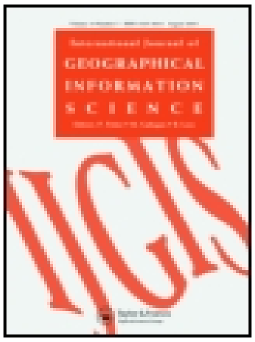

International Journal of Geographical Information Science

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/tgis20

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INTERNATIONAL JOURNAL OF GEOGRAPHICAL INFORMATION SCIENCE
https://doi.org/10.1080/13658816.2020.1863410

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RESEARCH ARTICLE

Understanding the modifiable areal unit problem in dockless bike sharing usage and exploring the interactive effects of built environment factors

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ABSTRACT

Understanding the influence mechanisms of dockless bike-sharing usage is essential for land use planning and bike scheduling strategy implementation. Although various studies have been carried out to explore the impact of built environment (BE) factors on bike-sharing usage, few studies have examined the modifiable areal unit problem (MAUP). Moreover, previous studies mainly focused on the separate effect of each factor but neglected the interactions between these factors. Taking Shenzhen, China as the case, this study fills these two gaps by employing the geographical detector method to examine the MAUP in dockless bike-sharing usage as well as the interactive effects of BE factors. The results revealed that the influences of most BE variables are sensitive to the spatial areal units, which have informed urban planners what built-environment factors should be paid more attention to at certain spatial scales. Additionally, through the comparisons between single effect and interactive effect, this study revealed some interesting findings that can provide scientific basis for temporal rebalance strategy for the innovative and high-density metropolis in China.

ARTICLE HISTORY
Received 27 December 2019
Accepted 8 December 2020

KEYWORDS
Geographical detector; interactions; dockless bike sharing; built environment; social media data; Modifiable areal unit problem

1. Introduction

In the past decades, public bike-sharing has grown rapidly and has spread across cities worldwide due to its benefits in providing convenient connections to the transit stations, alleviating traffic congestion, bringing healthy benefits, etc (Shaheen *et al*. 2010, Rixey 2012, Zhang *et al*. 2014, Fishman 2015, Faghih-Imani and Eluru 2015, 2016, Wang *et al*. 2016a, El-Assi *et al*. 2017, Ma *et al*. 2018, Chen *et al*. 2019). With the recent boom of the sharing economy, the dockless bike-sharing system, which allows users to rent a bicycle through a smart-phone application, has dramatically expanded around the world (Shen *et al*. 2018, Xu *et al*. 2019). Understanding the impact factors of dockless bike-sharing

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usages has two important meanings. On the one hand, bike-sharing travel is usually encouraged by urban planners dues to the fact that bike-sharing systems have numerous benefits, such as promoting public transit use, reducing traffic congestion, and increasing physical activity and health (Shaheen *et al*. 2010, Fishman 2015, Faghih-Imani and Eluru 2016, El-Assi *et al*. 2017, Chen *et al*. 2019). Examining the influencing mechanisms of bike-sharing usages is essential because it can provide implication for urban planners who aim to promote bike usages, in terms of land use development, road design, and so on (Faghih-Imani and Eluru 2015, Wang and Zhou 2016, Wang *et al*. 2016a, Shen *et al*. 2018). On the other hand, unlike public bike-sharing which requires users to rent and return bicycles at fixed docking stations, dockless bike-sharing provides stationless rental services, making the bicycles more convenient and flexible to use (Si *et al*. 2019). However, without accurate bicycle usage prediction and effective scheduling, the flexibility offered by dockless bike-sharing would lead to the mismatch between bicycle supply and demand, which may bring about some urban issues (Pan *et al*. 2019, Si *et al*. 2019). For example, when the supply of bicycles exceeds the demand, the problems such as overwhelming public space would arise. On the contrary, if the supply is less than demand, it will result in service insufficiency. Hence, understanding the influence mechanisms of dockless bike usage can provide a scientific basis for bicycle prediction and scheduling, which is essential to improve the management and services of dockless bike-sharing.

Examining the relationship between dockless bike-sharing usage and built environment (BE) factors is of great significance in many aspects including urban planning and cycling facilities design, bike scheduling strategy, bike-sharing service promoting and bike-sharing usage prediction and simulation (Shen *et al*. 2018). Though there is a large body of previous studies trying to understand the effects of BE factors on bike-sharing usage ((Buck and Buehler 2012, Kim *et al*. 2012, Fishman 2015, Faghih-Imani and Eluru 2016, Wang *et al*. 2016a, 2016b, El-Assi *et al*. 2017, Shen *et al*. 2018, Wang and Lindsey 2019), few studies have taken the modifiable areal unit problem (MAUP), a well-known problem in geography research (Openshaw 1984), into consideration in the process of data aggregating and modeling. However, studies have illustrated that MAUP is an essential and fundamental issue in travel behavior analysis (Zhang and Kukadia 2005, Mitra and Buliung 2012, Hong *et al*. 2013; Clark and Scott 2014, Yang *et al*. 2019, Zhou and Yeh 2020). Furthermore, none of the previous studies examined the interactive effects of factors, instead, the individual effects of factors on bike usage are quantified via regression coefficients (Noland *et al*. 2016, Faghih-Imani and Eluru 2016, Zhang *et al*. 2017, Shen *et al*. 2018), which is insufficient to understand the dockless bike-sharing usage in such a complicated built environment.

The aim of this study is to fill the above two research gaps with the geographical detector model which is a spatial statistical method (Wang *et al*. 2010) by taking Shenzhen, China as a case study to address the following research questions:

(1)How does MAUP affect the bike-sharing usage mechanism modeling results? How do the BE factors perform at different spatial scale units?

(2)How are the interactive effects of BE factors on dockless bike-sharing usage compared with the separate effect with the ideal spatial unit?

To answer these questions, first, the factor detector of geographical detector model was used to analyze the spatial associations between dockless bike-sharing usage and BE factors with different spatial areal units, and examine the effect of MAUP. The results can help land-use planners understand what BE factors should be paid more attention to at different spatial scales, and help determine the suitable spatial scale to better understand the interactive effects of BE factors for dockless bike-sharing usage. Second, the interactive detector from the geographical detector model was used to explore the interactions between these BE factors with the ideal spatial areal units. The interactive effects were further compared with the separated effects, which is meaningful to bike rebalance strategy. The rest of this paper is organized as follows: section 2 will review the related works; section 3 will present the study data and introduce the methodology and datasets; section 4 will present the results and address some meaningful findings; and section 5 will summarize the study and provide suggestions for further research.

2. Related works

The factors influencing the usage of bike-sharing are complicated. An increasing number of studies have been undertaken to explore this issue from different aspects, including the social-demographic (Ogilvie and Goodman 2012, Zhao *et al*. 2015, Wang *et al*. 2016a), weather and calendar events (Gebhart and Noland 2014, Corcoran *et al*. 2014, Meng *et al*. 2016), and built environment (BE) (Cervero and Kockelman 1997, Buck and Buehler 2012, Kim *et al*. 2012, Faghih-Imani and Eluru 2015, 2016, Wang *et al*. 2016a, 2016b, El-Assi *et al*. 2017, Shen *et al*. 2018, Wang and Lindsey 2019). Among these, the BE impact on travel behavior has become the most heavily researched subject in urban planning and travel behavior research (Buck and Buehler 2012, Kim *et al*. 2012, Faghih-Imani and Eluru 2015, Wang and Zhou 2016, Wang *et al*. 2016a, 2016b, El-Assi *et al*. 2017, Shen *et al*. 2018, Xu *et al*. 2019), and many researchers have attempted to provide explanations about why BE factors might be expected to impact travel behaviors (Cervero and Kockelman 1997, Wang and Zhou 2016, Shen *et al*. 2018). These studies indicated that BE characteristics are strongly associated with bike-sharing usage, and the influence mechanisms are complex, which need more attention and research efforts.

The measurement of the usage of bike-sharing and the models applied vary in existing studies due to different research purposes. First, in terms of measurement of bike usage, bike usage data used for analysis were measured at different geographic scales which were usually defined by different ways in different studies without MAUP addressed. Studies on the influencing factors of bike-sharing usage fall into two main categories: bike-sharing with fixed stations and free-floating dockless bike-sharing. The notable difference between them when modelling their relationships with potential factors is the definition of the spatial statistical unit of variables. For public bike-sharing studies, the dependent variables were counted at docking stations and the independent variables were linked to the stations' service area defined by Thiessen polygon (Noland *et al*. 2016) or buffers (Rixey 2012, Wang and Lindsey 2019). For dockless bike-sharing studies, data were usually aggregated to fishnet cell, and the spatial areal units were of different sizes among different studies (Shen *et al*. 2018, Mooney *et al*. 2018, Xu *et al*. 2019, Zhu *et al*. 2020). However, the MAUP received little attention in existing bike-sharing-related research.

Previous studies have shown that different areal units may generate inconsistent results in the relationship between BE and travel behavior (Zhang and Kukadia 2005, Mitra and Buliung 2012, Hong *et al*. 2013, Clark and Scott 2014, Yang *et al*. 2019, Zhou and Yeh 2020). For example, Mitra and Buliung (2012) found that both the spatial scale and zoning method affect the relationship between BE and active school transportation by comparing the results of buffers of four distances and two types of census boundaries. Clark and Scott (2014) proved that the relationship between active travel and the BE is affected by the MAUP by comparing the models results of 14 geographical scales. Yang *et al*. (2019) found that the relationship between trip-chaining behavior and the BE is different with several different spatial units. For bike-related study, with massive and high-precision bike-sharing usage GPS record data, the effects of the MAUP are nonnegligible in the results of data aggregating and modeling. It is essential to examine the effects of the MAUP in BE-bike-sharing usage relationship which can inform urban planners what factors are more important to promote bike-sharing usages at certain spatial scales. Moreover, the MAUP should be considered and carefully addressed to determine the ideal spatial units for explore the influencing mechanisms of bike-sharing usage.

Second, in terms of methods in modeling the relationship between bike usage and BE factors, previous studies focused on the individual effect of each factor on bike-sharing usage based on the regression coefficients but neglected the interactive effect. In these existing studies, non-spatial statistical methods (Buck and Buehler 2012, Kim *et al*. 2012, Faghih-Imani and Eluru 2015, Wang *et al*. 2016b, El-Assi *et al*. 2017), and spatial regression models (Noland *et al*. 2016, Faghih-Imani and Eluru 2016, Zhang *et al*. 2017, Shen *et al*. 2018) were used. The results have enriched the understanding of how BE factors affect bike-sharing usage. However, these studies mainly discussed the impact of the single BE factor on bike-sharing usage, the interactive effect between BE factors have not examined. As the effects of BE on dockless bike-sharing usage are complicated and should not be explained by each factor separately and simply, examining the interactive effects between BE factors on bike usage might help understand that mechanism closer to the actual situation and mining the meaningful spatiotemporal characteristics hidden behind.

To better understand the relationship between dockless bike-sharing usage and BE factors, this study tried to address the MAUP issue and examine the interactive effects by employing the Geographical detector. Geographical detector is a spatial statistical method that can effectively explore both the individual influence and interactive effect of geographical factors based on spatial variances analysis (Wang *et al*. 2010). This method has been widely used in geographical variation studies, such as the health risk assessment (Liao *et al*. 2010, Wang and Hu 2012, Ding *et al*. 2019, He *et al*. 2019), the risk assessment of the Wenchuan earthquake in China (Hu *et al*. 2011), the influencing mechanism of planting patterns on fluoroquinolone residues (Li *et al*. 2013), as well as the driving forces and their interactions of built-up land expansion (Ju *et al*. 2016) and the relationship between dissection density and environmental factors (Luo *et al*. 2016). However, it has rarely been applied in travel behaviors or transportation studies for the exploration of the interactive effects of BE factors on travel behaviors.

3. Data and methodology

3.1. Study area

Shenzhen (Figure 1) is located in southern China with the area of 1997.47 square kilometers. As one of the largest cities in China, this city is a link and bridge connecting Hong Kong and the Chinese mainland. As a highly urbanized and modern metropolis, Shenzhen's public transportation system has gradually developed and matured with 8 metro lines and 854 bus lines operating in 2018. Besides, Shenzhen is one of the earliest cities in China to put dockless bike-sharing into operation.

Dockless bike-sharing emerged in Shenzhen in early 2016, and subsequently this venture experienced explosive growth. In September 2017, the average daily use of bike-sharing in Shenzhen reached 5.173 million. The rapid expansion of dockless bike-sharing has changed the daily traveling mode of residents, played a remarkable role in solving the 'last kilometer' travel problem, and has reduced traffic congestion. Simultaneously, dockless bike-sharing has also created problems such as congestion caused by random parking, spatial and temporal mismatches between supply and demand, and an excessive presence of bicycles because of the vicious competition between operators. Thus, Shenzhen is a good case study area for investigating the complex influencing mechanisms of both the origin and destination involved with dockless bike-sharing usage from a spatial perspective. It will provide valuable insight into the planning and strategic management of sharing bikes.

3.2. Geographical detector model

The geographical detector is a kind of spatial statistic model proposed by Wang et al., which has been widely used to quantify the influencing effects of potential driving factors on geographical phenomena based on spatial variance analysis (Wang *et al*. 2010, 2017, Liao

Figure 1. Study area.

et al. 2010, Wang *et al.* 2016b). The geographical detector model is applied in this study based on the assumption that the spatial distribution of the origin or destination of bike-sharing resembles their potential driving factors. The geographical detector model consists of four detectors (sub models) including factor detector, interactive detector, risk detector, and ecological detector. Factor detector mainly addresses the question of 'What are the determinants of the geographical phenomena?'. Interactive detector addresses the question of 'Do the determinants operate individually or interconnectedly?'. Risk detector addresses the question of 'Are the geographical phenomena of two sub regions significantly different?'. Ecological detector addresses the question of 'What is the difference of the impacts between two explanatory variables?'. As the main purpose of the study is to understand the determinants of the dockless bike-sharing usage and the interactive effects as well as the MAUP in it, factor detector and interactive detector were employed to examine which factor has a more important impact on the use of bike-sharing and how different the pairs of factors interact with each other.

3.2.1. *The factor detector*

The function of factor detector is to calculate the PD (power determinant) value to quantitatively assess the impact of potential driving factors on the spatial pattern of the origin or destination of dockless bike-sharing. In this study, PD value is defined as the difference between one and the ratio of accumulated dispersion variance of the origin or destination of bike-sharing over each sub region to that of over the entire study region:

$$PD = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N_{\sigma^2}} = 1 - \frac{SSW}{SST} \tag{1}$$

$$ssw = \sum_{h=1}^{L} N_h \sigma_h^2 \tag{2}$$

$$SST = N_{\sigma^2} \tag{3}$$

where N refers that a study area consists of N units, which is stratified into $h = 1, 2, \ldots, L$ stratum; and stratum h consists of N_h units; σ^2 and σ_h^2 denote the global variance of the dependent variable of the study area and the variance of the dependent variable in the sub-areas; *SSW* and *SST* denote within sum of squares and total sum of squares, respectively. The value of PD lies between zero and one. A higher PD value means the driving factor has a stronger contribution to the spatial pattern of the origin or destination of bike-sharing. In this study, PD values indicate the consistency of the spatial patterns between the origin or destination of bike-sharing and its potential driving factors.

3.2.2. *The interaction detector*

The interaction detector determines whether two individual factors enhance or weaken each other by comparing their combined contribution, as well as their independent contributions(Wang *et al.* 2010). The model classifies the interactive relationship between two factors into seven types as follows:

$$
\begin{aligned}
&\text{Nonlinear} - \text{enhance}: \mathrm{PD}\left(\mathrm{A} \cap^{\mathrm{B}}\right) > (\mathrm{PD}(\mathrm{A}) + \mathrm{PD}(\mathrm{B}))\\
&\text{Independent}: \mathrm{PD}\left(\mathrm{A} \cap^{\mathrm{B}}\right) = \ (\mathrm{PD}(\mathrm{A}) + \mathrm{PD}(\mathrm{B}))\\
&\text{Bi} - \text{enhance}: \mathrm{Max}(\mathrm{PD}(\mathrm{A}), \mathrm{PD}(\mathrm{B})) < \mathrm{PD}\left(\mathrm{A} \cap^{\mathrm{B}}\right) < \ (\mathrm{PD}(\mathrm{A}) + \mathrm{PD}(\mathrm{B})\\
&\text{Uni} - \text{enhance/weaken}: \mathrm{Min}(\mathrm{PD}(\mathrm{A}), \mathrm{PD}(\mathrm{B})) < \mathrm{PD}\left(\mathrm{A} \cap^{\mathrm{B}}\right) < \mathrm{Max}(\mathrm{PD}(\mathrm{A}), \mathrm{PD}(\mathrm{B}))\\
&\text{Nonlinear} - \text{weaken}: \mathrm{PD}\left(\mathrm{A} \cap^{\mathrm{B}}\right) < \mathrm{Min}(\mathrm{PD}(\mathrm{A}), \mathrm{PD}(\mathrm{B}))
\end{aligned} \tag{4}
$$

3.2.3. The MAUP test

For dockless bike-sharing without fixed stations, a grid system is suitable for statistics of bike-sharing usage. However, as the scale of grid changes, the results of bike-sharing usage mechanism modeling differ greatly. This is regarded as the scale effect, one of the modifiable areal unit problems (MAUP) that generally exists in geographical studies (Jelinski and Wu. 1996, Zhou *et al*. 2018, Zhou and Yeh 2020). Another MAUP beyond that is the zoning effect, in which various conclusions might occur when rearranging the zones of the given set of areal units using different methods (Jelinski and Wu. 1996, Ju *et al*. 2016). To understand how do BE factors affect the dockless bike-sharing usage with different spatial scale units and zoning methods, both scale effect and zoning effect are tested to examine the MAUP before the geographical detector model is applied in this work.

First, the scale effect is tested for two main purposes: 1) to examine how do the BE factors perform at different spatial scale units, which would inform urban planners what BE factors should be paid more attention to at different spatial scales; 2) to determine the suitable spatial scale to better understand the influencing mechanisms of dockless bike-sharing usage for bike rebalance strategy. The range of PD values and the stability of their ranks can reflect the scale effect on the results of the geographical detector model. In consideration of the extent of the study area and the spatial resolution of the multi-source data, ten grid sizes (from 100 m to 1000 m, with an interval of 100 m) are selected to test the scale effect on the PD values and their ranks. Second, the zoning effect of the geographical detector is tested to help choose the zoning method for bike-sharing usage mechanism modeling. In order to test the zoning effect, these three commonly used zoning methods are selected: the natural breaks (NB) method (Brewer and Pickle 2002), the equal interval (EI) method, and the quantile (QU) method (Cao *et al*. 2013).

3.3. Datasets and variables

We obtained the real-time GPS data from dockless bike-sharing scheme operators including Mobike, Ofo, Bluegogo, Ubike and Xiaoming Bike. All of them were the major bike-sharing operators in Shenzhen in 2018. The GPS dataset used in this study ranges from the 8^{th} of October, 2018 to the 14^{th} of October, 2018 and it consists of five weekdays and a two-day weekend. The bikes' unique ID, time stamps and the GPS location of both the origin and destination (OD) of every trip were continually recorded then categorized by hour. The raw collection contains over 6 million riding trips, with some redundant records however. To sort out the real usage records, some necessary pre-processing steps are needed. First, redundant coordinate records of stationary bikes and errors from GPS drifting were removed. Next, some unrealistically long or short distance or duration trips were also excluded, which might be from bicycle reallocation and maintenance performed by the operators.

Large amount of literatures explore the association between travel behavior and built environment (Ewing and Cervero 2001, 2010). Based on previous studies on bike-sharing (Buck and Buehler 2012, Kim *et al*. 2012, Faghih-Imani and Eluru 2015, Wang and Zhou 2016, Wang *et al*. 2016a, El-Assi *et al*. 2017, Shen *et al*. 2018, Li *et al*. 2020a), four categories of potential influencing factors were selected to represent the built environment from different aspects including accessibility, facilities and land use as well as population distribution. These four types of factors contribute to the bike-sharing usage, while simultaneously interacting with each other (Figure 2).

According to the Athens Charter, living, work, recreation, and transportation are four important functions of a city. In this study, accessibility factors were selected to represent the transportation function of city with three potential factors including roads density, distance to metro stations and distance to bus stops. Moreover, facilities factors were used

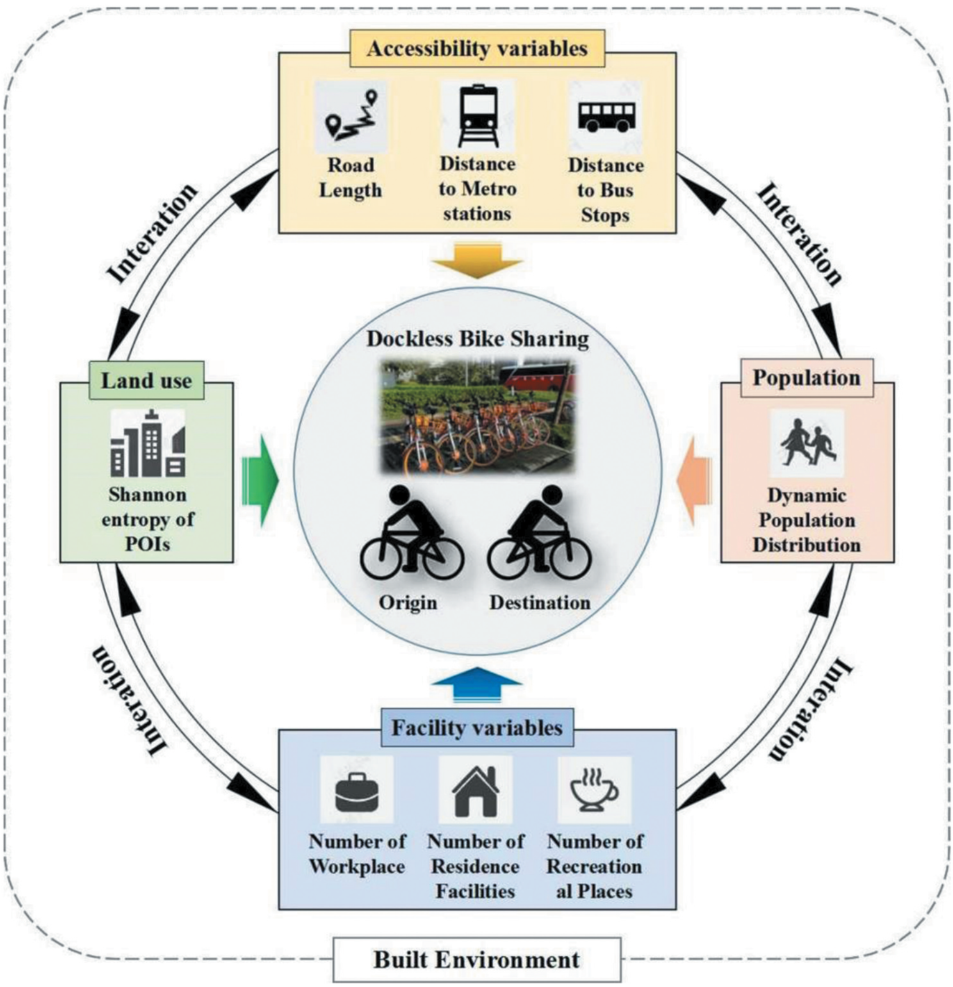

Figure 2. The selected BE variables of bike-sharing usage.

Table 1. The definition of POIs category and type.

Category	Type	Examples
WORK	Company and office	Companies, offices, industrial zone, business center, science park
	Government organizations	Department offices, post offices, police offices
LIVING	Residential	Residential quarters, Unit dormitories
	Hotels	Hotels, lodgings
REC	Restaurant	Restaurants, Cafes
	Retail	Shopping malls, supermarkets, book stores, department stores
	Recreation	Parks, KTVs, movie theaters

to reflect the city functions of living, work and recreation, which are also the urban residents' daily commuting purposes. Facilities factors including WORK, LIVING and REC were extracted from POIs datasets, and the definition of them was shown as Table 1 below. However, land use and activities of a POI can be complicated and mixed. Here, from the perspective of travel behavior, POIs were classified as Table 1 shown for the reason of visit quantity and purpose. For example, restaurants and retailing stores were defined as the category of REC rather than WORK since that firstly these facilities are typical work places but in terms of quantity, consumers are the groups with much more visits, rather than employees. Besides, land use mixture was also measured through POIs data based on POIs types in Table 1. The Shannon entropy index was applied to evaluate the degree of land use diversity (Shannon 1948) as

$$H = -\sum\nolimits_{i} p_i \log_n p_i \tag{5}$$

where H represents the value of entropy; $p_i$represents the percentage of the i^{th} type of POIs; n is the number of types.

Given the literature review and data availability, eight variables were selected as the potential BE-related driving factors of bike-sharing usage. Since the cycling path is still under construction in Shenzhen until November 2019, the variable of cycling facilities was not incorporated in this study.

In 2018, for this study, five types of data were obtained: (1) Road data were originally collected from OpenStreetMap (https://www.openstreetmap.org/). After careful examination, the bike-rideable roads were extracted. (2) Metro stations and bus stops location data were obtained using the geocoding interface of Baidu Map API (http://lbsyun.baidu.com/). These two distance variables were calculated via Network Analyst of ArcGIS 10.2 (Esri, Redlands, California, US). (3) The three facilities variables were extracted from a POIs dataset in 2018 from Baidu Map (http://lbsyun.baidu.com/). Also, the land use variable was also calculated based on POIs dataset. (4) The dynamic population distribution data were collected from the Tencent LBS service platform (https://heat.qq.com/document.php) which is the largest social media service in China, with a spatial resolution of 25 m and a temporal resolution of one hour, ranging from the 8th of October, 2018 to the 14th of October, 2018. With its advantages of substantial mass of users records and high spatial and temporal resolution, it has been involved in various spatial studies to reflect the dynamic population (Chen *et al*. 2017, 2018, Niu *et al*. 2017, Yao *et al*. 2017, Song *et al*. 2019, Li *et al*. 2020b, 2020c). The population distribution data in the same period as the dependent variable (dockless bike-sharing usages) was used to represent the POP variable.

4. Results and discussion

4.1. How does MAUP affect the bike-sharing usage mechanism modeling results?

To examine the effect of the MAUP on the relationship between BE factors and the dockless bike-sharing usage, both the most suitable and meaningful scale and the information hidden behind the changes of model results with different spatial scales and zoning method should be carefully discussed. In the study, the number of classes of each factor was set at five for both scale effect and zoning effect. Both scale effect and zoning effect were tested with ten candidate grid scales ranging from 100 m to 1000 m (Figure 3). Figure 4(a,b) show the PD values of each factor and the rank of them. It can be obviously seen from Figure 4(a) that the PD values of all factors tend to increase with increasing grid size, which is consistent with the result of Ju *et al*. (2016)'s study on driving force of built-up land expansion with use of geographical detector. However, the relative importance of factors should be discussed by the ranks of them, which is nonnegligible (Ju *et al*. 2016).

For scale effect, first, some interesting findings are generated from the ranking results of factors with different grid scales (Figure 4(b)), which could provide valuable insights into urban planners who aim to promote bicycle usage. These findings can be summarized as follows: 1) The ranks of different factors show different relationships at different grid scales, which indicates that different grid scales generate inconsistent results in the influence of these BE factors on dockless bike-sharing usage. Among these factors, BUS

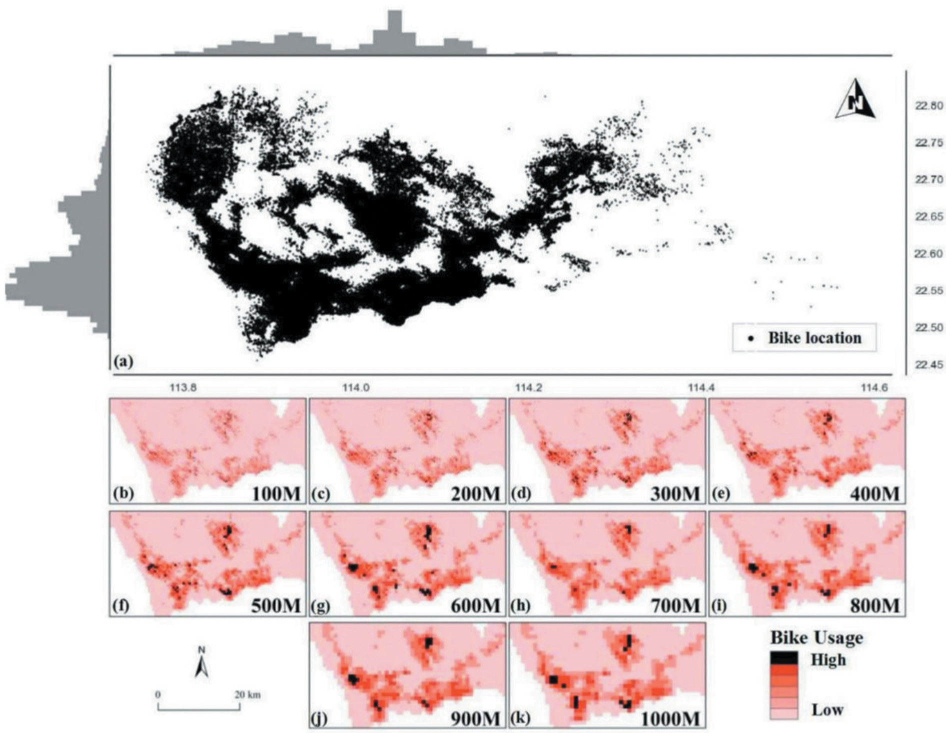

Figure 3. Distribution of bike-sharing and its aggregation with ten candidate grid scales.

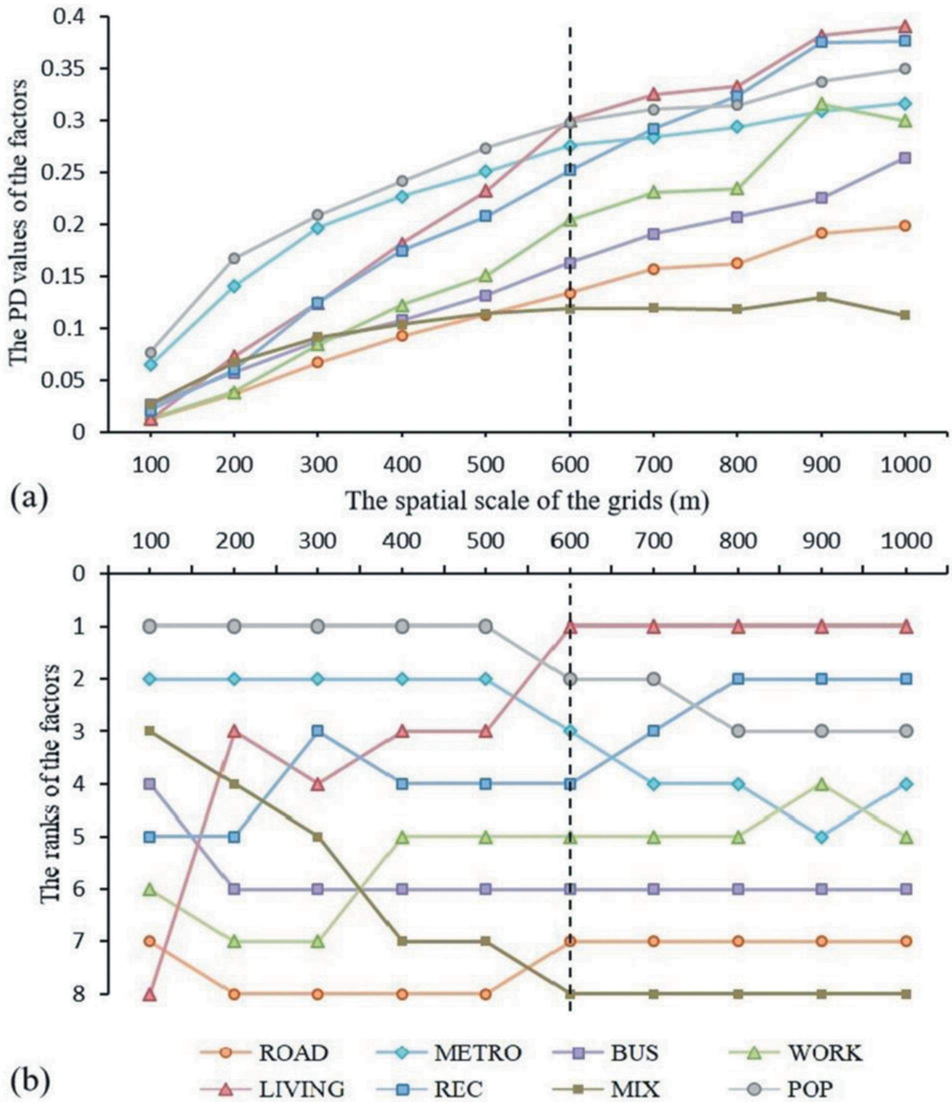

Figure 4. Scale effect on the results of geographical detector (PD values and the ranks of factors).

and ROAD are stable factors with least changes in the ranks of PD values. This indicates that the influence of these two factors on dockless bike-sharing usage are less sensitive to grid size. However, the ranks of other factors' PD values are more sensitive to the grid scales, including METRO, WORK, LIVING, REC, MIX and POP. It is suggested that the planners should pay attention to the spatial scale in the planning of these scale-sensitive factors. 2) For the variables regarding to facilities, such as LIVING, WORK and REC, they are less influential to bike-sharing usages as the scale becomes smaller, especially when the grid is smaller than 600 m. This implies that at a small grid scale less than 600 m, increasing the density of these facilities does not necessarily lead to significant increase in dockless bike-sharing usage. 3) With regard to MIX variable, the relative importance decreases with the increase of grid scale, when the scale is less than 600 m. It hints that the land use mixture planning at a smaller spatial unit is more meaningful to promote dockless bike-sharing use. 4) For POP and METRO factors, the relative importance decreases with increasing grid size, when the scale is more than 600 m. This suggests urban planners to pay much attention on the planning of these two factors at grid size less than 600 m.

Second, the scale effect was also tested to help choose the appropriate spatial scale for the influencing mechanisms analysis in the next sections. Taking both PD values and their ranks into consideration and comparison, 600 m was determined as the spatial scale to analyze the individual and interactive factors of dockless bike-sharing usage which is helpful for bike rebalance strategy for three reasons. Firstly, the growth rate of PD values is relatively high with grid scale smaller than 600 m, while it begins to slow down with grid scale larger than 600 m (Figure 4(a)). Secondly, the ranks of PD values experience great changes with grid scale smaller than 600 m, and then tend to be relatively stable when scale is smaller than 600 m (Figure 4(b)). Thirdly, as a type of human mobility behaviors, bike-sharing usage and its mechanism study should be based on a possibly fine scale level to better characterize the built environment accurately, while oversized grid scales might hide some realistic spatial heterogeneity of dockless bike-sharing usage.

For zoning effect, the PD values differ as classification method changes. Table 2 shows different PD values with various kinds of zoning methods, and the results of zoning effect that the natural break method is the optimal zoning method with highest PD values, followed by equal break and quantile method. The geographical detector model is based on the spatial variance analysis, and the natural break is the method designed to define the optimal arrangement of values into different intervals by minimizing each interval's average deviation within class and maximizing it between classes. Arbitrary zoning methods might mislead the actual relationship between geographical phenomena and its influencing factors (Hu *et al*. 2011). Previous studies noted that various methods can be used to classify numerical variables into type variables in the data processing of the geographical detector, and the criteria to select the optimal zoning method are the PD values of the results (Wang *et al*. 2010). Hence, the natural break method was selected as the zoning methods in the following analysis.

Table 2. The zoning effect of the geographical detector.

Category	Variable	Range	Cutting values	Method	PD value
Accessibility	Metro	[10.19, 43.6]	5.1, 11.3, 19.1, 29.5, 43.6	NB	0.2933
			8.9, 17.6, 26.3, 34.9, 43.6	EI	0.2350
			1.9, 4.8, 9.2, 16.5, 43.6	QU	0.2445
Facilities	Work	[0, 768]	33, 101, 198, 383, 768	NB	0.2342
			153.6, 307.2, 460.8, 614.4, 768	EI	0.2101
			0, 8, 42, 98, 768	QU	0.2270
Land use	Mix	[0, 1]	0.17, 0.50, 0.68, 0.84, 1	NB	0.1178
			0.2, 0.4, 0.6, 0.8, 1	EI	0.1013
			0, 0.58, 0.73, 0.84, 1	QU	0.1003
Population	Pop	[0, 239.3]	14.2, 38.4, 70, 116.1, 239.3	NB	0.3143
			47.9, 95.7, 143.6, 191.4, 239.3	EI	0.2151
			1.0, 9.9, 27.5, 55.8, 239.3	QU	0.2259

4.2. How are the interactive effects of BE factors on dockless bike-sharing usage compared with the single effect?

The factor detector was conducted to examine the relative importance (single effect) of the BE factors to dockless bike-sharing usage. Figure 5 shows and compares the PD values of origin and destination of different periods on weekdays and the weekend, from which we get some findings as following. First, regarding facility variables, there are significant differences in their PD values for different periods. On weekdays, the PD value of LIVING on origin is higher than that on destination at morning peak and noon period, while it is higher on destination at evening peak and night period. Differently, on weekend, the PD

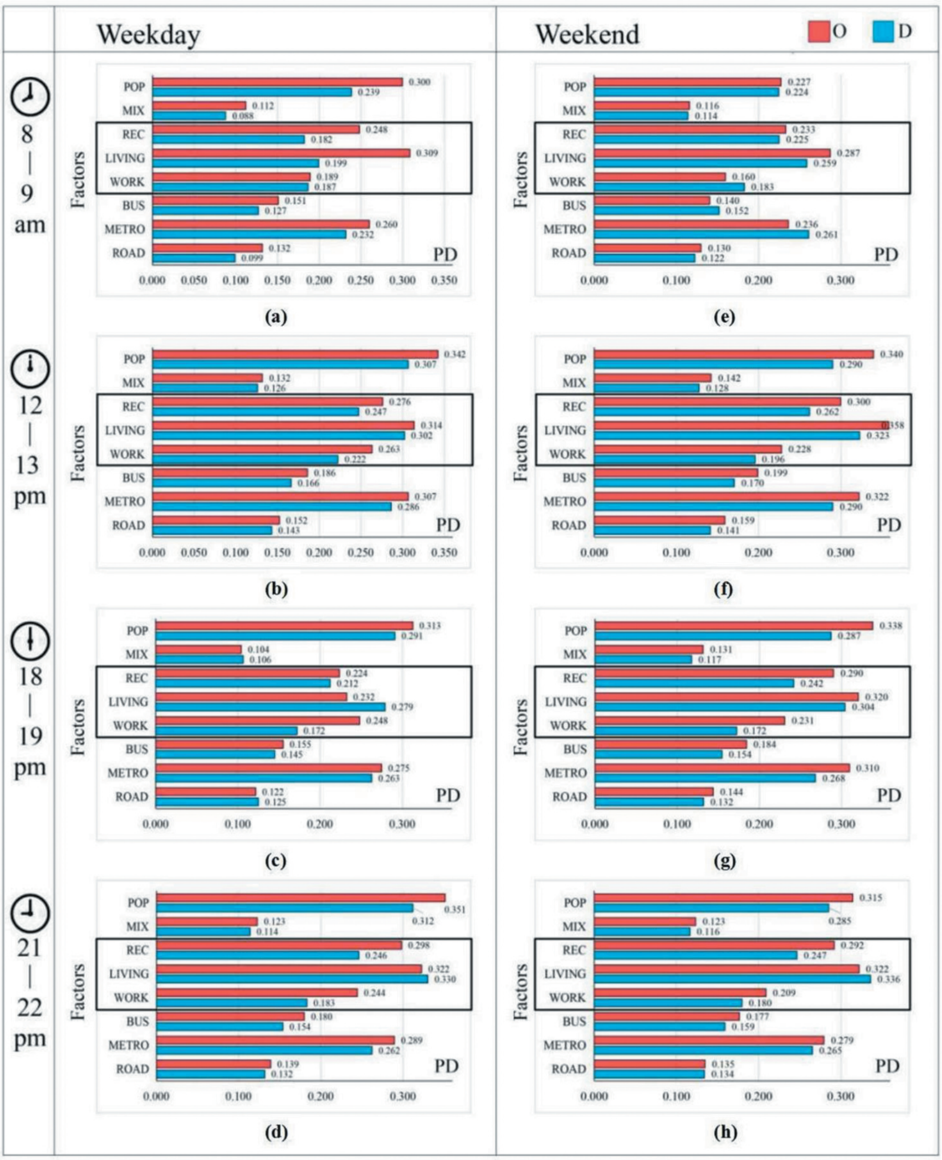

Figure 5. The PD values of factors of different period on weekday and weekend.

value of LIVING is higher on origin for all the periods except night time. This indicates that on workdays, the commuting travel time of residents is relatively regular. On weekend, residents tend to be more available and flexible to start to use bike-sharing near living facilities before night time. These results match human daily activities and travel behaviors, which are consistent with our common knowledge. Second, in terms of the three accessibility variables (METRO, BUS, ROAD), METRO shows the strongest impact on the usages of dockless bikes including both origin and destination, as expected. It hints that transfer with metro is the main transfer mode of dockless bike-sharing usage in Shenzhen, rather than transfer with bus. This corresponds well with previous case studies in New York (Faghih-Imani and Eluru 2015), Seoul (Kim *et al*. 2012) and Saint Paul, Minnesota (Wang *et al*. 2016a), which confirms a commonly existing phenomenon in many metropolises that the accessibility of metro stations is positively correlated with bike-sharing usage. However, like the previous studies, it is difficult to provide further information about the influence mechanisms of dockless bike-sharing usage just through the individual impact of METRO factor. This suggests further research on the interactive effects of METRO and other facility variables.

The interaction detector was further applied in the study with a superior advantage of quantifying the interactive influence of factors on dockless bike-sharing usage. In this study, 28 pairs of interactions were calculated between eight factors, and the top three interactions of four periods on weekdays (Table 3) and weekend (Table 4) were presented. The strongest three interactions for each period are mainly the METRO interacting with facility factors which vary in terms of day of week, time of day and origin or destination. However, it should be noted that we will not compare the differences of the interaction

Table 3. The interactive detector results of factors on weekdays.

Days	Time	O/D	Ranks	Factors	Interactive PD	Enhancement with METRO compared with the single effect
Weekdays	8–9am	O	1	REC ∩ METRO	0.424	70.93%
			2	LIVING ∩ METRO	0.421	36.38%
			3	POP ∩ LIVING	0.400	/
		D	1	WORK ∩ METRO	0.344	84.48%
			2	REC ∩ METRO	0.333	82.51%
			3	POP ∩ METRO	0.322	35.13%
	12–13pm	O	1	REC ∩ METRO	0.469	70.02%
			2	WORK ∩ METRO	0.468	77.85%
			3	LIVING ∩ METRO	0.450	43.17%
		D	1	REC ∩ METRO	0.431	74.30%
			2	LIVING ∩ METRO	0.427	41.21%
			3	WORK ∩ METRO	0.420	88.74%
	18–19pm	O	1	WORK ∩ METRO	0.427	72.13%
			2	POP ∩ METRO	0.402	28.33%
			3	REC ∩ METRO	0.400	78.72%
		D	1	LIVING ∩ METRO	0.396	41.86%
			2	REC ∩ METRO	0.386	82.10%
			3	POP ∩ METRO	0.377	29.56%
	21–22pm	O	1	REC ∩ METRO	0.485	62.50%
			2	LIVING ∩ METRO	0.449	39.42%
			3	POP ∩ REC	0.447	/
		D	1	LIVING ∩ METRO	0.441	33.44%
			2	POP ∩ LIVING	0.427	/
			3	REC ∩ METRO	0.420	70.67%

Table 4. The interactive detector results of factors on weekend.

Days	Time	O/D	Ranks	Factors	Interactive PD	Enhancement with METRO compared with the single effect
Weekend	8–9am	O	1	REC ∩ METRO	0.392	68.19%
			2	LIVING ∩ METRO	0.387	34.80%
			3	POP ∩ LIVING	0.355	/
		D	1	REC ∩ METRO	0.394	75.29%
			2	LIVING ∩ METRO	0.379	46.47%
			3	WORK ∩ METRO	0.372	103.48%
	12–13pm	O	1	REC ∩ METRO	0.505	68.38%
			2	LIVING ∩ METRO	0.497	38.81%
			3	POP ∩ LIVING	0.460	/
		D	1	LIVING ∩ METRO	0.448	38.70%
			2	REC ∩ METRO	0.446	70.53%
			3	POP ∩ LIVING	0.405	/
	18–19pm	O	1	REC ∩ METRO	0.486	67.29%
			2	LIVING ∩ METRO	0.458	42.82%
			3	WORK ∩ METRO	0.444	92.36%
		D	1	LIVING ∩ METRO	0.419	37.88%
			2	REC ∩ METRO	0.415	71.52%
			3	POP ∩ LIVING	0.391	/
	21–22pm	O	1	REC ∩ METRO	0.469	60.72%
			2	LIVING ∩ METRO	0.442	37.30%
			3	POP ∩ LIVING	0.424	/
		D	1	LIVING ∩ METRO	0.446	38.44%
			2	REC ∩ METRO	0.422	44.54%
			3	POP ∩ LIVING	0.418	/

PD values of the same interactive factors in different periods, as the fact of the usage as well as the spatial characteristics of dockless bike-sharing usually vary with time. For example, it can be found that the interactive PD value of 'METRO∩WORK' is higher for bike destination (D) at morning peak time on weekend (0.372, in Table 4) than that on weekdays (0.344, in Table 3). This implies that 37.2% of the spatial distribution of bike destination at morning peak time on weekend is consistent with that of WORK factor interacting with METRO, whilst 34.4% of that at morning peak time on weekend is consistent with that of WORK factor interacting with METRO. However, we must realize that the bike usage is much lower on weekend than weekdays, and the spatial distribution is also quite different between different periods. Hence, we focus on what factors interact better in the same period, from which we get some interesting findings as following.

First, regarding morning-peak of weekdays, the largest interaction for bike origin is REC interacting with METRO, followed by LIVING interacting with METRO. Although REC has relative lower PD value than LIVING and METRO from the single factor detector results, the interactive effect of METRO and REC factor get 70.93% enhancement compared with the single effect. It was noted that the restaurant POI accounts for over 77% of the REC data we used. This may imply that in addition to residential areas, the areas with high dense of restaurants around metro stations are usually in high demand at morning peak on weekdays, which should not be neglected when relocating bikes. Additionally, though WORK factor does not show very important influence on bike destination from the single factor detector results, the strongest interaction for bike destination is WORK interacting with METRO, followed by REC interacting with METRO. This indicates that available bikes from other places should be relocated to those metro stations with high dense of companies and restaurants around before morning peak.

Second, in terms of the noon period of weekdays, over 40% of the spatial distribution of bike usage (origin/destination) is consistent with that of three facility factors intersecting with METRO. The interactive effect of REC and METRO as well as that of WORK and METRO get greatly improved, although the individual effects of REC and WORK are much lower than LIVING. This interactive result indicates that the areas with high dense of these three facilities around metro stations should not be ignored for bike relocating at noon of weekdays.

Third, the top three interactions for bike origin (destination) at evening peak time of weekdays is similar to those for bike destination (origin) at morning peak time. The bike rebalance strategy for evening peak should be the opposite of that for morning peak. It should be noted that we could not only focus on the restaurant POI of REC factors for evening peak. Other retail, recreational POI also should be paid attention to when relocating bikes at evening peak time.

Fourth, regarding the night time for weekdays, though the individual effect of REC is lower than LIVING, it shows great interactive enhancement of REC with METRO both for bike origin and destination. Additionally, 'POP ∩ REC' and 'POP ∩ LIVING' are the strong interactions for bike origin and destination respectively. This suggests the operators to pay more attention on high density areas of recreational facilities around metro stations, high density of population and recreational facilities, high density of residential facilities and population, as well as the metro station exits with high dense of recreational facilities around, as these areas are usually in high demand for bike trips at night time.

Last, for weekend, 'REC ∩ METRO' and 'LIVING ∩ METRO' are two strongest interactions for all the four periods. This indicates that available bikes should be relocated at the high-density area of living or recreational facilities around metro for weekend. It can be found that the interactive effect of WORK and METRO for bike destination at morning peak of weekend enhances by over 100% compared with the single effect of WORK, although this interactive PD value ranks third in this period. Similarly, WORK ∩ METRO is the third strongest interaction for bike origin at evening peak of weekend, but the interactive PD value is 92.36% higher than the individual effect of WORK. These findings imply overtime working phenomenon on weekend in Shenzhen. Moreover, the results also imply that the people who work overtime on weekend still rely on metro and connecting dockless bicycle when there is a metro station near the company. Hence, the need of dockless bike-sharing usage for commuting should not be ignored at the peak time on weekend.

5. Conclusions and future work

This study employed the geographical detector model to examine the influencing mechanisms of BE factors on the usage of dockless bike-sharing, so as to provide insights into land use planning and dockless bike rebalance strategy. The major contributions and findings from this study can be summarized as follows: (1) To test the MAUP in BE-related bike-sharing studies, the scale effect and zoning effect were conducted to explore the effect of MAUP in the influences of built environment factors on dockless bike-sharing usage. (2) This study proves that the geographical detector is an effective method for examining the interactive effects of built-environment factors on dockless bike-sharing travel. This method can be employed to other BE-travel behavior relationship studies with careful consideration.

Some interesting findings were generated from the present study, which can provide decision-support for urban planning and bike rebalance. First, the results of MAUP effect revealed that the influence of most BE variables, such as METRO, WORK, LIVING, REC, MIX and POP, are sensitive to the spatial areal units. This suggests urban planners who aim to promote dockless bike-sharing usages to pay more attentions on the spatial scale in the planning of these built-environment factors. The inconsistent results in the relative importance of these factors with different grid scales could inform urban planners what built-environment factors should be paid more attention to at certain spatial scale. Second, the comparisons between individual effect and interactive effect confirm the importance of interacting effect for bike rebalance strategy, as the individual effect is not sufficient. The results revealed some interesting findings, which have not been explored in previous studies and have provided valuable insights into bike rebalance for such an innovative and high-density metropolis in China.

The study proves that the MAUP does affect the dockless bike-sharing usage mechanism modeling results. The key to determining the most suitable areal unit for data aggregation and modeling with geographical detector model is to understand the changes of trend and characteristics of the modeling results (level of PD value and its relative stability) with different areal units. This study contributes to the existing literature of travel behavior and human mobility analysis by applying the geographical detector model in mechanism analysis with careful consideration of MAUP. A suitable and meaningful spatial areal unit for analyzing the effects of built-environment factors on dockless bike-sharing usage in Shenzhen might be 600 m scale grid. Though it would vary in different case study around the world, the procedure to select the suitable and meaningful spatial areal unit scale in this study could provide scientific basis for related analysis.

Despite the merits of this study, we have to acknowledge some limitations which remain to be addressed in future research. First, the BE factors that may affect dockless bike usage for physical purposes have not been considered in this work. In the future, this work should be extended by obtaining additional variables such as sports facilities, and greenways, to reveal their relationships with dockless bike usage. Second, the influence mechanisms of dockless bike-sharing have been analyzed from a spatial perspective, and bike scheduling suggestions have been put forward in this study. Future studies should be further performed to build a direct forecasting model to provide quantitative details for the dynamic spatial scheduling of dockless bike-sharing.

Data and codes availability statement

The model datasets and geographical detector model software that support the findings of the present study are available in figshare at https://doi.org/10.6084/m9.figshare.11438502.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This study was supported by Guangzhou Science and technology project [Grant No. 201904010198], the National Natural Science Foundation of China [Grant No. 41871290, 41401432], Key Special Project for Introduced Talents Team of Southern Marine Science and Engineering Guangdong Laboratory (Guangzhou) [GML2019ZD0301].

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