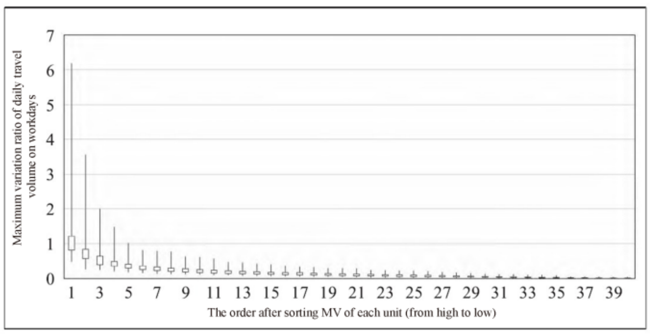


Fig. 4 Order distribution of travel volume variation on weekdays

Table 3 Clustering of travel modes in bike sharing areas

Mode		Workday mode			Nonwork day mode	Indefinite mode
		Periodic type	High intensity type	Normal type		
Cluster variables	V	355.244	1 009.908	281.464	251.424	258.634
	MR_W	0.454	0.474	0.464	1.148	0.637
	MR_NW	5.434	1.823	1.793	1.226	1.434
	MV	0.52	1.092	1.131	3.136	1.865
Example diurnal variation curve of a typical spatial unit						
Number of spatial units		10	60	269	14	70
Proportion/%		2.4	14.2	63.6	3.3	16.5

2) Nonwork day mode. Bike sharing trips in the spatial units in the nonwork day mode mainly occur on nonwork days. The bike sharing travel volume is likely to surge on holidays and change considerably on workdays.

3) Indefinite mode. The spatial units in the indefinite mode do not show notable differences between bike sharing trips on workdays and on non-work days.

The clustering results show that different areas have different long-term changes in bike sharing usage, and only a small portion of areas show periodic fluctuation in travel volume. Therefore, it is important to pay attention to the diurnal variation of travel characteristics in the study of bike sharing. The allocation and parking emphasis would be different for areas with different diurnal variation characteristics in travel volume and areas in different modes, and the clustering of areas with different bike sharing modes can be conducted for reference in bike sharing operations and management.

3 Modeling impact of built environment on variation of bike sharing daily travel volume

3.1 Variable selection

Studying the impact of built environment on the long-term change of bike sharing daily travel volume has great significance in analyzing the spatial differences of bike sharing travel behavior and formulating regional management strategies. The description indicators proposed in Section 2 are used as the dependent variables. Among them, the average daily travel volume varies substantially and its distribution is skewed to the right. Therefore, Ln (V) is used by taking a logarithm of average daily travel volume. The 5D indicators are considered to describe the built environment, including density, design, diversity proposed in Reference [15], and distance to transit and destination accessibility added in Reference [16]. This study finally selects the following independent variables: population density, road design, land use, transportation facilities, and destination accessibility (Table 4). The correlation test shows that the Pearson correlation coefficients between food service, domestic service, and other variables are greater than 0.7, so these two independent variables are not included in the model due to strong correlations.

3.2 Model selection

The Global Moran's Index shows that each dependent variable has a certain degree of spatial autocorrelation, which requires the use of Spatial Regression Model. According to different spatial lag terms, regression models can be divided into Spatial Lag Models (SLM) and Spatial Error Models (SEM). The spatial lag term of SLM is composed of the product of the spatial weight matrix and dependent variables, and it is used as an explanatory variable. The spatial lag term of SEM is composed of the product of the spatial weight matrix and error terms, and it is not used as an explanatory variable. Two Lagrange multipliers, LMERR and LMALG, as well as R-LMERR and R-LMALG, which are more robust, are constructed to select a more appropriate model. When LMALG is statistically more significant than LMERR with R-LMALG being significant and R-LMERR being insignificant, it is better to choose the Spatial Lag Model. Otherwise, the Spatial Error Model is more appropriate. Table 5 shows that the Spatial Lag Model is more suitable for the maximum ratio of daily travel volume on workdays (MR_W) and the maximum variation rate of daily travel volume on workdays (MV).

3.3 Model regression results

The formula for the Spatial Lag Model is $Y=\rho WY+X\beta+\varepsilon$, where Y is the dependent variable; X is the independent variable; ρWY is the lag factor; W is the spatial weight matrix, which is selected to be an inverse distance space matrix in this study and the weight becomes smaller when the distance between two spatial units becomes larger; ρ is the spatial autocorrelation coefficient; β is the coefficient of independent variables, and ε is the error. The model results from the Stata software package are shown in Table 6.

Table 4 Statistics for independent variable indicators

Variable types	Variable names	Variable description	Statistics		
			Mean	Maximum	Minimum
Population density	*p_popdensity*	It describes the population density level of a spatial unit. It is based on the Baidu nighttime population heat map, where areas are divided into four levels according to population density. From top to bottom, the levels are 1 for the purple and colorless areas, 2 for the cyan and indigo areas, 3 for the yellow and green areas, and 4 for the red and orange areas.		(=1)54 (=2)76 (=3)72 (=4)221	
Road design	*r_cyclewa*	It describes if there are non-motorized lanes in a spatial unit: 1 for yes and 0 for no.		(=0)138 (=1)285	
Land use	*l_diversity*	It describes the land use diversity of a spatial unit using the Point of Interest (POI) diversity value, calculated as POI information entropy.	0.215 6	0.275 0	0.044 3
Transportation facilities	*b_bus*	Number of bus stops in a spatial unit	1.927	9	0
	b_train	Number of rail transit stations within 800 m from the center of a spatial unit	0.522 5	3	0
	b_traindis	Distance from the center of a spatial unit to the nearest rail transit station /km	1.461	5.675	0.041 11
Destination accessibility	*p_catering*	Number of food service POIs	86.37	770	0
	p_work	Number of employment POIs	73.75	626	0
	p_spot	Number of tourism POIs	1.423	52	0
	p_commerce	Number of commerce POIs	119.6	1 299	0
	p_service	Number of domestic service POIs	59.58	389	0
	p_live	Number of residence POIs	6.790	55	0

Table 5 Moran's Index and Lagrange multiplier

Item		Logarithm of average daily travel volume	Maximum ratio of daily travel volume on workdays	Maximum ratio of daily travel volume on nonwork days	Maximum variation rate of daily travel volume on workdays
		Ln*V*	*MV*	*MR_W*	*MR_NW*
Moran's Index	Value	0.320	0.393	0.280	0.521
	Z value	227.703	29.541	21.310	38.907
Significance of Lagrange multipliers	LMALG	0.000	0.000	0.000	0.000
	LMERR	0.000	0.000	0.000	0.000
	R-LMALG	0.000	0.000	0.000	0.000
	R-LMERR	0.000	0.064	0.651	0.000

3.4 Model conclusions

Based on Table 6, the main impact of various built environmental factors on bike sharing diurnal variation characteristics is summarized as follows.

1) Population density and the numbers of bus stops, rail transit stations and each type of POIs positively affect the average daily travel volume of bike sharing. In areas with very high population density, such as Houpu Community and Mingfa Square, the average daily travel volume of bike sharing is higher. The number of bus stops and the number of rail transit stations also have a positive impact on bike sharing travel volume, which indicates that connecting to public transportation is still a main function of bike sharing. The number of POIs of an area represents its land development intensity and activity level to a certain extent. The bike sharing usage in areas with more POIs is more intense, and the daily travel volume on workdays in these units is more unstable. Compared with employment POIs and commerce POIs, tourism POIs and residence POIs have a greater impact on the average daily travel volume, and the workday daily travel volume in areas with more tourism POIs and residence POIs is more unstable. Therefore, more attention is needed to the parking and allocation issues in tourist attractions and residential areas.

2) Compared to other areas, periphery areas with very low population density and areas with high land use diversity have a higher proportion of nonwork day trips. In periphery areas, the trip purpose is random due to the small population. In areas with higher land use diversity, the difference in the travel volume between workdays and nonwork days is smaller and the travel volume on workdays is more stable. This finding shows that areas with mixed land use have stronger riding demand since they can attract riders with different purposes. These areas also have a smaller difference between workdays and nonwork days and a more balanced travel time distribution. Therefore, the diversity in land use can bring more stable bike sharing trips.

3) Compared to other areas, areas closer to rail transit stations and areas with more employment POIs have a higher proportion of workday bike sharing trips. These areas also have smaller fluctuation in travel volume on workdays and a higher portion of bike commute trips. Therefore, special attention should be paid to the bike sharing operations during the morning and evening commute peaks on workdays.

Table 6 Regression of spatial lag model

Variable type	Variable names	Logarithm of average daily travel volume	Maximum ratio of daily travel volume on workdays	Maximum ratio of daily travel volume on nonwork days	Maximum variation rate of daily travel volume on workdays
		Ln*V*	*MR_W*	*MR_NW*	*MV*
Spatial weight matrix	*W*	0.116 3***	0.332 6***		−0.395 3***
Constant term	*CONSTANT*	4.394 9***	2.991 5***	0.692 1***	0.774 3***
Lowest population density	*p_popdensity_1*		−0.336 3***	0.331 6***	0.084 2***
Low population density	*p_popdensity_2*				
High population density	*p_popdensity_3*				
Highest population density	*p_popdensity_4*	0.104 7*	−0.265 3***		
Non-motorized lanes	*r_cyclewa*				
Land use diversity	*l_diversity*		−7.108 6***	1.671 6**	−0.455 0*
Bus station	*b_bus*	0.081 2***			
Distance from the center of a spatial unit to the nearest rail transit station	*b_traindis*		−0.059 7**	0.172 3***	0.012 9**
Number of rail transit stations within 800 m from the center of a spatial unit	*b_train*	0.1038***		0.077 3**	
Employment POI	*p_work*	0.001 5***	0.003 1***	−0.001 5***	−0.000 2***
TourismPOI	*p_spot*	0.024 6***		0.034 6***	0.010 8***
Commerce POI	*p_commerce*	0.001 2***	−0.001 6***		−0.000 2***
Residence POI	*p_live*	0.016 5***			0.002 5**
Pseudo coefficient of determination	R^2	0.466 7	0.448 4	0.370 2	0.314 3

Note: *, * *, * * * represent the coefficient is significant at the confidence level of 90%, 95% and 99%, respectively.

4) Whether there are non-motorized lanes in a spatial unit has no significant impact on all dependent variables, which indicates that the daily travel volume of bike sharing in an area is not limited by this area’s road conditions for non-motorized vehicles. Bike sharing travel demand is mostly non-discretionary, and riding environment can affect riding comforts but has a limited impact on bike sharing demand.

4 Strategy guidance for bike sharing management by zone

4.1 Appropriate zoning for monitoring, operations and maintenance

In terms of spatial layout planning and management for bike sharing, governments should limit the number of shared bikes and regulate parking areas, such as putting a quota on the number of shared bikes, planning parking areas reasonably, and setting up “electric fences”. On the other hand, bike sharing enterprises should pay more attention to cost reduction by optimizing operations and selecting sites appropriately. Formulating management strategies would require an understanding of the long-term characteristics of bike sharing usage, and management zones should be developed appropriately for monitoring, operations, and maintenance based on the travel volume and long-term fluctuation characteristics in different areas. For example, areas of the periodic type in the workday mode have significantly different travel volumes on workdays and nonwork days, and their travel volume on workdays is stable. For these areas, fixed parking areas, such as “electric fences”, can be built according to the needs. It is also necessary to pay attention to the allocation of shared bikes during commute hours on workdays and to adjust the number of shared bikes in operation on Friday nights and Sunday nights. For areas in the indefinite mode, the allocation and parking problems caused by the large variation in travel volume should be considered when more shared bikes are about to be put on the market, and stripes should be used as much as possible to delineate parking areas.

4.2 Formulating management strategies according to built environment

The built environment affects the travel volume and diurnal variation of bike sharing in an area for a long time. Managers can formulate preliminary management strategies and measures according to the characteristics of the built environment in an area, such as rail transit conditions, land use, and the numbers of various POIs (Fig. 5). For example, the multi-point dynamic parking strategy can be adopted for residential areas to deal with the large variation in workday demand: small scattered parking areas can be built at major departure points and they can be converted back to pedestrian space when the parking demand is low. Suitable areas near tourist attractions can be designated as temporary parking spots during holiday peaks. Areas with high land use diversity have relatively stable bike sharing usage, so fixed parking areas can be built. For example, Wuyuan Bay Thanksgiving Square and Torch Xintiandi have high land use diversity but they are far away from subway stations. Therefore, centralized parking areas can be built to connect to surrounding areas and to the subway system. On the other hand, for subway stations with low land use diversity, such as Wutong Station, weekday temporary parking spots can be designated on the station square, and the allocation emphasis should be placed on the morning and evening peaks on weekdays.

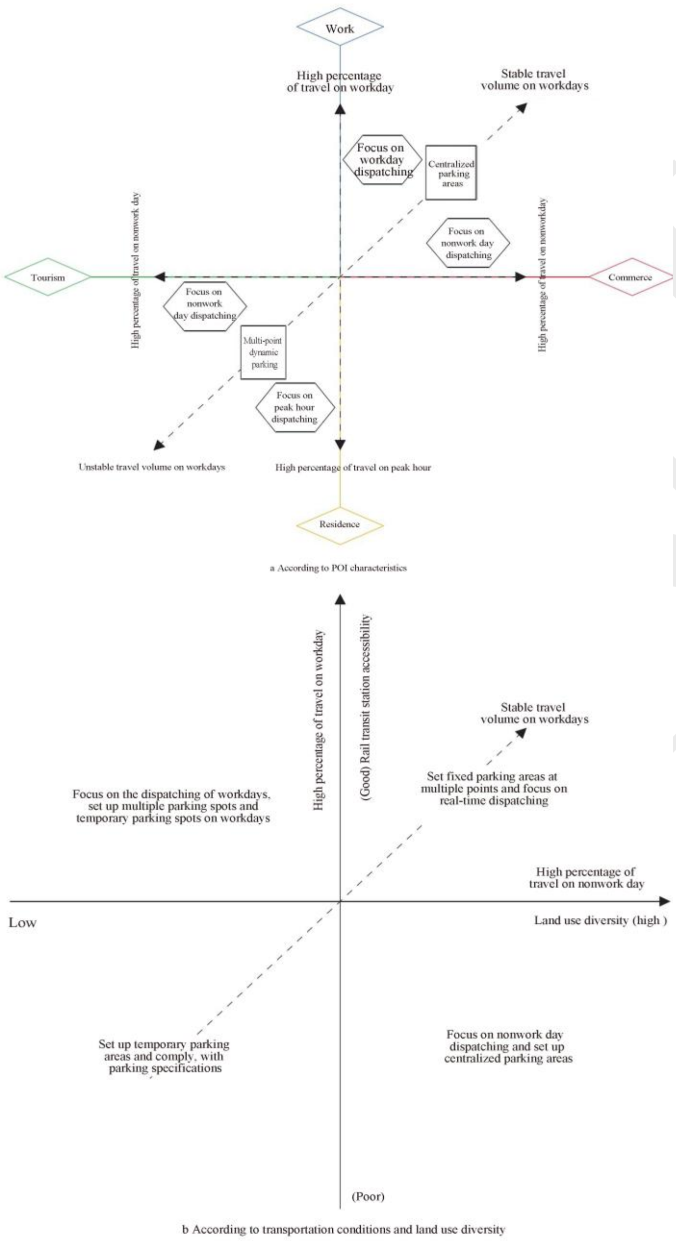


Fig. 5 Management strategy guidance based on regional built environment

4.3 Real-time monitoring and management in key areas

Targeted management strategies can effectively solve the problems in bike sharing operations and management most of the time. However, the bike sharing volume could suddenly surge or drop sharply due to uncertain factors such as weather and emergencies. These factors are usually aperiodic. For example, the travel volume in tourist areas could surge during holidays, which requires attention. Therefore, it is necessary to monitor areas that are likely to have a large fluctuation in travel volume. At the same time, for areas with large daily travel volumes, it is also necessary to pay attention to the time-varying characteristics of inflow and outflow in order to deal with the parking and allocation problems caused by peak directional flow. For example, various measures can be taken to achieve the balance of bike sharing within an area, such as real-time monitoring of the peak hours in key areas, allocating shared bikes appropriately, and encouraging users to get and return shared bikes from nearby locations through price incentives.

5 Conclusions

By defining spatial units, this paper studied 11 weeks of bike sharing data for 423 spatial units in Xiamen, analyzed the diurnal variation characteristics of bike sharing daily travel volume, and developed indicators to describe these characteristics. The paper then analyzed the impact of the built environment on the variation of bike sharing daily travel volume and proposed corresponding management strategies and suggestions. The main conclusions and suggestions of this study are as follows.

1) The study of long-term diurnal variation characteristics of bike sharing travel volume is critical for grasping the situation of bike sharing usage in an area. The bike sharing travel volume is significantly different on workdays and on nonwork days, and it fluctuates unevenly in the long term. The short-term travel status cannot fully reflect the regional differences in bike sharing usage.

2) The bike sharing volume and fluctuation in different areas can be described by the average daily travel volume, maximum ratio of daily travel volume on workdays, maximum ratio of daily travel volume on nonwork days, and maximum variation rate of daily travel volume on workdays. Based on these indicators, spatial units can be divided into the workday mode, nonwork day mode, and indefinite mode. The workday mode can be further divided into the periodic type, the high-intensity type, and the normal type. Areas of the periodic type only account for a very small portion, indicating that the daily travel volume fluctuates relatively widely in most spatial units.

3) Built environment will affect bike sharing diurnal variation characteristics. Population, transportation accessibility

and the number of POIs positively affect the bike sharing average daily travel volume. In areas with high land use diversity, the difference between workdays and nonwork days is smaller, and the diurnal variation is more stable. Bike sharing usage on workdays accounts for a larger proportion in areas near rail transit stations and areas with a high number of employment POIs. The influence of non-motorized lanes on bike sharing diurnal variation characteristics is not significant.

4) Managers can develop management measures by area based on each area's bike sharing travel volume and diurnal variation characteristics. Different allocation and parking management strategies should be adopted based on the characteristics of the built environment, and real-time monitoring should be applied during peak hours in key areas.

The conclusions from this paper could be used to understand bike sharing diurnal variation characteristics, and provide managers and enterprises with thoughts and theoretical support for management by area. Future studies should focus on multi-level classifications, further analysis of diurnal variation characteristics of bike sharing daily inflow and outflow, and analysis based on data from more cities.

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