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A comparison in travel patterns and determinants of user demand between docked and dockless bike-sharing systems using multi-sourced data

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Abstract

The co-existence of traditional docked bike-sharing and emerging dockless systems presents new opportunities for sustainable transportation in cities all over the world, both serving door to door trips and accessing/egressing to/from public transport stations. However, most of previous studies have separately examined the travel patterns of docked and dockless bike-sharing schemes, whereas the difference in travel patterns and the determinants of user demand for both systems have not been fully understood. To fill this gap, this study firstly compares the travel characteristics, including travel distance, travel time, usage frequency and spatio-temporal travel patterns by exploring the smart card data from a docked bike-sharing scheme and trip origin-destination (OD) data from a dockless bike-sharing scheme in the city of Nanjing, China over the same spatio-temporal dimension. Next, this study examines the influence of the bike-sharing fleets, socio-demographic factors and land use factors on user demand of both bike-sharing systems using multi-sourced data (e.g., trip OD information, smart card, survey, land use information, and housing prices data). To this end, geographically and temporally weighted regression (GTWR) models are built to examine the determinants of user demand over space and time. Comparative analysis shows that dockless bike-sharing systems have a shorter average travel distance and travel time, but a higher use frequency and hourly usage volume compared to docked bike-sharing systems. Trips of docked and dockless bike-sharing on workdays are more frequent than those on weekends, especially during the morning and evening rush hours. Significant differences in the spatial distribution between docked and dockless bike-sharing systems are observed in different city areas. The results of the GTWR model reveal that hourly docked bike-sharing trips and dockless bike-share trips influence each other throughout the week. The density of Entertainment points of interest (POIs) is positively correlated with the usage of dockless bike-sharing, but negatively correlated with docked bike-sharing usage. On the contrary, the proportion of the elderly has a positive association with the usage of docked bike-sharing, but a negative association with the usage of dockless bike-sharing. Finally, policy implications and suggestions are proposed to improve the performance of docked and dockless bike-sharing systems, such as increasing the flexibility of docked bike-sharing, designing and promoting mobile applications (APP) for docked bike-sharing, improving the quality of dockless shared bikes, and implementing dynamic time-based pricing strategies for dockless bike-sharing.

Keywords

Docked bike-sharing, Dockless bike-sharing, Travel behavior, Land use, Spatiotemporal variation, Geographically and temporally weighted regression (GTWR) model

1. Introduction

As a short-term bike rental service, bike-sharing has become common in many cities around the world during the last decade. It has not only been regarded as an economical, flexible, convenient and sustainable travel mode, but also as a means to mitigate problems like air pollution and traffic congestion, to promote a healthy lifestyle by involving more physical activity benefits and to support multimodal transport connections (Maizlish et al., 2013; Yang et al., 2016). Bike-sharing systems enable smooth door-door transport by itself or by serving as access/egress mode of public transport (Mil et al., 2018; Shelat et al., 2018). This will increase the catchment areas of rail transit stops and thereby increasing ridership (Brand et al., 2017). By October 2019, more than 2080 bike-sharing schemes are already in operation and 360 others are under construction in more than 50 countries (Meddin and Demaio, 2019).

Currently, the bike-sharing systems operated worldwide can be divided into two categories: docked bike-sharing and dockless bike-sharing (Liu et al., 2018b). In the docked bike-sharing system, users have to rent bikes from designated docking stations and then return them to the available lockers in docking stations. As a result, the docked bike-sharing system cannot provide door-to-door services. Another challenge in operating a docked bike-sharing system is that the numbers of bikes and docks required at some stations are often insufficient to satisfy the corresponding cycling demand (Szeto et al., 2018). Compared with the traditional docked systems, the dockless bike-sharing system is connected to the internet with a mobile phone application (APP) to help users rent dockless bikes (Shaheen et al., 2010). The dockless bike-sharing system allows the users to park the bikes in the physical or geo-fencing designated parking areas (Pal and Zhang, 2017). Without being constrained by docking-station infrastructure, it saves users the last-mile walking distance from nearby bike stations to final destinations (Cheng and Gao, 2018) and strengthens the seamless connection with public transport (Ai et al., 2018; Shelat et al., 2018). However, dockless bike-sharing could also bring negative societal effects. Because it is often lacking an adequate demand estimation, dockless bike-sharing often experiences oversupply of bike fleets in high population density areas, which hurts its economic sustainability, occupies urban space resources, harms the urban transport system and causes visual pollution (Du and Cheng, 2018). While in low population density areas, dockless bike-sharing often experiences low bike utilization levels (Shen et al., 2018).

The joint deployment of traditional docked and emerging dockless bike-sharing systems presents new opportunities for sustainable transportation in cities all over the world. In order to provide users with better services and to help operators enhance the bike fleet reallocation, it is necessary to compare and comprehend the travel characteristics and influential factors between docked and dockless bike-sharing (Gu et al., 2019; Shen et al., 2018). However, most of previous studies have separately examined different aspects of docked and dockless bike-sharing schemes, whereas the investigation of the similarities and differences in travel patterns between the two systems is scarce, due to the difficulty of acquiring historical trip data of both systems over the same spatio-temporal dimension. The aim of this paper is to better understand the difference between the travel patterns of bike-sharing users of the two systems and to examine the influence of bike-sharing fleets, socio-demographic factors and land use factors on user demand. This is achieved by using a state-of-the-arts regression model - geographically and temporally weighted regression (GTWR), based on multi-sourced data (e.g., trip origin-destination (OD) data, smart card, survey, land use information, Gross Domestic Product (GDP) and housing prices data) from the city of Nanjing, China. Particularly, the main contributions of this paper lie in:

1) Revealing the difference in travel characteristics, including riding distance, riding time, usage frequency and spatio-temporal usage patterns by mining smart card data from docked bike-sharing and the trip OD data from dockless bike-sharing over the same spatio-temportal dimension;

2) Establishing a GTWR model to analyze the influential factors (bike-sharing fleets, socio-demographic, points of interest (POIs), etc.) associating with user demand of docked and dockless bike-sharing.

The remainder of this paper is structured as follows. In Section 2, a literature review of the evolution history, usage patterns and influential factors of both docked and dockless bike-sharing is provided. In Section 3, the study area and dataset are introduced. In section 4, the basic frameworks of GTWR model and its counterpart models (ordinary least squares model and geographically weighted regression model) used in the study are described. In Section 5, the results of historical data analysis are discussed, and the results of three regression models are compared. Next, the regression coefficients of the GTWR model are analyzed in detail spatially and temporally. The conclusions and suggestions for future research are summarized in the last part of the paper.

2. Literature review

Compared with docked bike-sharing, dockless bike-sharing is different in terms of operating and management mode, user demand, travel characteristics, user demographics and the influential factors. A brief review that focuses on the evolution history, usage patterns and influential factors of docked and dockless bike-sharing systems is provided below.

2.1 A short history of docked and dockless bike-sharing

Regarding docked bike-sharing schemes, they firstly started in 1991 at Denmark with coin-deposit locks at bike-sharing stations (Mack et al., 1993). Until 1995, this kind of bike-sharing program began to develop in a large-scale in Copenhagen called as Bycyklen. This scheme introduced docking stations and deposits to the bike-sharing model and had been operated by a nonprofit organization (Shaheen et al., 2010). Then in 1996, magnetic stripe card opened the gate of IT-based bike-sharing systems at Portsmouth University in England (Demaio et al., 2014). This new IT technology enabled cashless payment, real-name registration, and dynamic pricing schemes, which encouraged these IT-based systems with docking stations to rapidly spread from Europe to Asia Pacific, North America, and South America (Shaheen et al., 2010).

The first dockless bike-sharing scheme, known as “White Bikes”, was launched in Amsterdam in July 1965. The bicycles were painted in white and distributed around the city, and they could be freely used by anyone. This program lasted for only a short time, ultimately succumbing to a series of problems such as theft and vandalism (Demaio et al. 2014; Shaheen et al., 2010). In 2000, a call-a-bike system is launched in Germany, which eliminated the need for a docking station and used GPS technology and geofencing to enable “dockless” bike access (Lin et al. 2019b; Parkes et al., 2013; DeMaio, 2014). Other examples include the Bixi system in Canada and the Social Bicycles (SoBi) in the US (Shaheen et al., 2013). In 2015, two start-up companies, Ofo and Mobike, initiated an innovative generation of fully dockless bike-sharing services in China. This newest type of dockless bike-sharing system integrated mobile payment and GPS tracking technology into the system so that users can pick up and drop off bikes almost everywhere in the transportation network (Zhang & Mi, 2018). Similar dockless systems such as Obike in Singapore, LimeBike in the United States and Gobee Bike in Hong Kong also adopted Ofo and Mobike's concept and launched in 2017 (Yu and Paul, 2018).

2.2 Travel patterns and influential factors of docked bike-sharing

There is a vast body of literature on docked bike-sharing. Earlier studies examined docked bike-sharing from different perspectives, including its history and evolution, optimization of the location of bike-sharing stations, impacts on other transportation modes, measures to promote bike-sharing, demand analysis and rebalancing problems (Fishman et al., 2016). Several studies analyzed different aspects of users and usage of docked bike-sharing. Generally speaking, docked bike-sharing users are more likely to possess the following characteristics: male, employed, younger, more affluent and more educated and more likely to have non-motorized vehicles (Ricci, 2015; Shaheen et al., 2013). In contrast, the applications in China show different user characteristics. Zhang (2015) concluded that people with lower income were more willing to use docked shared bikes in China. Shaheen et al. (2011) revealed that older people were more willing to use docked bike-sharing in China. Fishman et al. (2013) discovered that travelers owning cars were more likely to use the docked bike-sharing. Regarding usage rate, it was found that the number of trips per day per docked shared bicycle varies between 0.22 and 8.4 worldwide (Boor, 2019). Work-related trips dominate docked bike-sharing usage, however, the prevalence of different purposes may be influenced by gender and temporal variables, such as time of the day and day of the week (Ricci, 2015; Shaheen et al., 2013). In general, docked bike-sharing usage rate is higher for weekdays compared to weekends, and on weekdays there are a morning peak and an evening peak in passenger flow (Kaltenbrunner et al., 2010; Nair et al., 2013), indicating that commuting is the main purpose for using the docked bike-sharing on weekdays (O'Brien et al., 2014; Rixey, 2013). The acceptable travel distance for docked bike-sharing is between 1 km and 5 km (Du and Cheng, 2018; Rahul and Verma, 2014), and the critical travel time for cycling is within half an hour (Zhao et al., 2015). Several studies also investigated the factors influential the docked bike-sharing user demand. The most common factors considered in the literature are temporal, socio-demographic, meteorological, land use and preference factors (Xin et al., 2018; Zhao et al., 2015; Zhaoyang et al., 2018). Recently, McKenzie (2018, 2019) found that docked bike-sharing trips tend to be more commuting oriented and these trips are generated in central business district whereas dockless bike-sharing and scooter-share trips reflect more non-commuting related activities (e.g. leisure, recreation, or tourism). Similarly, Lazarus et al. (2020) explored the complementary and competitive relationship between docked bike-sharing and dockless ebike-sharing systems. They found that docked bike-sharing trips tended to be commuting trips, and mostly to connect with public transit stations and dense employment areas.

2.3 Travel patterns and influential factors of dockless bike-sharing

Compared with traditional docked systems, only few studies have been conducted for dockless bike-sharing, because these systems mainly exist in China and large amount of trip data cannot be shared to the public due to privacy issues. These studies discovered that dockless users were more likely to possess the following characteristics: male, younger, more educated, single, middle-income level and mobile internet preferred users (Li et al., 2018; Xin et al., 2018). Regarding occupation, company employees constitute the main body of dockless bike-sharing users, followed by university students and the self-employed (Xin et al., 2018). On weekdays, there are two obvious usage peaks, namely, the morning and evening rush hours, whereas a completely different pattern is observed at weekends that the demand trend is much smoother without clear commuter peaks (Bao et al., 2017a; Shen et al., 2018). This result can be explained by the fact that during peak hours on weekdays, trips are dominantly made by commuting users, while more bike-sharing trips for leisure-related purposes take place at weekends (Liu et al., 2018a; Shen et al., 2018). Link et al. (2020) analyzed user characteristics and usage patterns of dockless bike-sharing. They found that 44% of dockless bike-sharing trips are for leisure purpose, followed by commuting purpose (36%). For the spatial distribution of dockless shared bikes, the results from previous studies are inconsistent across different cities around the world. Liu et al. (2018c) found that city central areas and business center surroundings had more dockless bike users than suburban areas. However, Shen et al. (2018) found that the number of dockless bikes in the central business district was lower than that in peripheral residential areas with high population density. Lin et al. (2020) analyzed the spatio-temporal distributions of dockless bike-sharing around metro stations by using metro station-related data and dockless bike trajectory data. They found that more dockless bike-sharing trips for accessing/egressing metro were generated during the morning peak than the afternoon peak, and more trips were generated at the city center. The average riding time of dockless bike-sharing in different cities is less than 20 min and the average travel distance is within 3 km (Bao et al., 2017a; Xin et al., 2018; Zhang and Mi, 2018). Recently, Younes et al. (2020) compared the temporal determinants between docked and dockless bike-sharing systems. It was found that dockless bike-sharing users were less sensitive to weather changes than docked bike-sharing user. Therefore, dockless bike-sharing is more competitive with car and public transportation modes, which are less affected by the weather factors. Several studies also investigated the factors influential the dockless bike-sharing user demand, including attitudes attributes, socio-demographic, weather conditions, surrounding built environment and bike infrastructure factors (Du and Cheng, 2018; Li et al., 2018; Ma,et al., 2020; Mooney et al., 2019; Shen et al., 2018;).

2.4 Research gaps

In sum, most of the aforementioned studies have separately examined different aspects of docked and dockless bike-sharing schemes. Although previous studies have compared the usage difference between docked and dockless bike-sharing, most of them have used survey data, and thus have a series of problems, such as inadequate sample size, restricted study generalizability, and failure to analyze the travel behavior from a dynamic variation of the spatio-temporal pattern perspective (Chen et al., 2018; Li et al., 2019c; Li & Tang, 2019). In addition, by using the historical trip data of both systems, a few studies have applied for instance choice models, Ordinary Least Squares (OLS) models and count time series models to unravel the complex relationship between docked and dockless bike-sharing user demand with temporal variables, built environment, weather conditions and urban density (Ji et al., 2020; Lazarus et al., 2020; Younes et al., 2020). However, none of the methods consider spatial and temporal heterogeneity simultaneously. As a result, we do not know how the effects of influential factors vary over different time periods of the day and spatial locations. This study pioneers to address these issues by exploring the smart card data from a docked bike-sharing scheme and the trip OD data from a dockless bike-sharing scheme over the same spatio-temporal dimension, and next applying a GTWR model to explore the spatiotemporal influence of the bike-sharing fleets, socio-demographic factors and land use factors on the usage demand of docked and dockless bike-sharing using multi-sourced data.

3. Description of study area and data

This section introduces the study area and multiple data sources with their descriptive statistics.

3.1 Study area

As the capital of Jiangsu province and a core city of Yangtze River Delta economic zone, Nanjing, following Shanghai, has long been famed as the second largest commercial center in the East China region. Covering an area of 6,587 km^2, it has population of 8.33 million with 6.85 million being urban residents. Thanks to its good infrastructure, people here are able to travel by private car, bus, subway, taxi, private bike, docked sharing-bike, dockless sharing-bike and walking. By end-2017, ten metro lines were operating on 377 km and 705 bus lines operating on more than 10,000 lane km (Baidu Encyclopedia, 2018; Wikipedia, 2018). For better travel experience and convenience of citizens, Nanjing launched the docked and dockless bike-sharing programs in January, 2013 and January, 2017, respectively. There is only one docked bike-sharing service in Nanjing. Nanjing docked bike-sharing system is classified as a third-generation bike-sharing system, which enables smartcards for automated check-in and check-out (Shaheen et al., 2011). Supported by the government as a non-profit project for citizens, Nanjing docked bike-sharing system has launched 60,000 docked shared bikes by the end of 2017. This docked bike-sharing system can be used for free of charge within the first two hours after delivering a deposit of \$35 (250 CNY). At the same time, a total of 10 dockless bike-sharing systems operated by companies have been used in Nanjing, launching 450,000 dockless shared bikes (Nanjing Planning Bureau, 2018). The dockless shared bikes can be used at a cost of \$0.14 or 0.28 (1 or 2 CNY) per hour with a deposit varying from \$13.86 (99 CNY) to \$41.86 (299 CNY) for different companies (Tian et al., 2018). Mobike is one of the largest systems, launching approximately 160,000 dockless shared bikes in Nanjing (Nanjing Planning Bureau, 2018). The study area of this paper focuses on five urban districts (Xuanwu, Qinhuai, Gulou, Jianye and Yuhua), where there is a good development of both docked and dockless bike-sharing. Statistics from the historical trip data provided by Nanjing docked bike-sharing system and Mobike showed that there were 35,683 docked shared bikes and 146,505 dockless shared bikes (Mobike) in the study area. The geospatial unit of analysis is a traffic analysis zone (TAZ) defined by Nanjing Urban Planning Bureau, and the total number of TAZs is 176. Figure 1 shows the TAZ distribution map of study area.

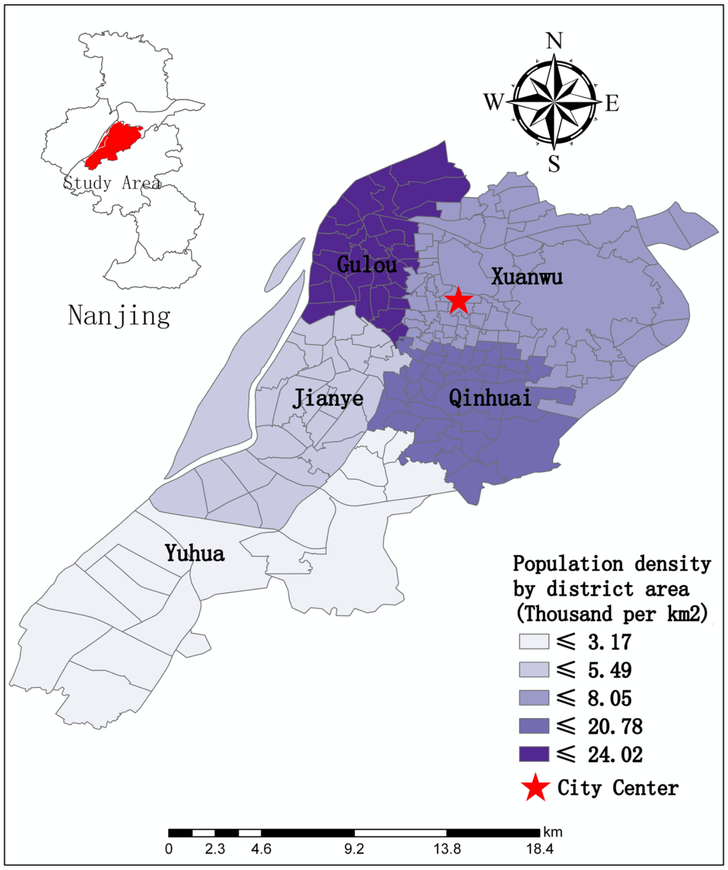


Fig. 1. Map of study area.

3.2 Data

Numerous types of data sources, such as docked bike-sharing data (smart card data), dockless bike-sharing data (trip OD data), travel survey data, land use data, GDP data and housing prices data employed in this study are introduced here. Subsequently, the descriptive statistics of the dependent and explanatory variables are described.

Smart card data of docked bike-sharing from September 18th to 24th, 2017 obtained from Nanjing Public Bicycle Company includes two profiles: Trips and Stations. Trips profile anonymously includes: member ID, trip starting date and time, trip ending date and time, trip starting station ID, trip ending station ID. Stations file includes station ID, station name, and the longitude/latitude of the docking station. However, some data needs pre-processing before further analysis. Trips with the following properties have been removed: trips started or ended outside the study area; trip length shorter than 100 m or longer than 5 km, as suggested by Shen et al. (2018); trip duration less than 30 s or longer than 2 hours, as suggested by Pal et al. (2018); trips without complete journey details. Then a valid sample of 890,369 docked bike-sharing records is obtained.

Trip OD data of dockless bike-sharing from September 18th to 24th, 2017 (the same period as the one from the docked system) is provided by Mobike company. Each Mobike trip contains a member ID, user ID, starting timestamps, starting latitude, starting longitude, ending timestamps, ending latitude, ending longitude. Trip OD data of dockless bike-sharing is pre-processed in the same way as smart card data of docked bike-sharing. In this way, a valid sample of 2,058,819 dockless bike-sharing records is obtained. Table 1 and Table 2 show the typical sequence of docked and dockless transaction records.

Table 1 A sequence of docked bike-sharing transaction records

User ID	Starting Timestamps	Starting Longitude	Starting Altitude	Ending Timestamps	Ending Longitude	Ending Altitude
NJ1120000***	2017/9/19 19:25:56	119.791	32.097	2017/9/19 19:39:04	119.909	32.102
NJHX00099***	2017/9/19 19:25:56	119.732	32.016	2017/9/19 19:34:51	119.725	32.022
NJHX00095***	2017/9/19 19:25:56	119.741	32.049	2017/9/19 19:33:49	119.749	32.040
NJHX00134***	2017/9/19 19:25:56	119.734	32.033	2017/9/19 19:41:57	119.737	32.036
NJ1110000***	2017/9/19 19:25:55	119.925	32.101	2017/9/19 19:31:49	119.913	32.103

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

Table 2 A sequence of dockless bike-sharing transaction records

User ID	Starting Timestamps	Starting Longitude	Starting Altitude	Ending Timestamps	Ending Longitude	Ending Altitude
990a6979e***	2017-09-19 19:25:55	119.734	32.151	2017/9/19 19:32:20	119.726	32.149
39e3fcf29***	2017-09-19 19:25:39	119.754	32.074	2017/9/19 19:31:19	119.754	32.073
113a647be***	2017-09-19 19:25:31	119.969	32.010	2017/9/19 19:49:07	119.966	32.011
5602e1cfa***	2017-09-19 19:25:50	119.799	31.911	2017/9/19 19:33:23	119.790	31.916
0227997b***	2017-09-19 19:25:19	119.757	31.962	2017/9/19 19:32:56	119.752	31.967

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

Land use data of 2015 are provided by Jiangsu Institute of Urban Planning and Design and the Jiangsu Institute of Urban Transport Planning, including:

- the distance from each TAZ to the central business district (CBD);
- the density of bus stops, the density of docked bike-sharing stations in TAZ;
- the density of metro stations in TAZ;
- the density of minor local streets in TAZ;
- the density of Cultural, Residential, Governmental, Entertainment and Commercial/Industrial POIs in TAZ. Detailed POIs facilities within each category are listed in Table A1 in the Appendix.

Socio-demographic data used for this research is obtained from the 2015 Nanjing Household Travel Survey conducted by Jiangsu Institute of Urban Transport Planning. The Household Travel Survey consists of household characteristics and social-demographics of each household member. Household characteristics include household location (longitude and latitude), household income level and the ownership of private bike, e-bike and car. The social-demographics of each member contain gender, age, education level. Populations are segregated in each TAZ by gender, age cohort, education level, household income level and the ownership of private bike, e-bike and car.

Additionally, the density of local population and GDP data are obtained from Nanjing Urban Planning Bureau and the average housing prices data are obtained from Lianjia Housing Prices Report (Lianjia, 2018) in each TAZ. The final number of TAZs for modeling analysis is 127 (after removing TAZs where the docked bike-sharing data or household travel survey data cannot cover).

Hourly docked and dockless bike-sharing usage volume for each TAZ (as the dependent variable) is computed based on the same period from Monday to Friday for weekdays, and two weekend days (Ma et al., 2018). In this study, we chose the number of rentals of two bike-sharing systems as the indicator for the approximate user demand as suggested by Pal et al. (2018). Explanatory variables used in the multivariate analysis fall into three main categories: docked (dockless) bike-sharing trips, urban land use variables and socio-demographic variables (Buehler et al., 2019; Chen et al., 2018; Li et al., 2019a; Shen et al., 2018; Wang et al., 2019; Wang et al., 2015). Both the dependent and explanatory variables for each TAZ were measured using the

ArcGIS platform as Ji et al. (2018) used. We provide a descriptive summary of the variables in Table 3. It can be seen that hourly docked bike-sharing trips on weekends are around half of that on weekdays, and similar observation applies to the hourly dockless bike-sharing trips.

Table 3 Definition of dependent and explanatory variables.

Type	Variables	Description	Mean	St.Dev.
Docked bike-sharing trips	Hourly docked bike trips on weekdays in TAZ	Average hourly docked bike-sharing trips for each TAZ on weekdays	52.680	92.504
	Hourly docked bike trips on weekends in TAZ	Average hourly docked bike-sharing trips for each TAZ on weekends	38.407	60.372
Dockless bike-sharing trips	Hourly dockless bike-sharing trips on weekdays	Average hourly dockless bike-sharing trips for each TAZ on weekdays	101.258	121.665
	Hourly dockless bike-sharing trips on weekends	Average hourly dockless bike-sharing trips for each TAZ on weekends	57.530	63.300
Land use variables	Density of metro stations	Number of metro stations per km^2 in each TAZ	0.408	0.780
	Density of docked bike-sharing stations	Number of docked bike-sharing stations per km^2 in each TAZ	5.504	3.502
	Density of bus stations	Number of bus stations per km^2 in each TAZ	7.837	4.658
	Density of road	Length of road per km^2 in each TAZ	13.244	4.853
	Distance to CBD	Distance between each TAZ center to CBD	4.820	2.785
	Density of Cultural POIs	Number of Cultural POIs per km^2 in each TAZ	70.481	79.009
	Density of Residential POIs	Number of Residential POIs per km^2 in each TAZ	31.485	41.399
	Density of Governmental POIs	Number of Governmental POIs per km^2 in each TAZ	43.801	41.373
	Density of Entertainment POIs	Number of Entertainment POIs per km^2 in each TAZ	112.808	121.152
	Density of Commercial/Industrial POIs	Number of Commercial/Industrial POIs per km^2 in each TAZ	246.541	287.834
Socio-demographic variables	GDP	GPD in each TAZ (100 million CNY =US$ 14 million)	1.117	0.319
	Housing Prices	Average housing price in each TAZ (1,000 CNY =US$ 140)	31.052	8.403
	Proportion of Car ownership	Proportion of Car ownership in each TAZ	0.242	0.102
	Proportion of Private bike ownership	Proportion of Private bike ownership in each TAZ	0.350	0.121
	Proportion of E-bike ownership	Proportion of E-bike ownership in each TAZ	0.373	0.092
	Density of Non-locals	Density of Non-locals in each TAZ (Thousands/km^2)	3.431	2.431
	Density of Locals	Density of Locals in each TAZ (Thousands/km^2)	8.325	5.994
	Proportion of Male	Proportion of Male in each TAZ	0.478	0.069
	Proportion of Female	Proportion of Female in each TAZ	0.507	0.073

	Proportion in population under18 years old	Proportion in population under18 years old in each TAZ	0.043	0.034
	Proportion in population between 18 and 35 years old	Proportion in population between 18 and 35 years old in each TAZ	0.285	0.096
	Proportion in population between 35 and 45 years old	Proportion in population between 35 and 45 years old in each TAZ	0.220	0.075
	Proportion in population between 45 and retirement age	Proportion in population between 45 and retirement age in each TAZ	0.190	0.098
	Proportion of the elderly	Proportion of the elderly in each TAZ	0.245	0.095
	Proportion of senior high school or bellow	Proportion in population graduated from senior high school or bellow in each TAZ	0.285	0.111
	Proportion of junior college or college	Proportion in population graduated from junior college or college in each TAZ	0.673	0.127
	Proportion of graduate and above	Proportion in population with graduate degree and above in each TAZ	0.027	0.033
	Proportion of low-income level (Household annual income 0~80,000 CNY)	Proportion in population with low-income level in each TAZ	0.524	0.173
	Proportion of middle-income level (Household annual income 80,000~160,000 CNY)	Proportion in population with middle-income level in each TAZ	0.450	0.163
	Proportion of high-income level (Household annual income: more than 160,000 CNY)	Proportion in population with high-income level in each TAZ	0.010	0.020

4. Research methodology

One of the primary objectives of this study is to explore the factors that influence bike-sharing user demand from a spatiotemporal perspective. Multicollinearity and spatial autocorrelation are briefly introduced to reveal the relations amongst various explanatory variables, and then three methods (OLS, GWR and GTWR) developed for comparisons are briefly illustrated as follows.

4.1 Multicollinearity

Multicollinearity means that several particular explanatory variables have a strong linear correlation with each other, which might cause bias when interpreting the significance and influence of other explanatory variables. To eliminate this phenomenon, we adopted the variance inflation factor (VIF), which is an indicator that represents the severity of multicollinearity. Variables with VIF values greater than ten are assumed to be multicollinearity variables and should be removed from the models (Kutner et al., 2004).

4.2 Spatial autocorrelation

The most commonly used spatial variability test is called Moran's I test, which shows the spatial autocorrelation of each explanatory variable and can be expressed as follows (Moran, 1950):

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i-\bar{y})(y_j-\bar{y})}{\sum_{i=1}^{n}(y_i-\bar{y})^2} \quad (1)$$

where n is the number of spatial units; w_{ij} is the weight between location i and j; y_i, y_j represents the selected attribute value at locations i and j, respectively; and $\bar{y}$ is the average value of all observations.

The range of Moran's I statistic is between -1 and +1. Higher positive values mean that close observations tend to have similar attribute values while distant observations have different attribute values, which indicates spatial aggregation. However, a negative value indicates spatial dispersion, and a value near zero indicates a spatially random distribution. The null hypothesis of Moran's I test is that the explanatory variables are spatially independent, which means that Moran's I statistic is close enough to zero. A Z-score is usually used as the indicator of significance of the Moran's I statistic to verify the null hypothesis, and it can be calculated as follows (Moran, 1950):

$$Z(I) = \frac{I-E(I)}{\sqrt{Var(I)}} \quad (2)$$

where *E (I)* and *Var (I)* are the expectation and the standard deviation of the Moran's I statistic, respectively. The significance level in this study is set as $P < 0.05$.

4.3 Regression models

Several regression models revealing the relationships between user demand of docked and dockless bike-sharing and other influential variables have been developed, including ordinary least squares (OLS) models (El-Assi et al., 2017; Lin et al., 2019a; Zhao et al., 2014) and geographically weighted regression (GWR) models (Ma et al., 2018; Xu et al., 2017; Bao et al., 2017a). Notably, the user demand pattern of both docked and dockless bike-sharing systems shows highly and spatiotemporally dynamics, and the shared bikes of the two schemes scatter across their service territory and their positions may change during the day and from day to day. Thus, both location and time can be considered as important determinants of the user demand of docked and dockless bike-sharing. Compared to the traditional OLS and GWR models, a geographically and temporally weighted regression (GTWR) model proposed by Huang (Huang et al., 2010) can combine temporal and spatial characteristic when modeling the relationship between explanatory variables, thereby it will be chosen to explore the relationship between bike-sharing user demand and its influential factors considering spatial and temporal heterogeneity simultaneously. In this study, three models namely OLS, GWR and GTWR model are deployed to conduct the empirical analysis for both weekdays and weekends. Also, the explanatory powers of the three statistical models are compared.

OLS regression is conducted in which the dependent variable is modelled as a linear function of multiple predictors using least square approach (Brunsdon et al., 1996). However, the applicability of the OLS approach has been criticized for neglecting the spatial variations of the bike-sharing usage (Shen et al., 2018). GWR is specifically designed to deal with spatial data regression, allowing for coefficients to vary across spaces. It can be viewed as an extension of OLS models by associating explanatory variables with geographical locations, which takes the following form (Brunsdon et al., 1996):

$$Y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i) X_{ik} + \varepsilon_i \quad (3)$$

where i (i =1, 2, …, n) denotes a TAZ, which is a most common regionalism in transportation studies; (u_i, v_i) are the coordinates of TAZ i; Y_i is the bike-sharing usage volume in TAZ i; X_k is the kth explanatory variable; ε_i is the error term for TAZ i; $\beta_0(u_i, v_i)$ represents the intercept; and $\beta_k(u_i, v_i)$ is the regression coefficient between bike-sharing usage volume and the explanatory variable. The distinct characteristic of GWR model is that coefficient $\beta_k(u_i, v_i)$ varies across the model to measure the spatial variations of observations compared with the OLS model in which parameter estimation is fixed for each observation.

As a temporal extension of GWR, GTWR embeds temporal data into regression parameters to measure spatial and temporal variation simultaneously (Brunsdon et al., 1996). This condition is particularly valid when modeling bike-sharing usage volume in a TAZ where the obvious tidal property of passenger flows exists, especially during morning and evening peaks. The general structure of the GTWR model developed in this study to depict the spatiotemporal quantitative relationship of bike-sharing usage volume is described as follows (Brunsdon et al., 1996):

$$y_i = \beta_0(u_i, v_i, t_i) + \sum_k \beta_k(u_i, v_i, t_i)\, X_{ik} + \varepsilon_i \qquad (4)$$

where i (i=1, 2, …, n) denotes a TAZ; the dependent variable Y_i refers to the hourly bike-sharing usage volume for TAZ i; X_i represent the explanatory variables, including hourly docked bike-sharing usage volume, socio-demographic and urban land uses variables. u_i, v_i and t_i are the longitude, latitude and time respectively of TAZ i; (u_i, v_i, t_i) are the coordinates of TAZ i in the spatiotemporal dimensions (ST); X_{ik} is the kth variable for TAZ i; β_0 (u_i, v_i, t_i) is the intercept value; and β_k(u_i, v_i, t_i) denotes a set of parameter values at TAZ i. Similar to GWR, the regression coefficients of GTWR are estimated based on local weighted least squares. The estimated parameters can be expressed as follows (Brunsdon et al., 1996):

$$\widehat{\beta}(u_i, v_i, t_i) = [X^T W(u_i, v_i, t_i) X]^{-1} X^T W(u_i, v_i, t_i) Y \qquad (5)$$

where the spatiotemporal weight matrix $W(u_i, v_i, t_i)$ is an n×n diagonal matrix and $W(u_i, v_i, t_i)$=diag (W_{i1}, W_{i2}…W_{ij}…W_{in}). W_{ij}(1≤j ≤n) is the spatiotemporal distance decay function, which is described as follows (O'Sullivan, 2003) :

$$W_{ij} = \exp\left[-\frac{(d_{ij}^{ST})^2}{h^2}\right] \qquad (6)$$

Here, d_{ij}^{ST} is the spatiotemporal distance between TAZs i and j , which is calculated as follows (Brunsdon et al., 1996):

$$\mathrm{d}_{ij}^{ST} = \sqrt{\lambda\left[\left(u_i - u_j\right)^2 - \left(v_i - v_j\right)^2\right] + \mu(t_i - t_j)^2} \qquad (7)$$

where λ and μ are the weights for balancing different effects because space distance and time are measured using different units.

h in Eq. (6) is a nonnegative parameter called spatiotemporal bandwidth, and the optimal bandwidth is chosen based on the minimum cross-validation (CV) value (Hurvich et al., 1998). The CV value is the sum of the squared error between the actual value y_i and predicted value $\widehat{y}_i(h)$:

$$CV(h) = \sum_i (y_i - \widehat{y}_i(h))^2 \qquad (8)$$

The Corrected Akaike Information Criterion (AICc) is a commonly used metric in the bandwidth selection and the decision of final model (Hurvich et al., 1998; O'Sullivan, 2003). Models with the lowest AICc are selected. A GTWR plugin of ArcGIS was employed to construct OLS, GWR and GTWR models in this study. The GTWR plugin is accessible online (Huang & Wang, 2020).

5. Results

This section explores and compares differences in travel patterns and the determinants of user demand between docked and dockless bike-sharing systems. Specifically, section 5.1 reveals the difference in travel characteristics, including travel distance and time (section 5.1.1), usage frequency (section 5.1.2), temporal pattern (Section 5.1.3) and spatial pattern (section 5.1.4). Next, section 5.2 firstly compares the model fit of OLS, GWR and GTWR models (section 5.2.1), and then GTWR model results are analyzed by visualizing the coefficients of explanatory variables from the temporal perspective (5.2.2) and spatial perspective (5.2.3), respectively.

5.1 Comparative analysis on usage patterns

In this first section, we explain the difference in travel patterns (travel distance, travel time, usage frequency and spatio-temporal distribution) between docked and dockless bike-sharing systems by mining the smart card data of docked bike-sharing and the trip OD data of dockless bike-sharing.

5.1.1 Travel distance and travel time

By analyzing the historical trip data of docked and dockless bike-sharing systems, we found that the average travel distances (Manhattan Distance (Li et al., 2020)) and travel times are 1286.8 m and 10.4 min respectively for dockless bike-sharing whereas for docked bike-sharing, the related quantities are larger, namely 1808.4 m and 15.9 min respectively during the week.

Figure 2 visualizes the distribution of travel distance of docked and dockless bike-sharing. It shows that 56.68 % of docked bike-sharing users and 37.70 % of dockless bike-sharing users completed their trips within 1 km. For trips within 2 km and 3 km, the ratios for the two kinds of users reach 73.30% and 85.56%, 88.46% and 94.49% respectively. This indicates a longer average travel distance by docked bike-sharing users. The interval that records the highest proportion of riding is 750-1000 m for docked bike-sharing and the value for dockless bike-sharing is 500-750 m. The proportion gap between two modes reaches the peak in the interval of 250 - 500 m. Within the travel distance of 1000 m, the proportion of dockless bike-sharing is higher than that of docked bike-sharing, yet when the distance exceeds 1000 m, the situation is exactly the opposite. This can be explained by the fact that dockless bike-sharing, as convenient as it is, is more popular when trips are within 1000 m, as people can simply look for the nearest bike, rather than the nearest docking station. As for distance over 1000 m, docked bike-sharing is more attractive because in Nanjing, riding within two hours is free of charge.

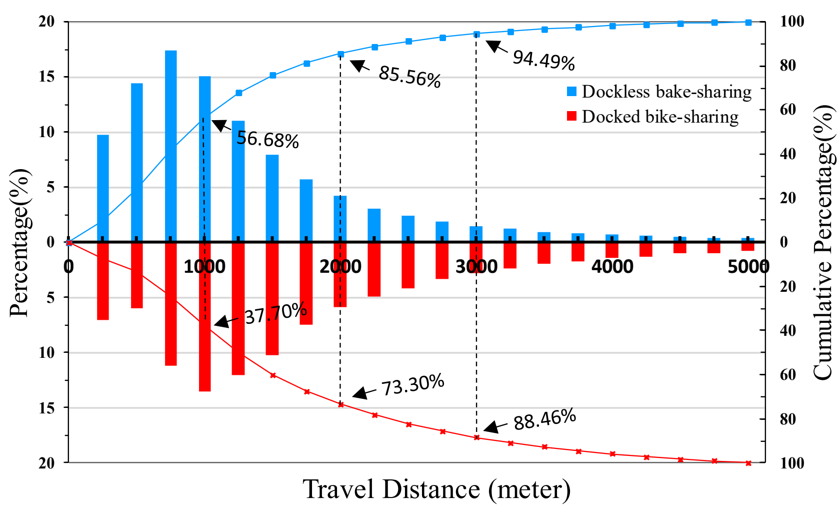


Fig. 2. Distribution of the travel distances of docked and dockless bike-sharing.

As shown in Figure 3, 67.78% of the docked bike-sharing trips and 83.43% of dockless bike-sharing trips last less than 15 minutes, and trips within 30 minuses take up 90.31% for docked bike-sharing and 96.82% for dockless bike-sharing of all trips respectively. This higher proportion of dockless bike-sharing riding within 30 minutes compared to docked bike-sharing riding is credited to the price policy: cost of \$0.14 (1 CNY) for dockless bike-sharing trips within half an hour, whereas the first two hours of riding of docked bike-sharing is free of charge, which is consistent with the result of Bao et al. (2017a). This can also be explained by that, compared with docked bike-sharing users, dockless bike-sharing users are generally younger and riding faster (Chen et al. 2018).

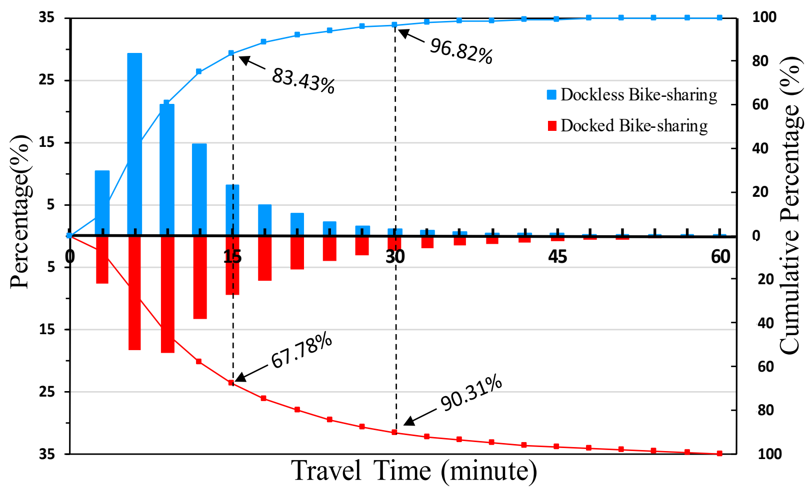


Fig. 3. Distribution of the travel times of docked and dockless bike-sharing.

5.1.2 Usage frequency

Usage frequency (UF) is adopted to measure the effectiveness degree of docked and dockless bike-sharing systems and is calculated as follows:

$$UF_i = \frac{Total\ number\ of\ bikesharing\ trips_i\ \text{in one week}}{Total\ numbers\ of\ shared\ bikes} \tag{9}$$

Here UF_i is the usage frequency of shared bikes (trips generated per bike per week) of bike-sharing type i (either docked or dockless system). Regarding the usage frequency, dockless shared bikes are used at an average number of 44 times in one week whereas for docked shared bikes the value is only 17. The possible reason could be that dockless shared bikes are more convenient for not being restricted by docking stations (Younes et al., 2020). As shown in Figure 4, the usage frequency distribution of docked and dockless shared bikes in a week records significant difference. In terms of docked shared bikes, more than 30% are used less than 5 times in a week, and 96.54% used less than 50 times, indicating a very low utilization rate for docked bike-sharing systems. For dockless bike-sharing, usage frequency reaches its peak at 30-35 times and concentrates at the range between 20 and 80 times during one week. Thus, the turnover rate of dockless bike-sharing is higher than the docked one. This may be owing to the convenience and effectiveness of using mobile phones to unlock dockless bikes and their flexibility of borrowing and returning, although their usage is charged. This finding is consistent with the result of Li and Tang (2019), who concluded that more than 53.7% of the docked bike-sharing users thought that the available bikes and parking docks were not sufficient. On the contrary, 63.7% of the users thought that it was more convenient to borrow or return a dockless shared bike. In addition, Li and Tang (2019) found that most docked and dockless bike-sharing users cycle to commute. They have had strict time requirements and prefer dockless bike-sharing to avoid the drawback of the docked bike-sharing system if they were forced to return the bike at a perceptibly significant distance from their destinations.

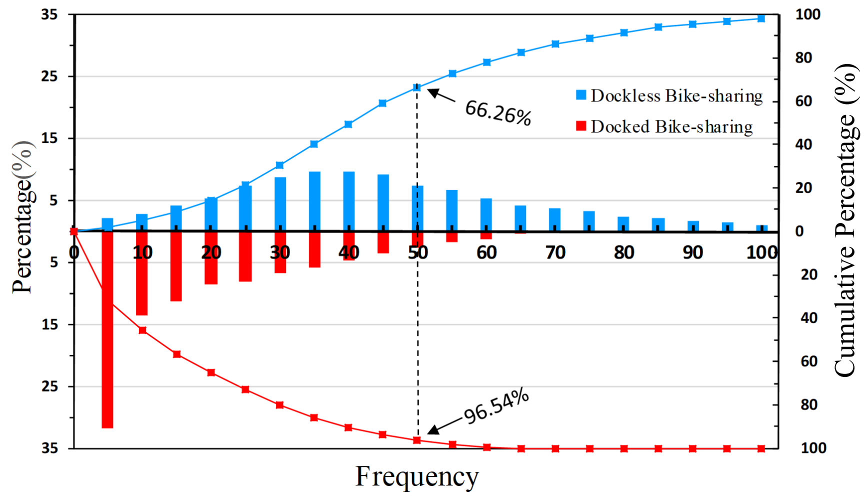
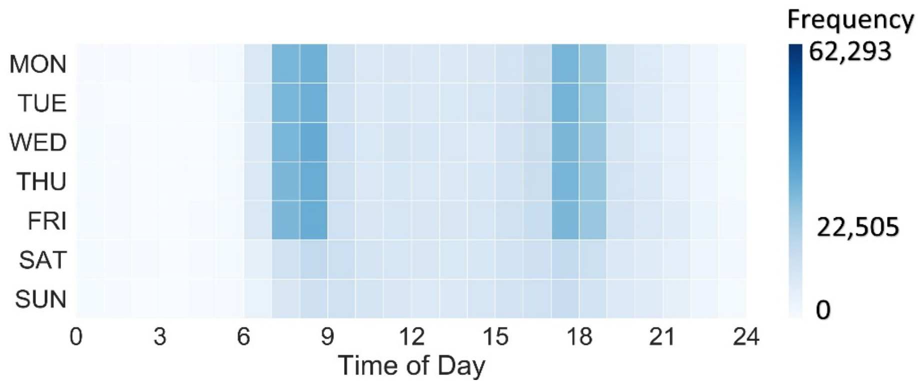


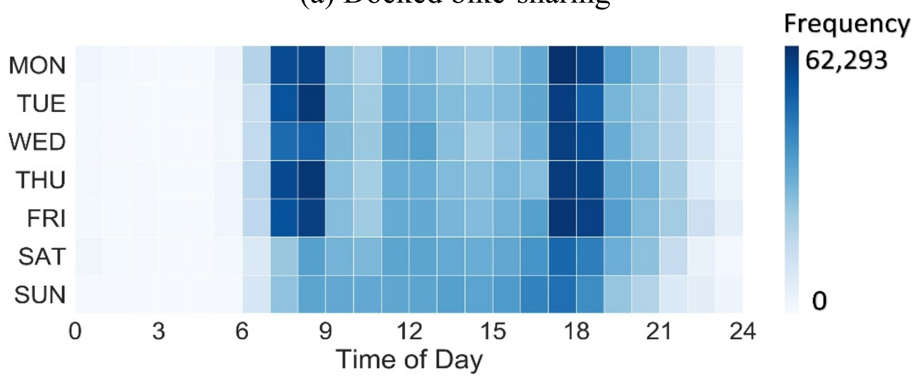
Fig. 4. Distribution of usage frequency of docked and dockless shared bikes.

5.1.3 Temporal usage pattern

Figure 5 compares the temporal patterns of docked and dockless bike-sharing. Darker color in the figure indicates a higher usage volume of shared bikes. In Figure 5 (a) and (b), the maximum hourly usage of docked bike-sharing is 22,505 (trips), which is much lower than 62,293 (trips) of dockless bike-sharing. One possible reason may be that, the total number of dockless shared bikes (146,505 as indicated in Section 3.1) is significantly larger than that of docked shared bikes (35,683 as indicated in Section 3.1) in the study area. In addition, dockless shared bikes are more efficient and flexible than docked bicycles. The daily distribution of bike-sharing trips during weekdays shows that both types of bike-sharing systems have a morning and afternoon peak usage periods, from Monday to Friday, which are 7:00-9:00 and 17:00-19:00, indicating that trips on weekdays are mainly commuting journeys, which is consistent with the previous research (Cai et al., 2019; Martin and Shaheen, 2014). In addition, during weekdays, a small peak of dockless bike-sharing is observed between 11:00 and 13:00, which may because some corporation employees ride for lunch near their workplaces. In contrast, docked bike-sharing cycling has no such a characteristic, which may because docked bike-sharing stations are generally a bit far away from working sites. Still, during off-peak hours, the number of docked bike-sharing users is lower than that of dockless bike-sharing users, which indicates that dockless bike-sharing not only facilitates daily commuting but also plays an important role in relation to other activities (e.g., leisure and social activities), perhaps due to their flexibility and availability in space and time (Chen et al., 2018; Wang et al., 2019). On weekends, there are no significant peak hours for both systems and the volume is significantly lower than that on weekdays. Compared to the docked one, dockless bike-sharing users did not show sharp decline on weekends, reaffirming the same finding in the previous literature (Kiana et al., 2019).



(a) Docked bike-sharing



(b) Dockless bike-sharing

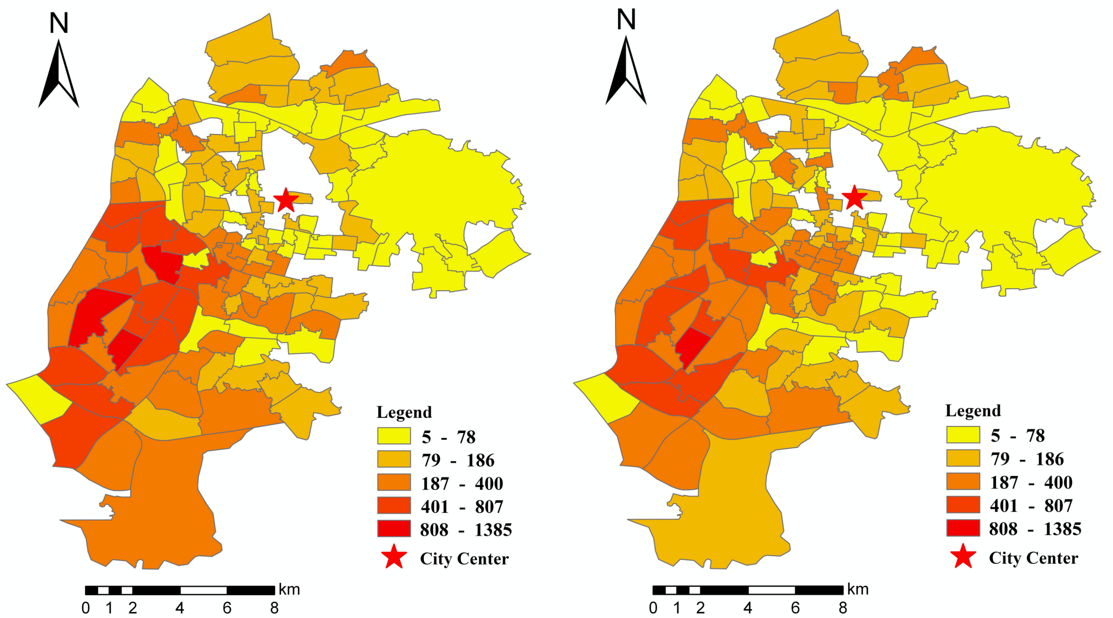
Fig. 5. Docked (a) and Dockless (b) bike-sharing usage with aggregation levels of 1 hour for dimension time and one calendar day for dimension date.

5.1.4 Spatial usage pattern

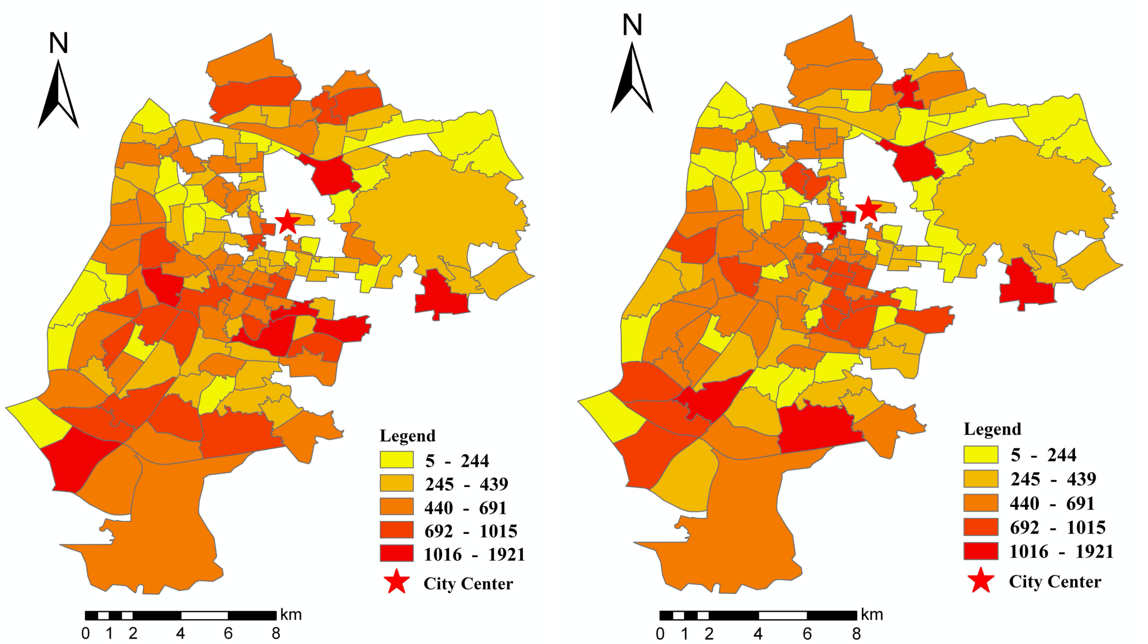
It can be seen from Section 5.1.3 that both bike-sharing systems have the highest demand during the morning and evening rush hours on weekdays. To make the difference obvious, the morning and afternoon peak hours on weekdays were chosen as the two representative time periods, as used in Kiana et al. (2019). Figure 6 visualizes the spatial distribution of average hourly bike-sharing usage in the peak hours on weekdays based on traffic analysis zone (TAZ), as Xu et al. (2018) used.

In general, the average hourly cumulative usage of dockless bike-sharing is much higher than the docked one. The main reasons can be found in the previous analysis in Section 5.1.2 and Section 5.1.3. More shared bikes are used during morning peak hours than afternoon peak hours for both dockless and docked bike-sharing. This is reasonable because during morning rush hours, travelers are more likely to choose shared bikes to avoid traffic jams and save travel time. Whereas people usually travel for multiple purposes with enough travel time during afternoon peak hours.

Figure 6 shows that both docked and dockless bike-sharing usage remains at a high level in the northern and southern suburban. The main reason is that there is a large demand of commuters who live in the suburban area and use both docked and dockless bike-sharing for accessing/egressing trips. In the northeast, where many national-level scenic spots are located, the supply of both kinds of bike-sharing is low due to the challenging topography for cycling. There is little use for docked bike-sharing in this area. As for the dockless bike-sharing, some trips generated in the area. It can be explained that commuters who work in this area will use the dockless bike-sharing due to the advantages of free registration and flexibility (Li and Tang, 2019). In the center, dockless bike-sharing is more popular than docked bike-sharing because of the larger supply of dockless shared bikes and their flexibility, convenience, and door-to-door services (Li et al., 2018). Docked bike-sharing usage concentrates in the center-west, which is consistent with the development features of this area. This area is a newly built area with well-designed bike infrastructure and public transport system, particularly the docked bike-sharing system.



(a) Docked bike-sharing usage during morning peak hour (b) Docked bike-sharing usage during afternoon peak hour



(c) Dockless bike-sharing usage during morning peak hours (d) Dockless bike-sharing usage during afternoon peak hours

Fig. 6. Spatial distribution of the average docked and dockless bike-sharing usage
(Note: As the usage volume of dockless bike-sharing is much more than docked bike-sharing, the Legend is not unified.)

5.2 GTWR model results

This section firstly proves that the GTWR model outperforms the other two counterpart models (OLS and GWR) when explaining the spatiotemporal data, and then the GTWR model results are illustrated by analyzing the influence of the bike-sharing fleets, socio-demographic factors and land use factors on user demand of docked and dockless bike-sharing over space and time.

5.2.1 Model comparison

To avoid multicollinearity between explanatory variables, VIF indicators of explanatory variables are calculated and variables with VIF greater than 10 are eliminated. The results of VIF values of significant explanatory variables are given in Table A2 (for the docked system) and Table A3 (for the dockless system) in the Appendix. Additionally, Moran's I statistics were conducted for determining if the significant explanatory variables in Table A2 and Table A3 are spatially associated (Bao et al., 2017b; Cardozo et al., 2012; Calvo et al., 2019; Pan et al. 2020). The results of the Moran's I tests are given in A3 in the Appendix. Variables with a *p-value* below 0.05 are included in the regression models, indicating that all the chosen variables are spatially autocorrelated.

After the test of the multicollinearity and spatial autocorrelation, a comparison with two traditional models (OLS and GWR) was conducted to observe the performance of the GTWR model on the same dataset. As shown in Table 4, GTWR outperforms OLS and GWR in terms of model fit, indicating that GTWR better explained the spatiotemporal data. Taking the docked bike-sharing model for weekday as an example, R^2 values increase from 0.799 in the OLS model and 0.885 in the GWR model, to 0.911 in the GTWR model. The AICc values reduce from 8107.49 in the OLS and 6571.23 in the GWR model, to 6114.31 in the GTWR model. The explanatory power increases significantly given that spatial information and temporal information are considered in the model. In the rest of the paper, we will only analyze the results from the GTWR model.

Table 4 Comparison results of OLS, GWR, and GTWR models.

	Docked bike-sharing				**Dockless bike-sharing**			
	Weekday		**Weekend**		**Weekday**		**Weekend**	
	AICc	**R^2**	**AICc**	**R^2**	**AICc**	**R^2**	**AICc**	**R^2**
OLS	8107.49	0.799	7417.88	0.783	7745.08	0.761	7636.79	0.751
GWR	6571.23	0.885	5764.15	0.880	6123.75	0.866	6337.09	0.846
GTWR	6114.31	0.911	5375.38	0.905	5304.54	0.908	5527.12	0.895

The estimation of the GTWR models for docked and dockless bike-sharing are given in Table A5 and A6 in the Appendix. The model results share some similarities with other findings from previous work, for instance, the positive effect of male proportion on docked bike-sharing (Ji et al., 2016), the negative effect of bus station density on docked bike-sharing usage (Zhao et al., 2017), the positive effect of road density on dockless bike-sharing (Chen et al., 2018), the positive effect of distance to the CBD on dockless bike-sharing (Shen et al., 2018) and the negative effect of individual motorized modal share on both docked and dockless bike-sharing usage (Audikana et al., 2017). In addition, the study also reveals some new insights, for instance, the negative effect of non-local proportion on dockless bike-sharing usage and the positive effect of housing prices on docked bike-sharing.

In next section, we have decided to analyze the temporal and spatial variation of several key variables using their average values, including hourly docked bike-sharing trips, hourly dockless bike-sharing trips, the density of Entertainment POIs for both docked and dockless bike-sharing (land use variables), proportion of the elderly for both docked and dockless bike-sharing (socio-demographic variables). These selected variables cover the three categories of explanatory variables (see Table 4), and their associations with the user demand of two types of bike-sharing are not fully revealed in previous studies. For the brevity of the analysis, the other variables in the models will not be discussed in detail in this work.

5.2.2 Temporal features of variable coefficients

The aforementioned improvement of GTWR is extended by incorporating the temporal dimension into the traditional GWR model. From the GTWR model results, we can obtain the time series of the hourly coefficient over time. Figure 7 presents the fluctuation of average coefficients of explanatory variables over time of a day. The negative coefficients indicate the reverse correlation between the dependent and explanatory variables and vice versa. The solid line represents weekday, and the dashed line represents weekend.

Bike-sharing fleet for each other: As Figure 7 (a) and (b) show, hourly docked bike-sharing trips and dockless bike-share trips effect each other throughout the week in Nanjing. This is in line with the finding of Gu et al. (2019). They concluded that in Hangzhou and Zhuzhou, China, the usage rate of docked bike-sharing kept increasing along with the high dockless bike-sharing penetration. However, Li et al. (2019c) found that the majority of docked bike-sharing trips were replaced by the dockless bike-sharing trips in London, because dockless shared bikes were cheaper than docked shared bikes for short trips for casual users. This situation is different from Nanjing, where the docked bike-sharing can be used for free of charge within the first two hours. The positive effects on the usage at weekdays are generally larger than those of weekends. A likely reason for this is that both docked and dockless bikes are mainly used for commuting on weekdays and the demand on weekdays is much higher than that on weekends (see the temporal usage pattern as revealed in Section 5.1.3).

The positive effect of docked bike-sharing trips on dockless bike-sharing in the morning is larger than that in the afternoon (see Figure 7 (a)). The reason can be explained as follows. Low convenience has been identified as a major cause of low docked bike-sharing performance (Fishman, 2014; Fishman et al., 2012; Fishman et al., 2014). Docked bike-sharing users complain that docks are often unavailable when they want to return bikes, or there are no available bikes when users want to rent them (Ji et al., 2016). Thus, dockless bike-sharing could supplement docked bike-sharing, especially during morning peak hour. In this period, people have limited tolerance time, so dockless sharing bikes help them free from the trouble of getting docking bikes, especially when the docks are far from their destinations (Buehler et al., 2019; Li and Tang, 2019). Both types of bike-sharing systems can work together to reduce the pressure of commuting for short distances or through the integration with public transport (Chen et al., 2018). In the afternoon, dockless bike-sharing has larger positive effects on docked bike-sharing (see Figure 7 (b)). The reason can be explained as follows. The redistribution of shared bikes across the network using a fleet of vehicle(s) is known as bike-sharing rebalancing. Static rebalancing usually happened at night, in which the intervention by bike-sharing users is negligible. If user intervention is considered, it is regarded as dynamic rebalancing (Pal and Zhang, 2017). Both static and dynamic rebalancing strategies are proposed for meeting the morning usage demand. However, only dynamic rebalancing schemes are used for the docked bike-sharing usage demand in the afternoon, this leads to serious docked bike-sharing rebalancing problems in the afternoon. For this, dockless bike-sharing can be a supplement choice. Interestingly, dockless bike-sharing promoting docked bike-sharing usage decreases after 20:00 (see Figure 7 (b)).

Density of Entertainment POIs for both systems: The density of Entertainment POIs has a positive association with the usage of dockless bike-sharing (see Figure 7 (c)), but a negative association with docked bike-sharing usage (see Figure 7 (d)). This may be because docked sharing bikes have to be returned to stations, which reduces their flexibility and applicability compared with dockless bike-sharing (Gu et al., 2019; Li et al., 2019a). Entertainment POIs encourage dockless bike-sharing usage for working purpose most significantly at 8:00 on weekdays, also the effects of the density of Entertainment POIs on the dockless bike-sharing usage for entertainment activities increase after 14:00 both on weekdays and weekends (see Figure 7 (c)). This is consistent with the findings of studies (Chen et al., 2018; Wang et al., 2019; Wang et al., 2018). They found that dockless bike-sharing usage is more leisure-related during the afternoon, especially at weekends. For docked bike-sharing, the influential patterns of the density of Entertainment POIs are similar on weekdays and weekends (see Figure 7 (d)). The negative peak values appear during early morning, and in the evening, when people seldom use docked bike-sharing for entertainment activities (see Figure 7 (d)).

The proportion of the elderly for both systems: The proportion of the elderly is negatively associated with the usage of dockless bike-sharing (see Figure 7 (e)) while positively associated with the usage of docked bike-sharing (see Figure 7 (f)). Its effects on the usage of both bike-sharing systems are greater on weekdays than on weekends. This conclusion is consistent with the previous findings (Buehler et al., 2019; Chen et al., 2018; Li and Tang, 2019; Li et al., 2019a). Dockless bikeshare, which requires phone-registration and unlocking, is quite popular among young people who are inclined to embrace new innovations and are more familiar with smart phone and social media (Gu et al., 2019). However, the elderly are generally insensitive to and less interested in technological innovations and thus they are more willing to use docked bike-sharing by smart card (Li et al., 2019a). This result is probably caused by three reasons: 1) Dockless bike-sharing requires users to download mobile phone App and need to pay a refundable deposit through the mobile online payment system (Alipay and Wechat payment service). After the registration is verified, users need to scan the QR code to unlock the bike and start riding. This is complex for most old people (Gu et al., 2019); 2) Riding a dockless shared bike costs $0.14 or 0.28 (1 or 2 CNY) per hour, which is relatively expensive for retirees. However, riding docked sharing bike within the first two hours in Nanjing is free of charge (Ji et al., 2016). In addition, older people need longer cycling time than youngsters because of weaker physical conditions. Thus docked bike-sharing is more suitable for the elderly due to the two-hour free usage time; 3) Compared with the heavy weight of dockless bikes (25kg per Mobike) (Gu et al., 2019), and high damage rate (Li et al., 2019a), good quality of docked bikes and regular bike maintenance are seen as the main motivations for the elder users (Li and Tang, 2019). The coefficient peaks at 6:00 in the morning. The possible reason for this may be that the elderly would regularly use the docked bike-sharing for exercises in parks or squares near their places of residence (see Figure 7 (f)). Woodcock et al. (2014) concluded that cycling is regarded as a healthy travel mode for the elderly. Leden (2010) also found in a survey study that 94% of the elderly ride bikes for exercising. The coefficient increases after 14:00. We suspect that the elderly may ride the docked bikes for visiting friends or shopping (see Figure 7 (f)).

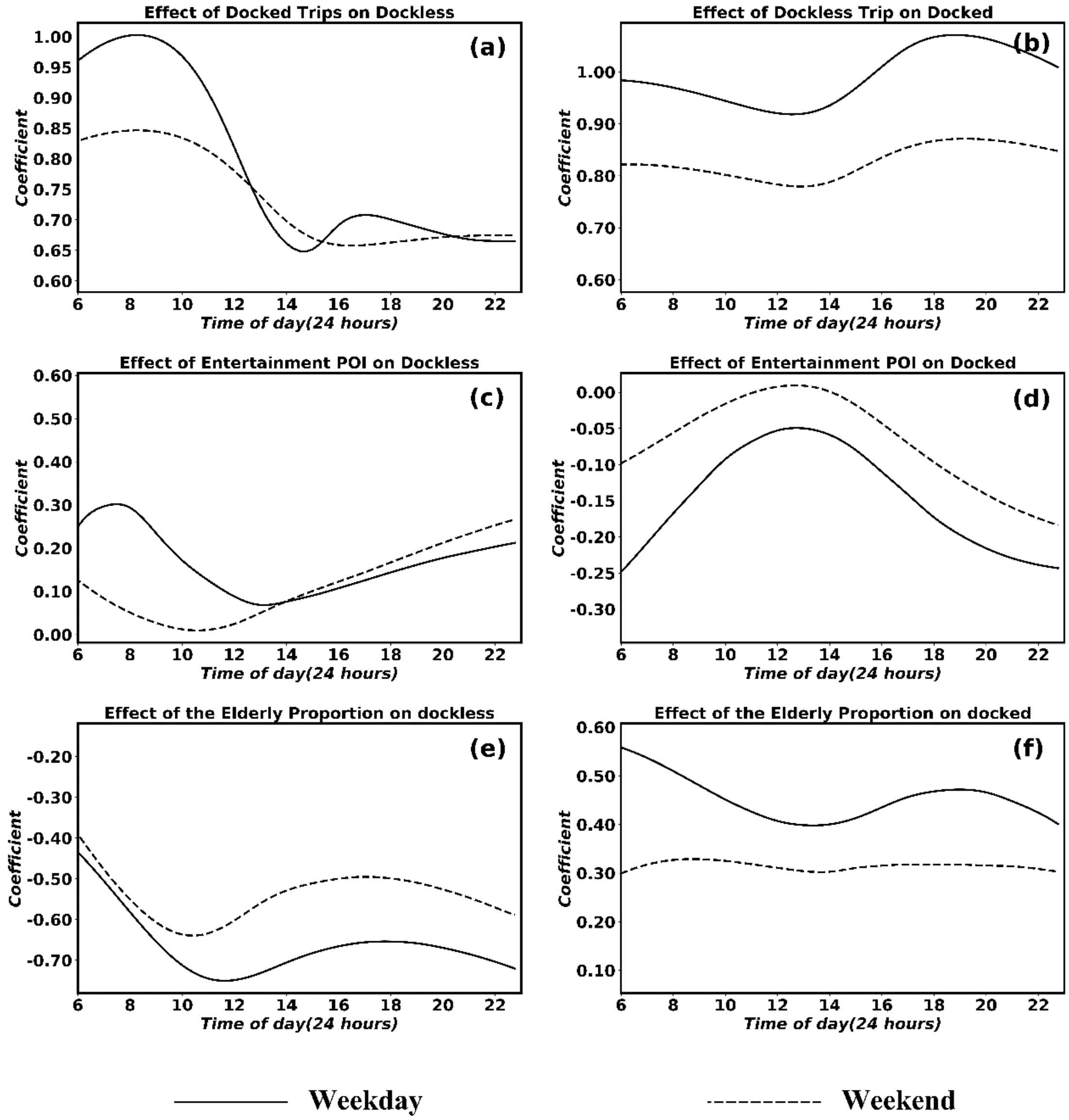
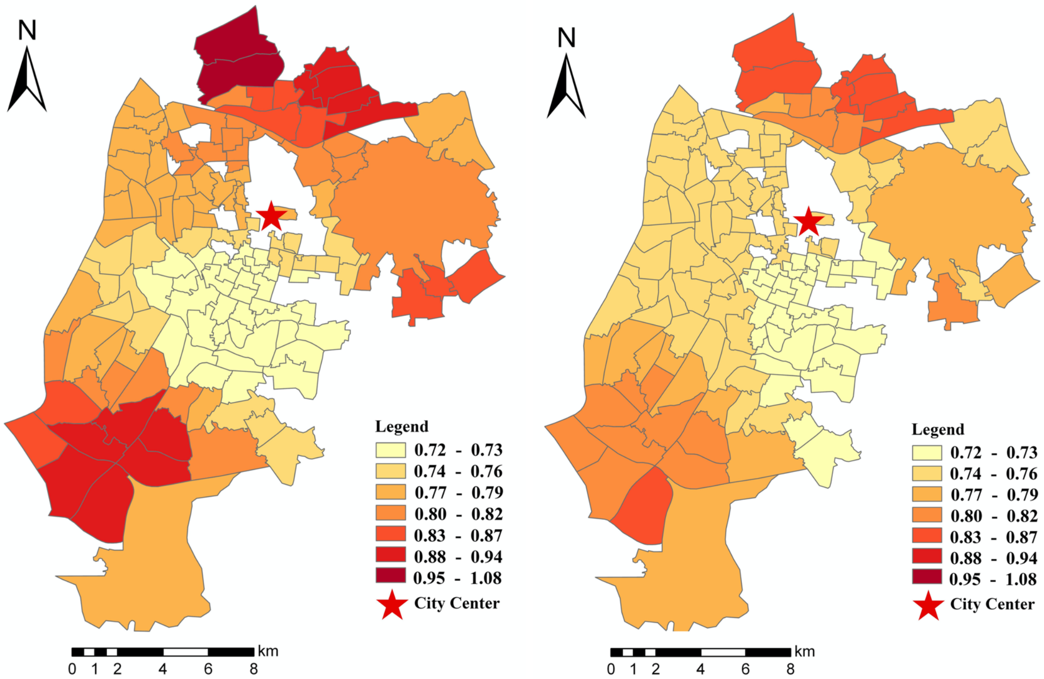


Fig. 7. Temporal distribution of average coefficients of the explanatory variables.

5.2.3 Spatial feature of variable coefficients

One important feature of GWR-based models is that the estimated coefficients are mappable for visual analysis. The spatial distributions of the effects of explanatory variables on weekdays and weekends are visualized in Figures 8-11. This study sets zero as a threshold to distinguish the positive and negative effects.

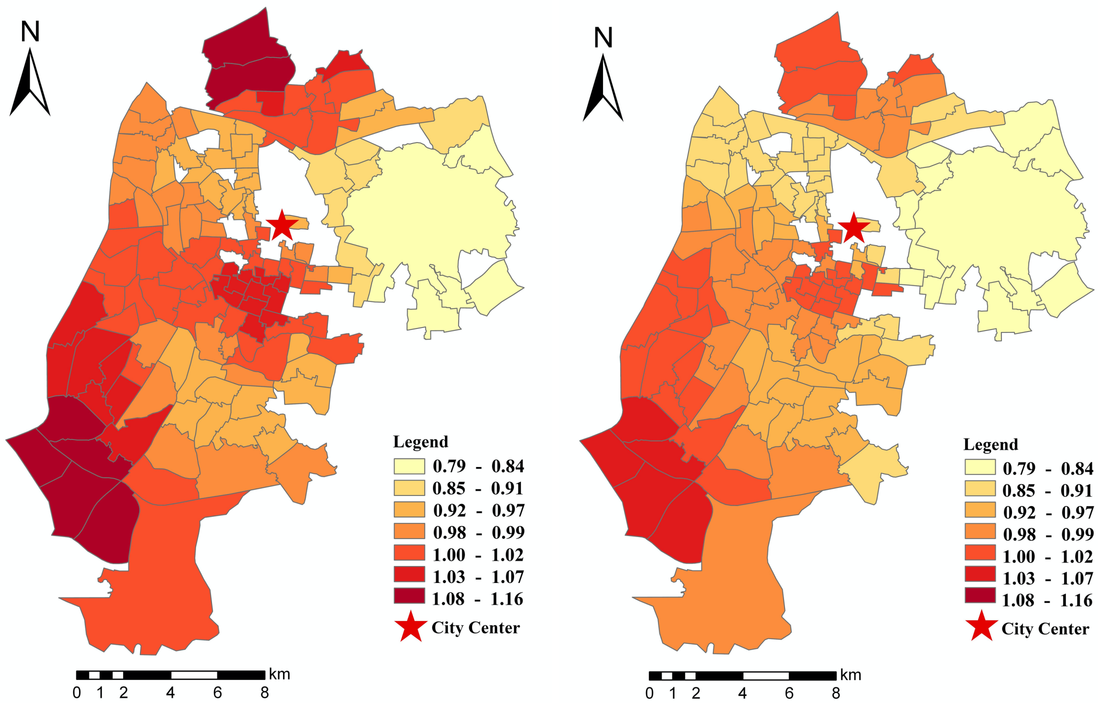
The effect of docked bike-sharing on dockless bike-sharing: as discussed in Section 5.2.2, hourly docked bike-sharing trips are positively associated with dockless bike-sharing usage throughout the week. The coefficient peaks in the northern and southern suburban (Figure 8). In these areas, dockless bike-sharing takes advantages of much spare public space for launching dockless shared bikes. Docked bike-sharing users in suburban area will shift to dockless bike-sharing when the docked shared bikes are can be found. The positive effects are smaller in the center due to high density of road and metro/bus stations and heavy on-road traffic, and people have other travel mode alternatives. (Gu et al., 2019; Ji et al., 2018; Shaheen and Cohen, 2019). In addition, the effects on weekdays are greater than on weekends, which is in line with the high usage for commuting feature of bike-sharing system (Buehler et al., 2019; Shaheen et al., 2012).



(a) Hourly Docked bike-sharing trips for dockless (Weekday) (b) Hourly Docked bike-sharing trips for dockless (Weekend)

Fig. 8. Spatial distribution of the average coefficients of hourly docked bike-sharing trips in the GTWR model for dockless bike user demand.

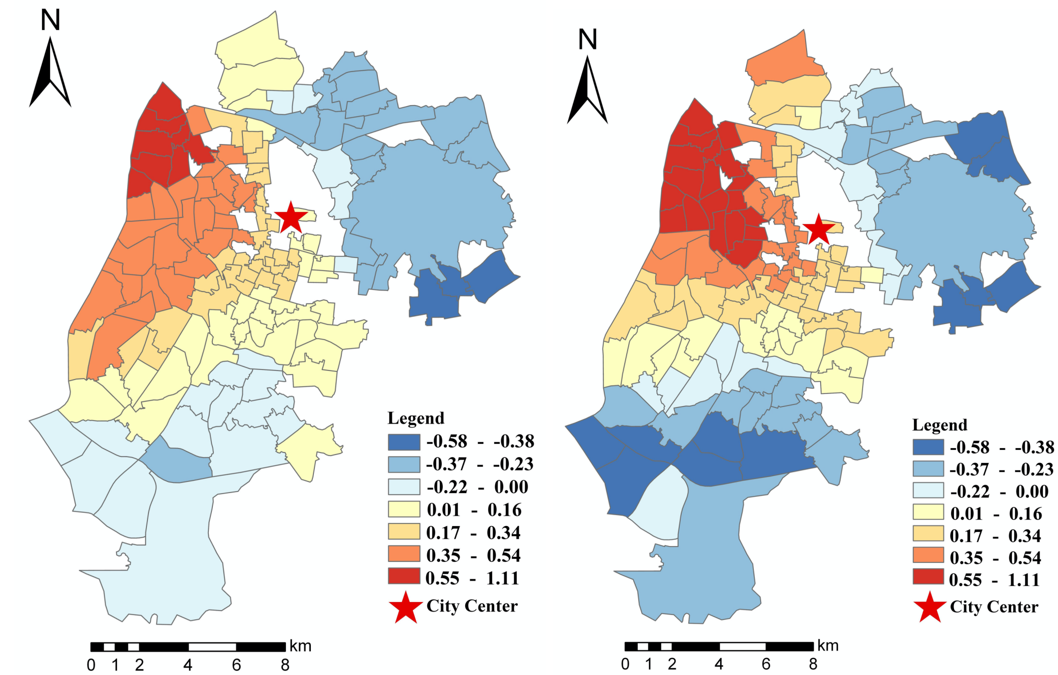
The effect of dockless bike-sharing on docked bike-sharing: as shown in Figure 9, dockless bike-sharing has positively associated with the usage of docked bike-sharing on both weekdays and on weekends. This positive effect is most evident in the northern and southern suburban. Both docked and dockless bike-sharing play important roles in integrating with public transport, especially for commuting purpose on weekdays in suburban areas (Li et al., 2019b; Ma et al., 2018a; Yang et al., 2016). Because of the popularity of dockless bike-sharing, many people who ignored docked bike-sharing before gradually start to accept docked bike-sharing. Different from the influence of docked bike-sharing on dockless bike-sharing, dockless bike-sharing has a stronger impact on docked bike-sharing in the center, while a smaller impact in the northeast. The docking stations of docked bike-sharing systems in the center are dense, so users can borrow and return bikes more easily for short-distance travels and for transferring to public transport. This result is consistent with the result of Chen et al. (2018), who found that it is most difficult to find car parking places in crowded city center, so users are likely to turn to docked bike-sharing for easier usage. On the contrary, the docking stations in the northeast are not as densely arranged as in downtown and the terrain in this area is not attractive for cycling (Li et al., 2019a). Therefore, the positive effect of dockless bike-sharing on docked bike-sharing is not significant. In all, dockless bike-sharing brings greater benefits in the areas with higher density of docking station and good accessibility.



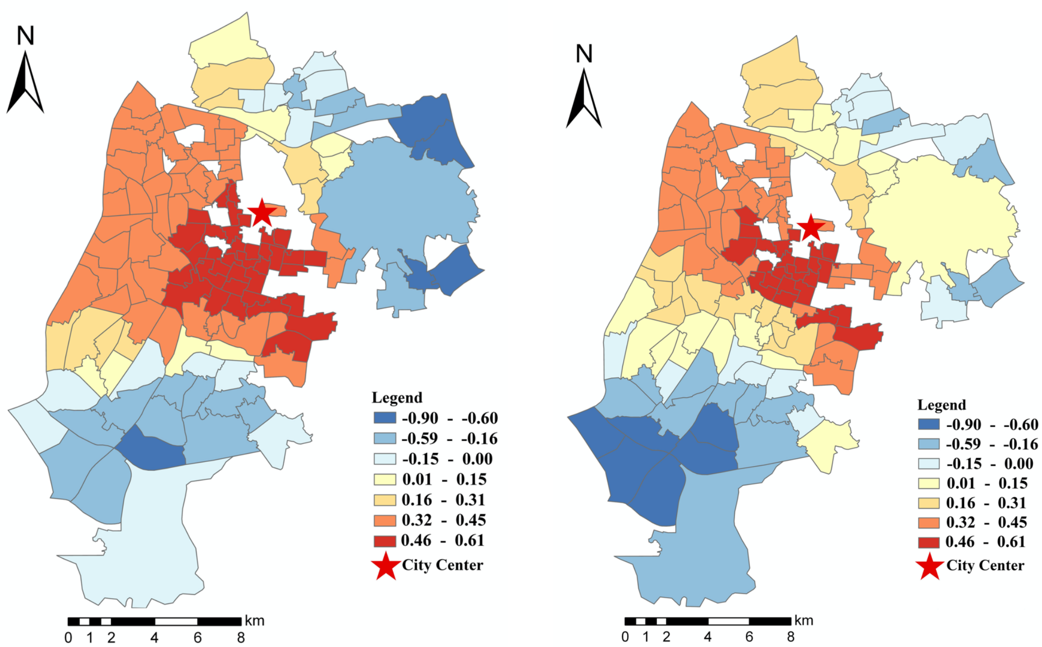
(a) Hourly Dockless bike-sharing trips (Weekday) (b) Hourly Dockless bike-sharing trips (Weekend)

Fig. 9. Spatial distribution of the average coefficients of hourly dockless bike-sharing trips in the GTWR model for docked bike user demand.

Density of Entertainment POIs for both systems: the spatial effect of the density of Entertainment POIs on docked and dockless bike-sharing is similar in the northern and southern suburban in Figure 10. The negative effect may be explained by that there are fewer cycling facilities in the suburbs than in the city center and that suburban roads are mainly built for motorized vehicles while local metro lines do not access to most large-scale entertainment sites (Ji et al., 2018; Zhao and Li, 2017). Another reason could be that both docked and dockless bike-sharing schemes in suburban areas are not as popular and convenient as those in urban areas (Li et al., 2017). As a result, people have to travel to entertainment sites by car or taxi instead of by shared bikes. In the center, Entertainment POIs encourage the usage of both docked and dockless bike-sharing. This is because the land is highly mixed-used in the center and most major shopping centers are established here. Travelers who prefer convenient and time-saving travel modes are more likely to choose dockless bike-sharing to reach entertainment destinations (Li et al., 2017). Specifically, the density of Entertainment POIs has a stronger positive effect on dockless bike-sharing than on docked bike-sharing in the center. This is reasonable because dockless shared bikes have a larger number of available bikes and do not have to be docked at stations. The density of Entertainment POIs is negatively associated with the user demand of both systems in the northeast, except for dockless bike-sharing at weekends. This is because that the bus service is relatively limited in this scenic area. On weekends, people (especially non-local tourists) prefer riding dockless bike-sharing to walking or taking a bus or taxi, mainly because they can use dockless shared bikes with their phone and return the bikes wherever they like within the parking area, although the terrain is not conducive to biking.



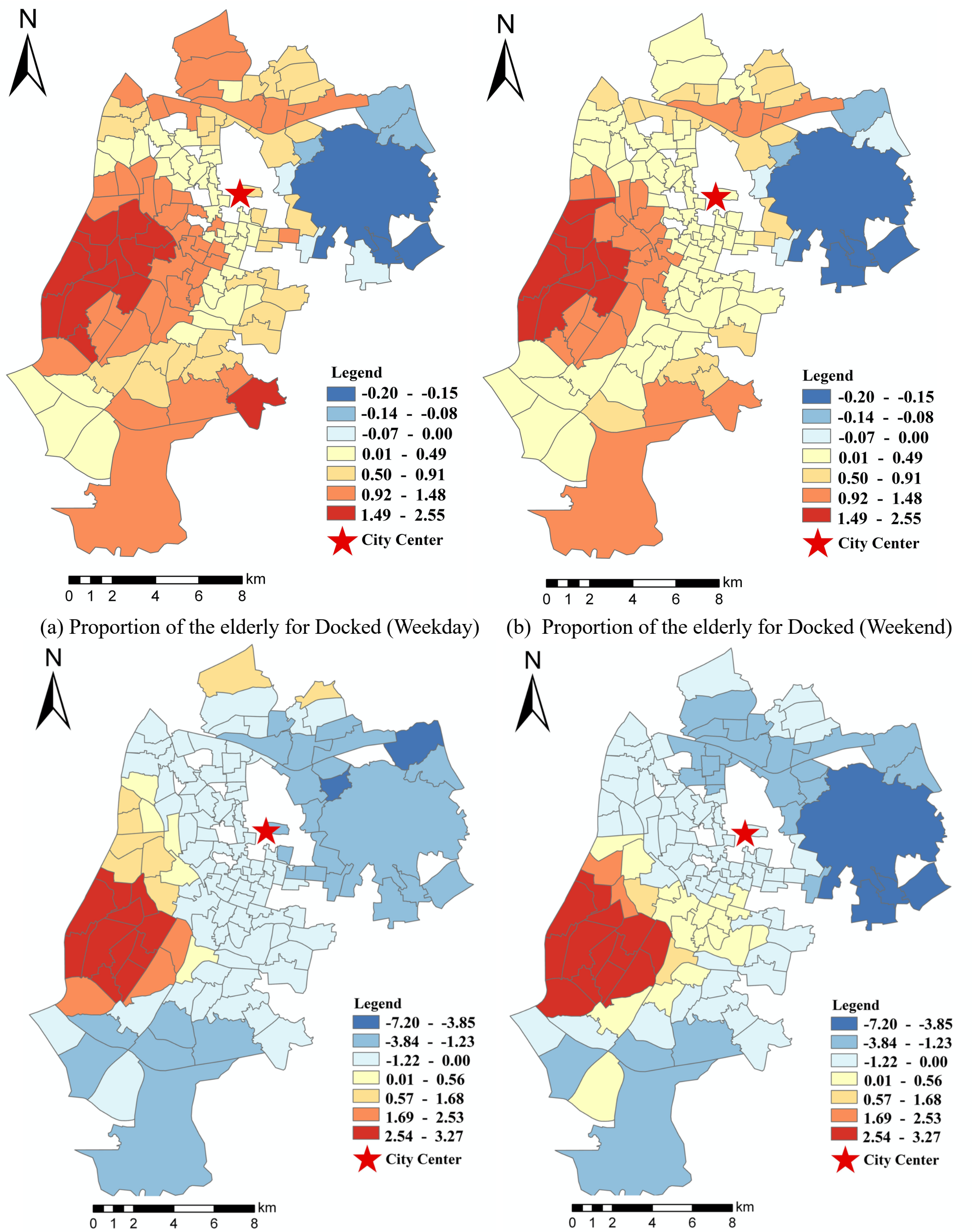
(a) Density of Entertainment POIs for Docked (Weekday) (b) Density of Entertainment POIs for Docked (Weekend)



(c) Density of Entertainment POIs for Dockless (Weekday) (d) Density of Entertainment POIs for Dockless (Weekend)

Fig. 10. Spatial distribution of the average coefficients of Entertainment POIs.

The proportion of the elderly for both systems: the proportion of the elderly is positively correlated with the docked bike-sharing usage, except for in the northeast (see Figure 11 (a) and (b)). For dockless bike-sharing, the proportion of the elderly is negatively associated with usage of dockless bike-sharing, except for in the center-west (see Figure 11 (c) and (d)). In this area, both docked and dockless bike-sharing are popular among the elderly people, which is consistent with the development features of this area. In 2013, this area launched the first docked bike-sharing system in Nanjing. One year later, it witnessed over 95% of the city's docked bike-sharing trips, with the average daily usage of the docked bikes significantly higher than that in other districts (Ji et al., 2016). The stable performance of docked bike-sharing makes the concept of sharing mobility popular among the elderly and helps them develop the habit of riding shared bikes. In light of this, elder people are willing to try the dockless bike-sharing. They may use both docked and dockless bike-sharing for short-distance trips, transferring to public transport, or for physical exercises because of good riding conditions in this area. In the northeast, the effects on the usage are negative due to the challenging topography for cycling.



(a) Proportion of the elderly for Docked (Weekday) (b) Proportion of the elderly for Docked (Weekend)

(c) Proportion of the elderly for Dockless (Weekday) (d) Proportion of the elderly for Dockless (Weekend)

Fig. 11. Spatial distribution of the average coefficients of the proportion of the elderly users

6. Conclusions and recommendations

This section firstly summarizes the main findings of this paper. Next, recommendations are proposed to improve bike-sharing services. Finally, limitations and suggestions for future research are presented.

6.1 Findings and conclusions

The co-existence of docked and dockless bike-sharing systems provides new opportunities for supplementing sustainable transportation modes. In order to provide better bike-sharing services, it is necessary to compare and comprehend the travel characteristics and influential factors between docked and dockless bike-sharing systems. This study is one of the pioneers to compare the usage patterns and the determinants of both systems using multi-sourced data. The results of this analysis yield policy and planning recommendations to help operators/providers of both bike-sharing systems to improve their operations.

To compare travel patterns of these two systems, this paper first compares the travel characteristics, including travel distance, travel time, usage frequency and spatio-temporal travel patterns by exploring the smart card data from a docked bike-sharing scheme and the trip OD data from a dockless bike-sharing scheme in the city of Nanjing, China over the same time period. By mining the historical trip data, travel patterns including travel distance, travel time, usage frequency and spatio-temporal usage pattern for both systems have been compared. Next, OLS, GWR and GTWR models are built to examine the influence of the bike-sharing fleets, socio-demographic factors and land use factors on the user demand of the two systems over space and time. As the GTWR model can simultaneously incorporate spatial and temporal heterogeneity of a system, the GTWR outperforms the traditional OLS and GWR models significantly in terms of model fit. In addition, the spatial and temporal variations of coefficients are visualized and analyzed. Results show that hourly docked bike-sharing trips and dockless bike-share trips are positively associated with each other throughout the week. The density of Entertainment POIs is positively corelated with the usage of dockless bike-sharing, but impedes docked bike-sharing usage. On the contrary, the proportion of the elderly promotes the usage of docked bike-sharing while hinders the usage of dockless bike-sharing.

6.2 Policy implications

The findings yield important policy implications for government agencies, docked and dockless bike-sharing companies to improve bike-sharing services, especially in the context of cities where both docked and dockless bike-sharing are heavily invested, and consequently, improve the city service quality and liveability. The main implications are given as follows:

1) Improving docked bike-sharing service

1.1) Designing and promoting a mobile App for docked bikes-haring

As Wu and Xue (2017) pointed out, the complex registration procedure and the need for deposit hinder high-rate adoption of docked bike-sharing service, especially for tourists. It is recommended that a mobile App should be designed to simplify the registration process and a “no-deposit” strategy could be considered to attract users like youths and tourists. Currently, smart-phone applications linking to citizen identity cards have been developed for docked bike-sharing system in Nanjing so that users can rent bikes from either their card or the dedicated App. However, it still cannot satisfy the demand during peak hours due to limited mobile App related docking stations. It is necessary to expand the App-based docked bike-sharing system to cover all docking stations.

1.2） Increasing the flexibility of docked bike-sharing

Docked shared bikes can only be borrowed and returned at fixed stations. This inconvenience has been regarded as a major barrier for docked bike-sharing (Fishman et al., 2014). In order to improve its flexibility, it is suggested that the electric fence parking area (Zhang & Mi, 2018) and/or locks for docked bike-sharing could be introduced.

1.3） Increasing number of docking stations in suburban areas

Docked bike-sharing is popular among commuters in suburban areas. They would need to walk a long time or wait for a long time for a bus to access/egress metros without using docked bike-sharing. To replace car/bus with share-bike in last/first mile trips and reduce high transportation costs, it is necessary to build more docking stations near metro stations and residential areas in suburban areas.

2) Improving the dockless bike-sharing service

2.1） Establishing maintenance service for dockless bikes

As docked bike-sharing are managed and maintained by governments, docked bike-sharing users are usually satisfied with the quality and they ride comfortably (Li and Tang, 2019). However, for dockless bike-sharing system, the maintenance of bikes is one of the biggest problems because the profit-orient companies cut down the maintenance and management costs and leave broken bikes to users. (Chen et al., 2018). Encountering bike malfunctions will reduce user satisfaction and thus the loyalty to dockless bike-sharing (Ma et al., 2019). Therefore, it is necessary to improve the quality of dockless shared bikes and strengthen their maintenance mechanism. Meanwhile, an effective mechanism for supervision and complaint feedback could be established to improve dockless bike-sharing service. In addition, dockless bike-sharing companies could install lighting devices to improve the safety performance of their bikes for riding at night (dockless bike-sharing usage is observed at night in Figure 5.

2.2） Implementing price-related strategies to adjust users' travel behavior

It has been revealed that discount scheme manages to attract dockless bike-sharing users (Li et al., 2019a). Dockless bike-sharing companies can design price strategies to adjust users' travel behaviors. For instance, they can provide discounts for regular users to maintain their loyalty to dockless bike-sharing system. They can encourage users to participate in the rebalancing process through incentive policies. In order to make the dockless bike-sharing friendlier to elderly population groups, they could also develop specialized mobile App and offer discounted deposit and rental price to the elderly groups. More meaningfully, they can design a dynamic time-based pricing system to ease transaction floods during peak hours.

2.3） Launching more dockless bikes near Entertainment POIs and tourist spots

Entertainment POIs promote dockless bike-sharing usage in urban areas, especially during weekend afternoons, while it impedes its usage in suburban areas. It is suggested that dockless bike-sharing companies could launch more shared bikes near entertainment places in urban areas. The government could enhance the construction of public transport in suburban districts to improve the accessibility of some entertainment places and in turn to increase dockless bike-sharing demand. In addition, more dockless bike-sharing bikes should be launched in some tourist spots to promote their modal shift from taxi and car-sharing to dockless bike-sharing for short trips.

2.4） Education and design for the elderly

The limited use of dockless bike-sharing among the elderly is reasonable: the mobile phone based dockless bike-sharing system may not be friendly to the tech-insensitive elders (Gu et al., 2019). Social marketing campaigns and public education efforts that target the elderly might help them learn how to use dockless bike-sharing. Additionally, another challenge for the elderly is physical strength due to heavy bike weight of dockless shared bikes (25 kg for a Mobike for instance). It is necessary to design the old age-friendly bikes (e.g. lighter bike) to remove barriers of dockless bike-sharing use among elderly population groups.

6.3 Limitations and future research

This study has several limitations. First, only four coefficients of the GTWR models are chosen to reflect spatiotemporal characteristics of the bike-sharing systems due to the limitation of article length. More insights based on other coefficients could be expected. Second, the authors used only one dockless bike-sharing vendor data which provides somewhat of an incomplete picture of dockless usage patterns. Third, since the data used in this study only cover a one-week period, the variations of influential factors in time dimension for a higher aggregation level (such as weekly, monthly, seasonal or annual level) can be conducted if the data collected over months and years. Fourth, it is necessary to recognize the travel purpose among different user groups (e.g. gender, age cohort, commuter and non-commuters) over time (e.g. weekdays, weekends, morning and evening rush hours). This helps for better understanding the usage pattern of both docked and dockless bike-sharing systems. Additionally, this work could be extended by obtaining bike-sharing data and land use data from other cities to examine and cross-compare the difference in travel patterns and their influential factors. Further studies on the interaction between bike-sharing and public transport usage, rebalancing strategies of docked and dockless bike-sharing in a synergistic way and modal shift behavior from car to docked and dockless bike-sharing are necessary.

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Author contribution statement

The authors confirm contribution to the paper as follows: study conception and design: Xinwei Ma, Yufei Yuan and Niels van Oort; data collection: Yanjie Ji and Xinwei Ma; analysis and interpretation of results: Xinwei Ma, Yanjie Ji, Yuchuan Jin, Yufei Yuan and Niels van Oort; comment to draft manuscript: Yufei Yuan, Niels van Oort and Serge Hoogendoorn. All authors reviewed the results and approved the final version of the manuscript.

Declarations of interest: none

Appendix

Table A1. POIs data classification

Preliminary category	Secondary category	Tertiary category
Density of Cultural POIs	Culture services	Museums, libraries, cultural palaces, exhibition halls, arts galleries, etc.
	Media services	TV/broadcasting stations, newspaper office, magazine office, publishing houses, etc.
Density of Residential POIs	Residential area	Apartment buildings, communities, house estates etc.
	Accommodation services	Hotels, rest houses, youth hostels, serviced apartments, etc.
Density of Governmental POIs	Governmental services	Government offices, government-affiliated institutions, industrial & commercial tax authorities, etc.
Density of Entertainment POIs	Sports & leisure services	Gymnasiums, amusement parks, cinemas, karaoke, etc.
	Shopping & catering services	Clothing stores, supermarkets, restaurants, convenience stores, etc.
Density of Commercial/Industrial POIs	Companies & enterprises	Petrochemical/mining enterprises, manufacturing companies, commercial and trading companies, small service companies, etc.
	Financial services	Securities companies, insurance companies, banks, etc.
	Industries	Factories (metallurgical & chemical producing factories, mechanical & electronics producing factories, etc.)

Table A2. VIF values of significant explanatory variables of OLS model for docked bike-sharing

Variables	Weekday			Weekend		
	Coef.	*P-Value*	*VIF*	*Coef.*	*P-Value*	*VIF*
Dockless bike-sharing						
Hourly dockless bike-sharing trips	0.975	0.000	1.080	0.836	0.000	1.060
Land use variables						
Density of docked bike-sharing stations	0.590	0.000	2.430	0.628	0.000	2.840
Density of bus stations	-	-	-	0.149	0.000	3.090
Density of road	0.250	0.000	1.870	0.156	0.000	1.890
Distance to CBD	-	-	-	-0.100	0.010	3.540
Density of Cultural POIs	-0.202	0.000	7.370	-0.197	0.000	6.380
Density of Residential POIs	-0.187	0.000	5.740	-0.168	0.000	4.900
Density of Governmental POIs	0.171	0.000	4.320	0.133	0.000	4.310
Density of Entertainment POIs	-0.237	0.000	7.710	-0.133	0.000	7.470
Socio-demographic variables						
Housing Price	0.355	0.000	2.270	0.152	0.000	2.360

Proportion of Car ownership	0.250	0.000	2.890	0.217	0.000	3.040
Proportion of Private bike ownership	-0.353	0.000	2.340	-0.425	0.000	2.380
Proportion of Female	-2.180	0.000	1.900	-1.792	0.000	1.800
Proportion in population between 35 and 45 years old	0.169	0.017	2.660	0.127	0.042	2.660
Proportion in population between 45 and retirement age	-0.333	0.000	2.270	-0.287	0.000	1.760
Proportion of the elderly	0.599	0.000	2.620	0.438	0.000	2.520
Proportion of junior college or college	-0.415	0.016	2.880	-	-	-
Proportion of high-income level	-0.026	0.001	1.320	-0.046	0.000	1.320

Note: Insignificant variables of OLS model for docked bike-sharing are not included.
The sign “-” means insignificant variables for either weekday or weekend.

Table A3. VIF values of significant explanatory variables of OLS model for dockless bike-sharing

Variables	**Weekday**			**Weekend**		
	Coef.	***P-Value***	***VIF***	***Coef.***	***P-Value***	***VIF***
Docked bike-sharing trips						
Hourly docked bike-sharing trips	0.785	0.000	1.150	0.886	0.000	1.230
Land use variables						
Density of metro stations	-0.224	0.000	1.680	-0.109	0.006	1.920
Density of docked bike-sharing stations	-0.363	0.000	3.070	-0.493	0.000	3.240
Density of bus stations	-0.107	0.006	2.700	-0.170	0.000	3.070
Density of road	-0.152	0.001	1.920	-0.129	0.006	1.890
Distance to CBD	0.124	0.002	3.370	0.203	0.000	3.530
Density of Cultural POIs	0.321	0.000	5.690	0.299	0.000	7.270
Density of Residential POIs	0.202	0.000	4.180	0.286	0.000	4.910
Density of Governmental POIs	-0.099	0.000	3.850	-0.104	0.000	4.140
Density of Entertainment POIs	0.087	0.026	7.010	0.146	0.000	7.660
Density of Commercial/Industrial POIs	-	-	-	-0.098	0.010	7.380
Socio-demographic variables						
Housing Price	-0.703	0.000	1.980	-0.290	0.000	2.370
Proportion of Car ownership	-1.709	0.000	2.430	-2.352	0.000	2.750
Proportion of E-bike ownership	-2.265	0.000	1.840	-2.424	0.000	2.430
Density of Non-locals	-0.074	0.001	1.790	-0.065	0.003	1.820
Proportion in population under18 years old	-	-	-	-5.283	0.000	2.590
Proportion in population between 35 and 45 years old	-1.308	0.000	1.450	1.198	0.001	3.540
Proportion in population between 45 and retirement age	1.547	0.000	1.680	1.744	0.000	2.090
Proportion of the elderly	-1.493	0.000	2.170	-1.211	0.000	3.160
Proportion of senior high school or bellow	2.117	0.000	2.770	1.116	0.001	5.670
Proportion of junior college or college	-	-	-	-0.952	0.000	3.940
Proportion of middle-income level	0.821	0.000	2.290	1.063	0.000	2.630

Note: Insignificant variables of OLS model for dockless bike-sharing are not included.
The sign “-” means insignificant for either weekday or weekend.

Table A4. Moran's I test result for significant explanatory variables in Table A2 and Table A3

Variables	**Moran's I**	***Z-score***	***P-value***
Bike-sharing trips			
Hourly dockless bike-sharing trips on weekday	0.082	6.687	0.000
Hourly dockless bike-sharing trips on weekend	0.077	6.367	0.000
Hourly docked bike-sharing trips on weekday	0.021	2.194	0.028
Hourly docked bike-sharing trips on weekend	0.021	2.191	0.028
Land use variables			
Density of metro stations	0.117	9.617	0.000
Density of docked bike-sharing stations	0.125	10.023	0.000
Density of bus stations	0.159	12.484	0.000
Density of road	0.199	15.567	0.000
Distance to CBD	0.511	38.925	0.000
Density of Cultural POIs	0.303	23.341	0.000
Density of Residential POIs	0.261	20.123	0.000
Density of Governmental POIs	0.270	20.833	0.000
Density of Entertainment POIs	0.279	21.543	0.000
Density of Commercial/Industrial POIs	0.306	23.524	0.000
Socio-demographic variables			
Housing Price	0.029	3.007	0.003
Proportion of Car ownership	0.145	11.491	0.000
Proportion of Private bike ownership	0.119	9.605	0.000
Proportion of E-bike ownership	0.045	4.047	0.000
Density of Non-locals	0.182	14.279	0.000
Proportion of Female	0.022	2.389	0.017
Proportion of the elderly	0.089	7.349	0.000
Proportion of senior high school or bellow	0.042	3.747	0.000
Proportion of junior college or college	0.038	3.599	0.000
Proportion of middle-income level	0.030	2.864	0.004
*Proportion of high-income level	0.008	1.207	**0.227**
*Proportion in population under18 years old	-0.005	0.229	**0.819**
*Proportion in population between 35 and 45 years old	-0.010	-0.182	**0.855**
*Proportion in population between 45 and retirement age	-0.009	-0.056	**0.956**

* explanatory variables with *p-value* larger than 0.05 not included in the GTWR models

Tables A5 and A6 show several characteristic values of the estimated coefficients of GTWR models to describe the influential extent of each variable for weekday and weekend respectively. In this study, six statistics, namely, minimum value (MIN), lower quartile (LQ), median (MED), upper quartile (UQ), maximum value (MAX) and average value (AVG) are selected.

Table A5. Estimation of the GTWR model for docked bike-sharing.

	Min	**LQ**	**MED**	**UQ**	**MAX**	**AVG**
Weekday						
Dockless bike-sharing						
Hourly dockless bike-sharing trips	0.535	0.934	0.988	1.057	1.311	0.990
Land use variables						
Density of docked bike-sharing stations	-0.495	0.351	0.551	0.705	1.734	0.555
Density of road	-1.674	-0.060	0.244	0.358	0.692	0.079
Density of Cultural POIs	-1.094	-0.301	-0.043	0.190	1.370	-0.053

Density of Residential POIs	-1.236	-0.309	-0.065	0.075	0.369	-0.130
Density of Governmental POIs	-0.896	0.006	0.168	0.283	0.625	0.130
Density of Entertainment POIs	-0.997	-0.476	-0.243	0.045	1.446	-0.189
Socio-demographic variables						
Housing Prices	-3.564	0.194	0.424	0.649	1.628	0.395
Proportion of Car ownership	-1.685	-0.033	0.119	0.289	1.105	0.116
Proportion of Private bike ownership	-4.043	-0.703	-0.502	-0.260	1.422	-0.520
Proportion of Female	-12.227	-1.554	-0.642	0.044	3.441	-0.888
Proportion of the elderly	-0.449	0.116	0.381	0.731	2.861	0.495
Proportion of junior college or college	-3.514	-0.825	-0.204	0.399	2.906	-0.249
Intercept	-10.082	-4.411	-2.656	-0.943	13.367	-2.662
Weekend						
Dockless bike-sharing						
Hourly dockless bike-sharing trips	0.326	0.764	0.823	0.862	1.115	0.803
Land use variables						
Density of docked bike-sharing stations	-0.938	0.457	0.655	0.768	2.136	0.634
Density of bus stations	-0.460	-0.106	0.028	0.208	0.996	0.069
Density of road	-1.436	-0.008	0.165	0.276	0.783	0.089
TAZ Distance to CBD	-3.622	-0.167	-0.043	0.145	1.736	-0.036
Density of Cultural POIs	-1.295	-0.301	-0.184	-0.052	1.610	-0.164
Density of Residential POIs	-1.744	-0.289	-0.020	0.078	0.232	-0.129
Density of Governmental POIs	-0.798	0.031	0.133	0.209	0.545	0.105
Density of Entertainment POIs	-0.696	-0.332	-0.165	0.145	1.348	-0.075
Socio-demographic variables						
Housing Prices	-2.002	-0.029	0.175	0.347	1.224	0.162
Proportion of Car ownership	-0.762	-0.101	0.009	0.127	1.610	0.037
Proportion of Private bike ownership	-3.258	-0.645	-0.508	-0.354	1.043	-0.524
Proportion of Female	-9.247	-0.987	-0.430	0.066	14.439	-0.422
Proportion of the elderly	-0.566	-0.063	0.153	0.535	2.918	0.306

Table A6. Estimation of the GTWR model for dockless bike-sharing.

	Min	**LQ**	**MED**	**UQ**	**MAX**	**AVG**
Weekday						
Docked bike-sharing trips						
Hourly docked bike-sharing trips	0.477	0.662	0.721	0.797	1.276	0.735
Land use variables						
Density of metro stations	-1.302	-0.403	-0.244	-0.103	0.658	-0.281
Density of docked bike-sharing stations	-1.634	-0.510	-0.371	-0.195	0.441	-0.392
Density of bus stations	-1.024	-0.093	0.036	0.123	1.769	-0.005
Density of road	-0.648	-0.188	-0.087	0.172	1.581	0.042
Distance to CBD	-1.605	-0.172	0.088	0.267	6.746	0.109
Density of Cultural POIs	-1.245	-0.138	0.088	0.242	1.166	0.060
Density of Residential POIs	-0.247	-0.031	0.061	0.263	1.699	0.149
Density of Governmental POIs	-0.645	-0.260	-0.154	-0.001	1.524	-0.102
Density of Entertainment POIs	-1.750	-0.033	0.313	0.529	1.093	0.230
Socio-demographic variables						
Housing Prices	-1.302	-0.549	-0.426	-0.242	4.775	-0.305
Proportion of Car ownership	-15.899	-1.935	-1.356	-0.293	2.894	-1.360

Proportion of E-bike ownership	-10.527	-2.608	-1.547	-0.294	5.470	-1.568
Proportion of Non-locals	-0.604	-0.092	-0.045	0.015	1.634	-0.020
Proportion of the elderly	-6.826	-1.297	-0.629	0.093	6.181	-0.579
Proportion of senior high school or bellow	-2.204	0.038	0.773	1.624	16.822	1.131
Proportion of middle-income level	-0.820	0.181	0.509	0.836	13.285	0.733
Intercept	-12.647	1.122	1.938	2.412	7.706	1.598
Weekend						
Docked bike-sharing trips						
Hourly docked bike-sharing trips	0.449	0.686	0.761	0.908	1.670	0.796
Land use variables						
Density of metro stations	-1.003	-0.338	-0.180	-0.009	2.598	-0.162
Density of docked bike-sharing stations	-2.257	-0.557	-0.393	-0.223	0.297	-0.421
Density of bus stations	-0.803	-0.139	-0.007	0.120	0.947	-0.020
Density of road	-0.629	-0.116	-0.025	0.140	1.587	0.017
Distance to CBD	-3.518	-0.087	0.053	0.162	6.045	0.068
Density of Cultural POIs	-0.467	0.065	0.203	0.318	1.918	0.203
Density of Residential POIs	-0.208	-0.001	0.097	0.235	1.185	0.150
Density of Governmental POIs	-0.450	-0.241	-0.157	-0.039	1.130	-0.120
Density of Entertainment POIs	-1.450	-0.025	0.257	0.422	0.889	0.172
Density of Commercial/Industrial POIs	-2.638	-0.180	-0.040	0.125	0.719	-0.032
Socio-demographic variables						
Housing Prices	-1.007	-0.420	-0.321	-0.207	2.319	-0.283
Proportion of Car ownership	-10.011	-2.054	-1.480	-0.450	11.158	-1.268
Proportion of E-bike ownership	-15.436	-2.519	-1.646	-0.984	7.630	-1.928
Proportion of Non-locals	-0.785	-0.093	-0.031	0.022	1.930	-0.021
Proportion of the elderly	-9.399	-1.119	-0.436	0.342	4.538	-0.458
Proportion of senior high school or bellow	-19.365	-0.603	0.260	1.461	11.401	0.518
Proportion of junior college or college	-6.151	-1.188	-0.306	0.975	18.481	0.263
Proportion of middle-income level	-8.315	0.232	0.600	0.881	3.161	0.506
Intercept	-9.738	0.186	2.371	4.002	6.685	1.912

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