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# Travel Behaviours of Sharing Bicycles in the Central Urban Area Based on Geographically Weighted Regression: The Case of Guangzhou, China

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**Abstract:** Mobile information and communication technologies (MICTs) have fully penetrated everyday life in smart societies; this has greatly compressed time, space, and distance, and consequently, reshaped residents' travel behaviour patterns. As a new mode of shared mobility, the sharing bicycle offers a variety of options for the daily travel of urban residents. Extant studies have mainly examined the travel characteristics and influencing factors of public bicycles with piles, while the travel patterns for sharing bicycles and their driving mechanisms have been largely ignored. Using one week's travel data for Mobike, this study investigated the spatial and temporal distribution patterns of sharing bicycle travel behaviours in the central urban area of Guangzhou, China; furthermore, it identified the influences of built environment density factors on sharing bicycle travel behaviours based on the geographically weighted regression method. Obvious morning and evening peaks were observed in the sharing bicycle travel patterns for both weekdays and weekends. The old urban area, which had a high degree of mixed function, dense road networks, and cycling-friendly built environments, was the main travel area that attracted sharing bicycles on both weekdays and weekends. Furthermore, factors including the point of interest (POI) for the density of public transport stations, the functional mixing degree, and the density of residential POIs significantly affected residents' travel behaviours. These findings could enrich discourse regarding shared mobility with a Chinese case characterised by rapidly developing MICTs and also provide references to local authorities for improving slow traffic environments.

**Keywords:** sharing bicycles; travel behaviours; smart societies; geographically weighted regression analysis; Guangzhou, China

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## 1 Introduction

Mobile information and communication technologies (MICTs) have fully penetrated everyday life in smart societies, resulting in highly compressed time, space, and distance; furthermore, these trends have reshaped residents' travel behaviour patterns, and promoted the rise of internet city (Zhen et al., 2015). Regarding the socio-spatial impacts of traditional ICTs (e.g., desktop computers and telephones), Castells (1996) argues that,

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in lieu of the traditional 'space of place', 'space of flow' is emerging as the main type of space in the information age. However, rapidly developing MICTs have advanced beyond the scope of the cheaper and more unregulated communication tools described by Castells (1996). One unique characteristic in smart societies promoted by MICTs is the simultaneous co-existence of fragmentation in time, space, and activities along with time-space flexibilities in activities such as shopping, leisure, and commuting. For instance, the proliferation of online shopping apps has enabled residents to purchase whatever they need within a preferred time window (Xi et al., 2017). In short, ICTs and various types of burgeoning online activities are redefining residents' everyday lives and related daily activity spaces (Zhen et al., 2019). Under such circumstances, it is necessary to further investigate whether arguments regarding the four effects of online activities on offline activities still apply (Zhen and Wei, 2008; Wang et al., 2015).

As a new mode of shared mobility, the sharing bicycle offers various options to meet the daily travel needs of urban residents (Mo et al., 2019). By directly connecting residents' destinations with the public transportation system, sharing bicycles have augmented residents' short-to-medium trips and generated a new travel pattern that has been embraced by millions of individuals. According to the 2017 travel report on sharing bicycles in South China, sharing bicycles offered some obvious advantages in terms of improving short-distance travel efficiency, especially within the 5 km range. Moreover, the number of bicycle-sharing service users reached 221 million, and the daily use order went up to 50 million nationwide in December 2017 (China Commercial Industry Research Institute, 2018). However, the explosive growth and over-saturation of sharing bicycles have imposed new challenges for urban traffic management and for reallocating urban space resources.

Extant studies on cyclists' travel behaviours in English literature have mainly focused on the characteristics and patterns of public bicycles as well as the impacts of built environment factors and individuals' socioeconomic characteristics. More specifically, existing studies have investigated planning methods (Lin and Yang, 2011; García-Palomares et al., 2012) and layout models for public bicycle stations (De Chardon and Caruso, 2015); they have also identified the impacts of public transportation facilities, including bicycle station levels (Garcia-Gutierrez et al., 2014), bicycle facilities (Carstensen et al., 2015), subway stations (Jun et al., 2015), urban service facilities (Wang et al., 2016), land use patterns (Cui et al., 2014), and space structures (Faghih-Imani et al., 2014), on the travel behaviours of public bicycles. Furthermore, from the perspectives of individual users, several studies have examined travel time and purpose (González et al., 2016), travel paths (McDonough, 2016), travel activity patterns (Vogel et al., 2011), behaviour characteristics (Vogel et al., 2014), and the influences of various factors, such as weather (El-Assi et al., 2017) and personal social attributes (Kaplan et al., 2015), on travel behaviours. However, travel behaviours related to pile-free sharing bicycles have received less attention.

The travel behaviours of public bicycles have received some scholarly attention in local literature since 2007. Research topics have ranged from site selection for bicycle stations (Zhou et al., 2015) to the characteristics of travel behaviours (Wei et al., 2018), travel satisfaction (Qian et al., 2014), and related social and environmental outcomes, including low carbon emission (Li et al., 2016), health (He et al., 2013), and other topics (Guo et al., 2017). Although the sharing bicycle has become a popular public transport tool since 2014, it remains a less researched area (Mo et al., 2019). Existing research, which involved a spatial perspective, covers the spatio-temporal features of travel behaviours (Lyu and Pan, 2018; Wei et al., 2018), usage willingness (Huang and Chen, 2017), suggestions for improving parking facilities (Mo et al., 2019), and enhancement strategies (Lyu and Pan, 2018). However, the influence of the built environment on bicycle-sharing travel behaviours has received little scholarly attention.

Guangzhou is one of the earliest Chinese cities to carry out the sharing bicycle program. The city deployed 800 000 sharing bicycles in August 2017 (Mo et al., 2019). According to a survey, around 41.7% of Guangzhou residents chose to travel using sharing bicycles (Ma and Lin, 2017). Nevertheless, the scale of sharing bicycle usage expanded beyond the city's carrying capacity; moreover, their disorderly deployment problems, which were caused by undisciplined parking, developed into a severe urban management challenge (Mo et al., 2019). Consequently, the question of how to precisely deliver sharing bicycles to targeted users has been put on the government's agenda (Yu and Fu, 2017). Additionally, massive and high-precision location-based services' big data, which are carried by sharing bicycles, facilitate an in-depth and accurate grasp of the daily travel behaviour characteristics of urban residents and their actual needs; furthermore, these data also provide evidence for improving the city's slow traffic system.

This paper aims to investigate the influences of built environment density factors on sharing bicycle travel and the extent to which they were using the geographically weighted regression (GWR) based on examination of the spatial and temporal distribution patterns of sharing bicycle travel behaviours in the Guangzhou central urban area on both weekdays and weekends. The findings of this paper could enrich relevant discussions regarding shared mobility with a Chinese case characterised by rapidly developing MICTs; furthermore, they may provide local authorities with references for improving slow traffic environments.

## 2 Research Design

### 2.1 Research scope

The central urban area of Guangzhou was selected as the research scope for this study; the selected areas include *Yuexiu*, *Liwan*, *Tianhe*, *Haizhu*, and the south *Baiyun* district (Fig. 1), with a total area of 418.91 km$^2$. This area enjoys the advantages of scientific and technological innovations, businesses, and comprehensive service provisions compared to other parts of Guangzhou. Considering the differences in construction times and built environments, the selected research area is categorised into an old urban area and a new urban area. The old urban area, including *Yuexiu*, *Liwan,* and south *Baiyun*, has a long history, highly mixed functions, and high road network densities. Specifically, south *Baiyun* (the area south of *Huangshi* Road), which is bound by the *Yuexiu* and *Liwan* districts, is home to densely distributed industrial parks and clothing wholesale markets and has close connections with the *Yuexiu* and *Liwan* districts, especially in terms of capital, information, and people. Therefore, south *Baiyun* was incorporated into the scope of this research. Additionally, the benefits of reforms and opening-up policies have enabled the new urban area to gradually develop into a new city centre with high heterogeneity in urban functions. For instance, the *Tianhe* central business district, which tops nationwide rankings in terms of economic strength, co-exists with the industrial parks located in the fringe area within the *Tianhe* district. Such considerable variations in built environments of the new urban area add uncertainties to travel behaviours regarding sharing bicycles.

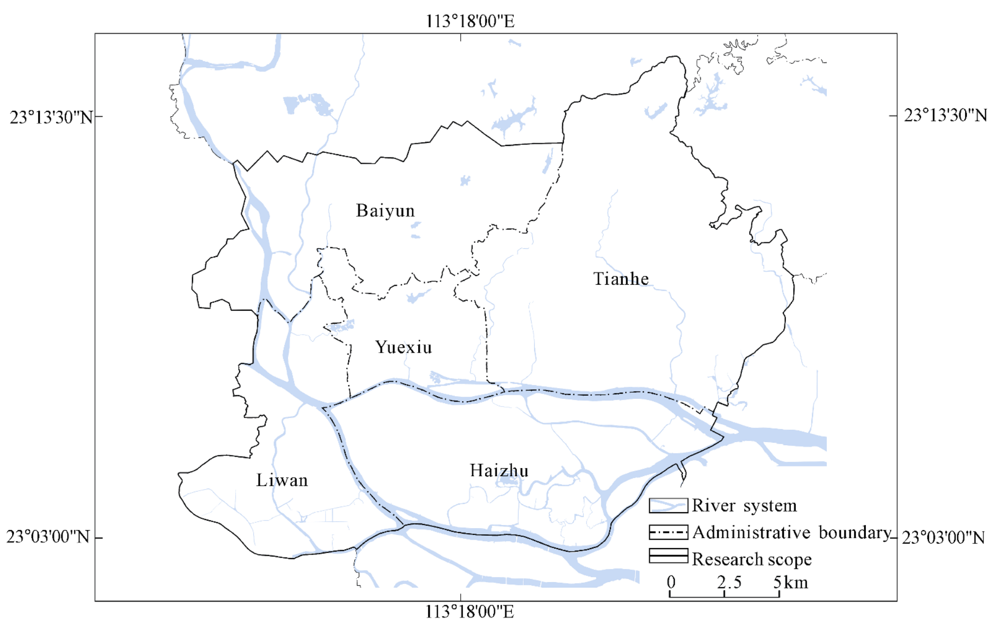


**Fig. 1** Research scope in this study

## 2.2 Data sources

### *2.2.1 Distribution of sharing bicycles*

Existing studies have mainly used sharing bicycles' travel data for two-day period; however, these data cannot, can effectively reflect the general situation (Wei et al., 2018; Mo et al., 2019) since the study period is too short. In 2018, 'Mobike Bicycles' and 'OFO Bicycles' were the top two bicycle rental operators in China in terms of ownership on the active user scale. Compared with OFO Bicycles, Mobike Bicycles enjoyed more stable active users in the second half of 2018, with around 20 million (Qianzhan Industry Research Institute, 2019). Therefore, this study utilised travel data of Mobike Bicycles (about 420 million pieces) for a 7-day period of 10–16 September, 2018; these data were taken from the Mobike Bicycles interface embedded in the WeChat program. Considering the spatial distribution of bicycle-sharing activities within a day, Wednesday and Saturday were selected as the representative days for weekdays and weekends, respectively; about 90 million pieces of bicycle-related data were included in the research scope. After using Python to exclude the stationary points, 20 million data points were further converted into simulated travel trajectories using Stata and ArcGIS software in order to investigate the spatio-temporal distribution of sharing bicycles. Furthermore, after removing the simulated travel trajectories with a travel time of under 3 min or over 1 h and eliminating the trajectories with travel distances of fewer 10 m, 17.5 million simulated travel trajectories were ultimately obtained.

### *2.2.2 Urban function*

Point of interest (POI), an emerging data type that represents urban built environments, has been used for exploring the spatial layout characteristics of express delivery points (Li G et al., 2018), and so on. However, little attention has been paid to the impacts of POIs on residents' travel behaviours. For this study, we hypothesised that there were significant differences in the influence levels of different built environment densities on the travel densities of sharing bicycles; as a result, POI and road data were taken as independent variables to test our hypothesis. Specifically, we obtained 561 000 pieces of POI data in Guangzhou from amap.com in April 2018. Corresponding to the four fundamental functions of a city, which were proposed by the Athens Charter—namely, residence, work, recreation, and transportation—data were organised as follows: POI data for commodity housing and residential services were treated as residential function data; company POI data were used as work function data; POI data for tourist sites, sports and recreation centres, shopping areas, and restaurant areas were treated as recreation function data; and POI data for public transport stations (including bus and subway stations) were treated as traffic function data. Additionally, 'urban roads' included data for highways and urban roads, and road slope data referred to the average slope data for the 15 m buffer zones of urban roads.

## 2.3 Research design

To achieve the research aim, this study undertook two steps. The first-step analysis involved investigating the spatio-temporal distribution characteristics of sharing bicycles' simulated travel trajectories. Initially, using cleaned data on sharing bicycles' spatial distribution, the travel trajectories for each vehicle with a unique identification number were generated with the support of the tracking analyst tool embedded in ArcGIS; next, the morning and evening peak hours were identified based on the all-day travel behaviour distribution during 10–16 September, 2018. In addition, Kernel density analyses were conducted for the simulated travel trajectories of the peak hours and all-day on both weekdays and weekends.

The second-step analysis involved identifying the factors influencing the travel behaviours of sharing bicycles and to what extent they were influenced. Since the travel trajectory data showed a co-existence of spatial homogeneous and heterogeneous attributes, this type of data may not easily satisfy the assumptions and requirements of the ordinary least squares (OLS) (Fischer and Getis, 2010). GWR embedded the spatial non-stationary within the spatially weighted matrix (Brunsdon et al., 1998); thus, GWR may be more applicable for identifying the factors that influenced the travel behaviours of sharing bicycles in central urban area. In these regression models, the single grid measuring 300 m × 300 m was utilised as an analysis unit, the travel densities of sharing bicycles were taken as the dependent variables, and the urban function density attributes and road gradient were treated as the independent variables.

The three sub-steps of the second-step analysis were as follows. First, according to the national norm for the planning and design of an urban residential area, a five-minute life circle with a distance of 300 m can satisfy residents' basic needs. Therefore, this research scope was divided into 3589 grids based on the 300 m × 300 m standard, and the number of motorway lengths, road gradients, and POI numbers for residence, work, recreation, and public transport stations within each grid were calculated. Second, for each grid, the travel density was acquired by dividing the sum of the origin and destination points of simulated travel trajectories by the grid area. Moreover, the density of motorways and the POI density for residence, work, recreation, and public transport stations were obtained by dividing these factors' values by the corresponding grid area. Additionally, a POI entropy indicator was introduced to further explore the influence of the functional mixture degree of built environment elements (i.e. residence, work, recreation, and public transportation) on sharing bicycle travel behaviours. In a given complex urban system, a higher entropy value indicates more diverse urban functions and more balanced function layouts (Li M et al., 2018). Based on the existing literature (Li M et al., 2018), POI entropy was used for calculating the degree of functional mix within each grid. The formula for POI entropy can be expressed as follows:

$$S_j = -\sum_{i=1}^{4} \frac{X_{ij}}{X_j} \times \log \frac{X_{ij}}{X_j}$$

where $S_j$ denotes the POI entropy value of the $j$th grid, $X_{ij}$ represents the number of POIs for the $i$th category within the $j$th grid, and $X_j$ is the sum of the POI points for four categories within the $j$th grid.

Third, the sharing bicycle travel densities were treated as dependent variables for this study's regression analysis, while the densities for urban function POIs (i.e., residence, work, recreation, and public transportation station), road gradients, motorway densities, and POI entropies were treated as the independent variables (Table 1). A GWR model was used along with an adaptive kernel weighting regime and the Gaussian distance decay-based function as a weighting matrix specification, and the corrected Akaike information criterion (AICc) was utilised for identifying the appropriate bandwidth within this model. The formula can be expressed as follows:

$$y_j = \beta_0\left(u_j, v_j\right) + \sum_{k=1}^{7} \beta_k\left(u_j, v_j\right) X_{jk} + \varepsilon_j$$

where $y_j$ represents the travel densities for sharing bicycles within the $j$th grid, $(u_j,v_j)$ denotes the geographical coordinates of the $j$th grid, $\beta_k(u_j,v_j)$ is the regression coefficient value for the $k$th independent variable in the $j$th grid, $X_{jk}$ is the $k$th independent variable, and $\varepsilon_j$ is a random error.

## 3 Spatio-temporal Distribution for Sharing Bicycles in the Central Urban Areas

### 3.1 Temporal distribution

The travel behaviours of sharing bicycles saw a sharp rise during the morning and evening peak hours on both weekdays and weekends. However, the all-day travel volume on the weekends was lower than that on weekdays. On weekdays, the travel times for the use of sharing bicycles reached its morning peak between 7:00 and 9:00, with a peak value of 55 129 times at 7:30. The evening peak, which occurred between 17:00 and 19:00 (with a peak value of 50 782 times at 18:00), witnessed lower travel times than the morning peak. On weekends, the travel times for use of sharing bicycles reached its morning peak between 7:00 and 9:00, with a peak value of 42 148 times at 8:00. The evening peak occurred between 17:00 and 19:00, with a peak value of 44 311 times at 18:00. The travel times for the use of sharing bicycles were generally higher on weekdays than on weekends. Moreover, on weekdays, the travel times for the use of sharing bicycles were higher in the morning than in the evening peak hours; the weekends showed the opposite situation.

**Table 1** Dependent and independent variables in the regression model

| Variables | Indicators | |
|---|---|---|
| Dependent variables | Travel density of sharing bicycles on weekdays | |
| | Travel density of sharing bicycles on weekends | |
| Independent variables | Built environment density | Density of residential POI (RSD) |
| | | Density of work POI (WD) |
| | | Density of recreational POI (RCD) |
| | | Density of public transport station POI (PTSD) |
| | | Motorway density (MD) |
| | | Road gradient (RG) |
| | Functional mixing degree | POI entropy (POIE) |

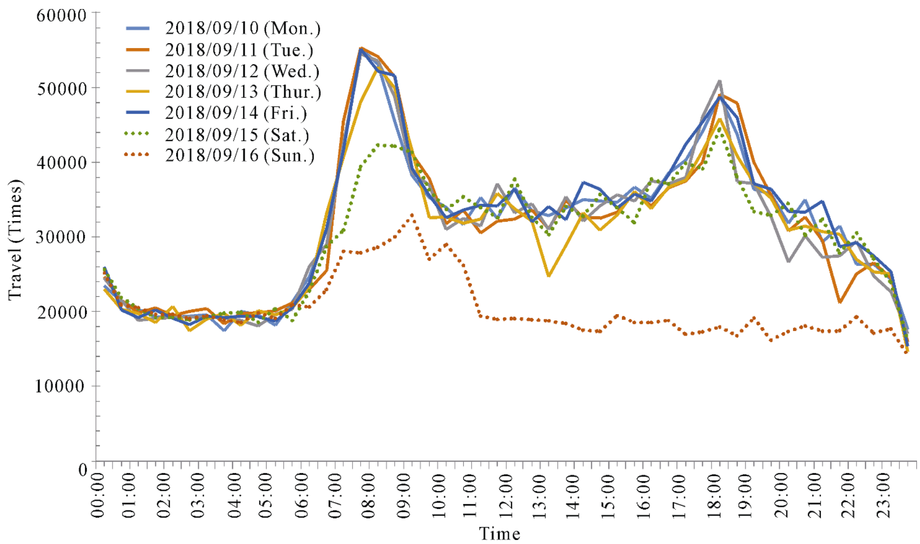


**Fig. 2** Temporal distribution of travel density for sharing bicycles in the central urban area of Guangzhou within one week

The temporal distribution of sharing bicycle travel times on each weekday was basically consistent. The travel times for the use of sharing bicycles on Wednesday reflected the average level for the five weekdays, and thus the travel density of sharing bicycles on Wednesday was taken as the dependent variable for investigating the factors influencing travel density on weekdays in the regression model. In addition, since the travel times for the use of sharing bicycles on Sunday declined significantly due to a heavy rainstorm, the travel density of sharing bicycles on Saturday was selected as the dependent variable to examine the factors influencing travel density on the weekends.

## 3.2 Spatial distribution

### *3.2.1 All-day spatial distribution*

The spatial distribution of the peak areas for the all-day travel density of sharing bicycles showed significant similarities between the weekdays and weekends. The old urban areas with large flows of people, high degrees of mixed functions, and cycling-friendly built environments were the main travel areas for sharing bicycles on both weekdays and weekends; these areas included Chen Clan Academy, *Shangxiajiu*, and *Beijing* Road. There was also heavy use of sharing bicycles in the new urban areas (e.g., *Zhujiang* New Town and *Tianhe* Sports Centre), which have high job density and many high-end shopping and leisure spaces. By contrast, *Yangji*, which features dense viaducts and an unfriendly cycling environment, became a 'low-lying land' for travel density.

Sharing bicycles had lower travel density on weekends than on weekdays, especially in newly developed urban areas with more jobs, such as *Zhujiang* New Town and *Tianhe* Sports Centre. On weekdays, these areas were the peak areas for the travel density of sharing bicycles; however, the travel density dropped sharply on weekends; this may be because fewer people go to work on the weekends. By contrast, old urban areas with a high functional mix still showed high travel density on the weekends. Noteworthily, in urban villages on the city fringe, such as *Chebei* village, the travel density on weekends was higher than that on weekdays, possibly because a large number of new migrants living there tended to engage in part-time work on the weekends.

### *3.2.2 Spatial distribution during morning and evening peak hours*

The spatial distribution of the peak travel density areas during evening rush hours on weekdays was generally consistent with that of the all-day distribution on weekdays. For the evening rush hours on weekdays, the peak areas were mainly concentrated in mixed-function old urban areas, such as Chen Clan Academy, *Shangxiajiu*, and *Beijing* Road, as well as in new urban areas with many employment opportunities, such as *Zhujiang* New Town, *Tianhe* Sports Centre, and *Tangxia*. Additionally, *Zhujiang* New Town, *Tianhe* Sports Centre, and *Tangxia* showed higher travel densities during the evening rush

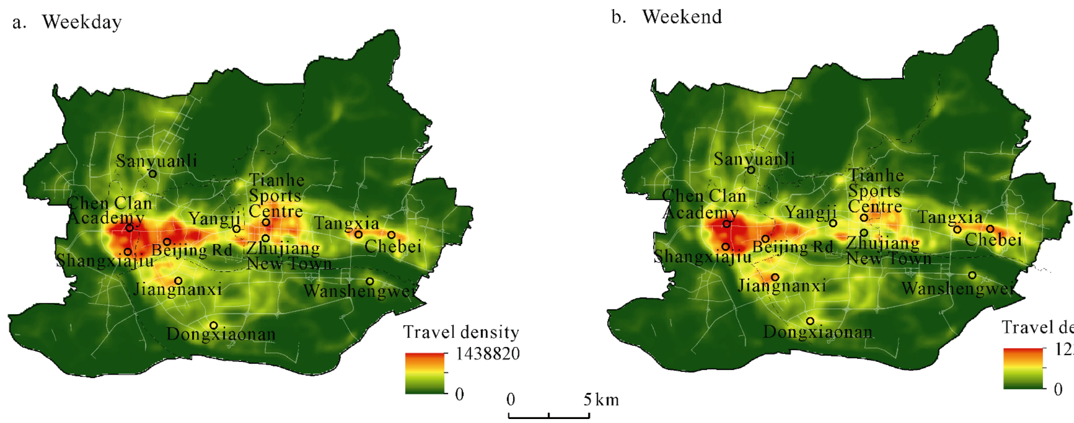


**Fig. 3** Spatial distribution of whole-day travel density for sharing bicycles in the central urban area of Guangzhouon both weekday and weekend

hours than those of the whole day. The spatial scope of the peak travel density areas was larger during morning rush hours on weekdays than during evening rush hours. In other words, in addition to the areas mentioned above, *Jiangnanxi* and several urban fringe areas including *Tangxia* and *Chebei* also became peak areas of travel density during morning rush hours. In summary, the travel behaviour regarding sharing bicycles was more concentrated in the urban core during the evening rush hours than during the morning rush hours. This may be because sharing bicycles were dispatched at night, resulting in a more even distribution in the morning than the evening.

The spatial scope of the peak travel density areas during morning rush hours was smaller on the weekends than that during the whole day. The peak morning rush hour areas on weekends were concentrated in the old urban areas such as Chen Clan Academy, *Shangxiajiu*, *Beijing* Road, and *Jiangnanxi*, new urban commercial areas such as *Shipai*, *Tancun*, and *Tangxia*, and the urban villages on the edge of the city such as *Chebei*. This spatial scope for the peak travel density areas was more dispersed than that during morning rush hours on weekdays. Moreover, on weekends, both the density value and spatial scope of travel behaviours were slightly larger during the evening rush hours than the morning rush hours, especially in *Zhujiang* New Town, *Shipai*, and *Chebei*. This might be because of late travel times resulting from the fact that travel was not constrained by fixed working hours on the weekends.

In addition, the spatial scope of the peak travel behaviour areas on weekdays was more concentrated in the old urban area compared to that on the weekends. This might be because the weekends saw higher flexibility in terms of travel destinations, as people might have chosen to visit leisure places other than their residence and workplace, and sharing bicycles may have been the potential vehicles used for such trips.

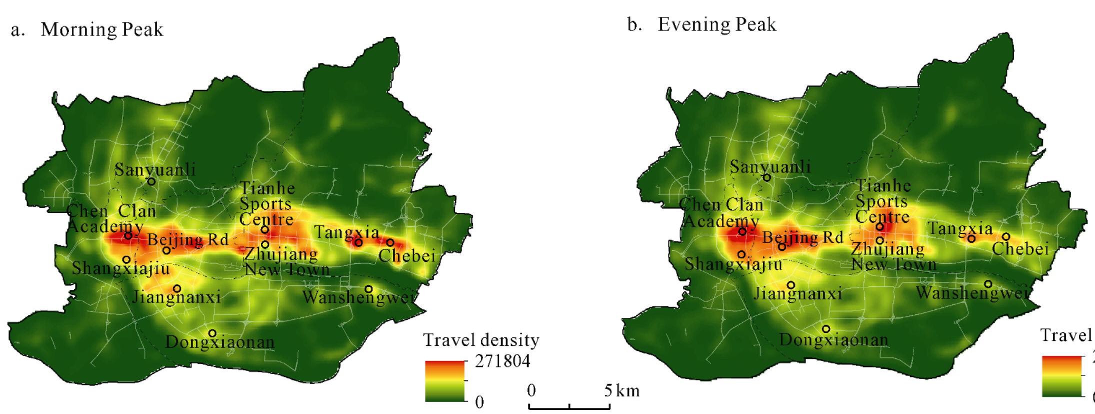


**Fig. 4** Spatial distribution of travel density during morning and evening peaks in the central urban area of Guangzhou on weekday

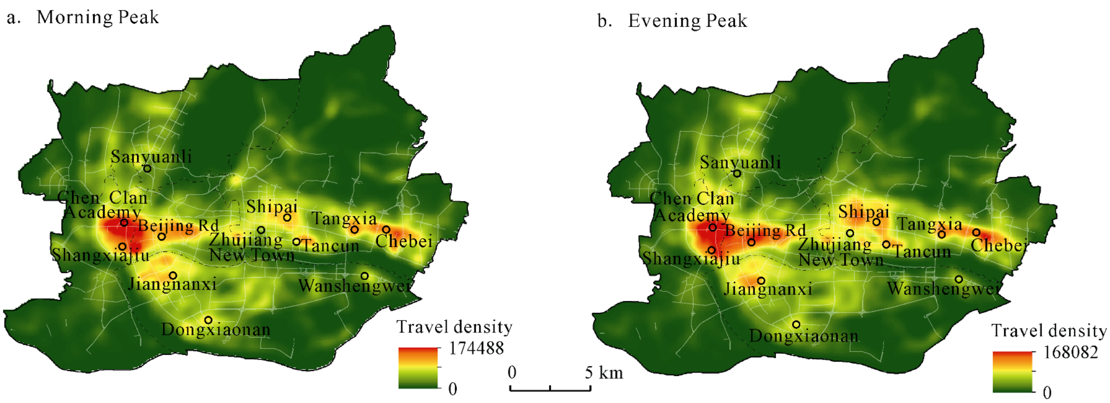


**Fig. 5** Spatial distribution of travel density during morning and evening peaks in the central urban area of Guangzhou on weekend

## 4 GWR-based Analyses on Factors Influencing Bicycle-sharing Travel Behaviours

### 4.1 Comparison between different regression methods

As discussed above, sharing bicycles' travel density was taken as the dependent variable, while urban functional densities, including WD, RSD, RCD, MD, PTSD, POIE, and RG, were utilised as the independent variables. Initially, the OLS regression analysis was carried out by using Stata. Subsequently, GWR and geographically and temporally weighted regression (GTWR) analyses were conducted using both the R language package and ArcGIS. Finally, comparisons were made among the results of the three analysis methods in order to identify the most applicable one.

As shown in Table 2, the OLS regression results were generally significant, though they could only explain 48.5% and 48.1% of total variation in travel density on weekdays and on weekends, respectively. However, the spatial autocorrelation test results revealed that OLS residuals results were spatially auto-correlated, and the large deviation value generated by the OLS regression method suggested that this method would not be applicable in this study. Additionally, the GTWR analysis results could explain 48.8% and 50.2% of the total variation in travel density on weekdays and on weekends, respectively. Nevertheless, the sum of the squared residuals for this method was much higher than those of the OLS and GWR analyses, and the fitting effect was not satisfactory. Notably, the results of the GWR method could explain 68.7% and 66.9% of the total variation in sharing bicycles' travel density on weekdays and on weekends, respectively. Moreover, the sum of the squared residuals of the GWR model was conspicuously lower than those of the OLS and GTWR analyses. Concurrently, the GWR method's corrected Akaike information criterion (AICc) value was only one-third that of the GTWR (Table 2). Consequently, the GWR method was used for analysing the factors influencing the travel density of sharing bicycles.

**Table 2** Comparison of the fitting results among OLS, GWR, and GTWR model estimations

| Dependent variables | Model | Residual square | Sigma | AICc | $R^2$ | Adjusted $R^2$ | $P$-value |
|---|---|---|---|---|---|---|---|
| Travel density on weekdays | OLS | 1846.059 | – | – | 0.486 | 0.485 | $0.000^{***}$ |
| | GTWR | 4543.660 | 0.748 | 18616.500 | 0.488 | 0.488 | – |
| | GWR | 993.019 | 0.559 | 6250.654 | 0.723 | 0.687 | $< 2.2\times10^{-16***}$ |
| Travel density on weekends | OLS | 1860.167 | – | – | 0.482 | 0.481 | $0.000^{***}$ |
| | GTWR | 4550.250 | 0.748 | 18628.300 | 0.502 | 0.502 | – |
| | GWR | 1051.993 | 0.576 | 6457.710 | 0.707 | 0.669 | $< 2.2\times10^{-16***}$ |

Notes: The significances of '$^{*}$, $^{**}$, and $^{***}$' were listed as follows: $^{*}P < 0.05$, $^{**}P < 0.01$, and $^{***}P < 0.001$; –represented no value

## 4.2 The impacts of different influencing factors

Tables 3 and 4 showed that the factors, including POIE, PTSD, and RSD, significantly influenced sharing bicycles' travel density on both weekdays and weekends, whereas the other four independent variables, including WD, RG, RCD, and MD, did not have statistically significant influences. Because of the aforementioned highly heterogeneous built environment of the research site, all of the influencing factors had both positive and negative effects on the travel density of sharing bicycles.

### *4.2.1 Impacts of POIE*

Generally, POIE had highly similar significant impacts on sharing bicycle travel for both the weekdays and weekends. The impacts of POIE on sharing bicycle travels tended to be negative in new urban areas and positive in old urban areas. Specifically, as shown in Fig. 6, the POIE of old urban areas which enjoyed high values, such as Chen Clan Academy, *Shangxiajiu*, *Beijing* Road, and *Jiangnanxi*, had a positive impact on sharing bicycle travel. By contrast, the POIE of new urban areas which held high negative values, such as *Zhujiang* New Town, had a negative impact. It was revealed that new urban areas tended to implement stricter regulations for sharing bicycle travel than old urban areas. For instance, the *Tianhe* District Government implemented strict regulations to address the excessive supply and indiscriminate parking of sharing bicycles. Bicycle sharing companies were also actively cooperating and setting up electronic non-parking zones in *Zhujiang* New Town (Meng and Yang, 2018), thus drastically reducing the amount of bicycle trips in this area. Additionally, factors such as unauthorised use of road space by street vendors and frequent loading and unloading of cargo in *Zhongda* Fabric Market, the largest clothing wholesale market in Guangzhou, compromised the riding experience (Li, 2018), resulting in fewer bicycle trips.

In addition, industrial areas in the urban fringe, wholesale markets for both building material and cloth, and exhibition areas were not suitable for sharing bicycle travel (Fig. 6); thus, POIE also had negative impacts on sharing bicycle travel in these areas. This indicates that the travel behaviour of sharing bicycles was also constrained by government policies and their own service

**Table 3** Coefficient results of travel density on weekday

| Variable types | Minimum | 1st Quartile | Median | 3rd Quartile | Maximum | *P*-value |
|---|---|---|---|---|---|---|
| *X*.Intercept. | –0.677 | –0.322 | –0.028 | 0.196 | 2.109 | $< 2.2\times10^{-16***}$ |
| WD | –0.550 | 0.003 | 0.069 | 0.193 | 0.559 | 0.071 |
| RSD | –0.283 | 0.109 | 0.210 | 0.397 | 1.001 | $0.001^{***}$ |
| RCD | –0.123 | 0.072 | 0.153 | 0.244 | 0.878 | 0.913 |
| MD | –0.136 | 0.018 | 0.059 | 0.115 | 0.390 | 0.996 |
| PTSD | –0.269 | 0.046 | 0.111 | 0.193 | 0.609 | $< 2.2\times10^{-16***}$ |
| POIE | –0.957 | –0.034 | 0.001 | 0.044 | 1.381 | $< 2.2\times10^{-16***}$ |
| RG | –0.468 | –0.055 | –0.007 | 0.044 | 0.369 | 0.786 |

Notes: The significances of '$^{*}$, $^{**}$, and $^{***}$' were listed as follows: $^{*}P < 0.05$, $^{**}P < 0.01$, and $^{***}P < 0.001$

**Table 4** Coefficient results of travel density on weekends

| Variable types | Minimum | 1st Quartile | Median | 3rd Quartile | Maximum | *P*-value |
|---|---|---|---|---|---|---|
| *X*.Intercept. | –0.677 | –0.321 | –0.029 | 0.195 | 2.109 | $< 2.0\times10^{-16***}$ |
| WD | –0.549 | 0.003 | 0.069 | 0.193 | 0.559 | 0.063 |
| RSD | –0.283 | 0.110 | 0.211 | 0.397 | 1.001 | $0.001^{***}$ |
| RCD | –0.123 | 0.072 | 0.153 | 0.244 | 0.878 | 0.904 |
| MD | –0.136 | 0.018 | 0.058 | 0.115 | 0.390 | 0.996 |
| PTSD | –0.269 | 0.046 | 0.110 | 0.193 | 0.609 | $< 2.0\times10^{-16***}$ |
| POIE | –0.957 | –0.034 | 0.001 | 0.044 | 1.381 | $< 2.0\times10^{-16***}$ |
| RG | –0.468 | –0.055 | –0.007 | 0.044 | 0.369 | 0.782 |

Notes: The significances of '$^{*}$, $^{**}$, and $^{***}$' were listed as follows: $^{*}P < 0.05$, $^{**}P < 0.01$, and $^{***}P < 0.001$

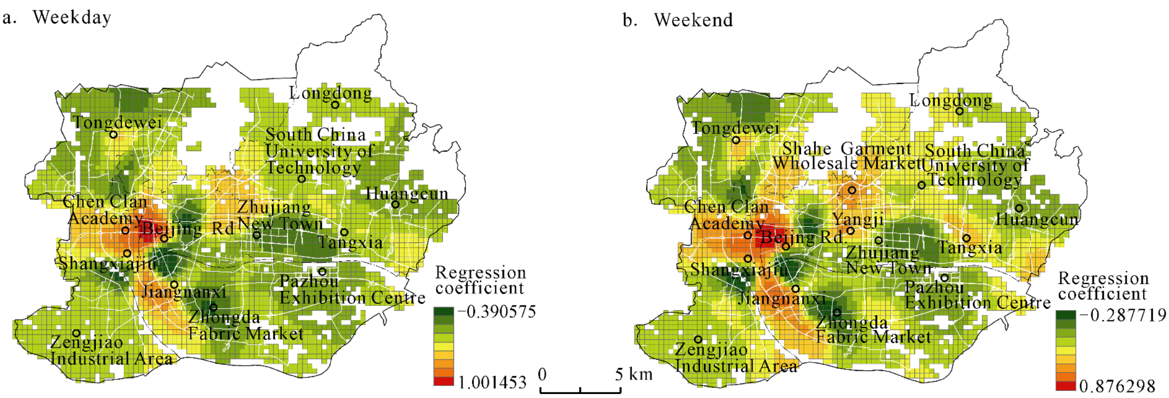


**Fig. 6** Impacts of POI entropy on travel behaviours of sharing bicycles in the central urban area of Guangzhou on both weekday and weekend

range. POIE was found to have greater positive impacts on sharing bicycle travel on weekends than on weekdays, especially in the *Wushan* University Area and *Tangxia* Creative Park. This indicates that residents tended to choose cycling as their preferred mode during weekends, when they enjoyed higher flexibility in terms of time management.

### *4.2.2 Impacts of PTSD*

PTSD had significant impacts on sharing bicycle travel on both weekdays and weekends. Specifically, it had positive impacts on sharing bicycle travel in most areas; meanwhile, it had negative effects in the marginal areas with disadvantaged locations. The study found that the scopes of PTSD's positive impacts on sharing bicycle travel on weekdays were highly similar to those on weekends.

On weekdays and weekends, the high-value areas of the positive regression coefficient were concentrated in the east and west sides of the central urban area. Specifically, in the west Inner Ring Road, which covered the traditional commercial centres of the old urban area (e.g., *Xichang*, *Shangxiajiu*, *Huangsha*, and the 2nd Workers' Cultural Palace), bicycle sharing played the role of shuttling commuters from public transportation stations to their destinations. The east side, including *Dongpu*, *Chebei*, and surrounding areas, was the location of many small creative industrial parks, residential areas, and shopping malls, where 'public transportation stations + bicycle sharing' was a popular travel mode.

Compared with weekends, the impacts of PTSD on sharing bicycle travel were more obvious in many places on weekdays. The route from *Guangzhou* Avenue to *Haizhu* Passenger Station via *Zhujiang* New Town and Canton Tower was Guangzhou's traffic artery in the north-south direction; the area along this route had a dense distribution of bus stops and employment opportunities. As a result, this area became a high-value one with a positive regression coefficient, where PTSD's role in promoting sharing bicycle travel was significant. On weekends, the positive regression coefficient in this area declined, signifying the weakening impacts of PTSD. High-value areas with negative regression coefficients were mainly concentrated in areas located near interchanges, industrial areas, and wholesale markets in the urban fringe; these included areas such as *Tancun*, *Baogang* Avenue, *Shahe* Street, and *Tongdewei* (Fig. 7). Use of sharing bicycles was restricted in these areas because they often did not have favourable conditions for cycling or because sharing bicycles were incapable of satisfying the needs of these areas' cargo transport industries.

### *4.2.3 Impacts of RSD*

RSD had similarly significant impacts on sharing bicycle travel for weekdays and weekends. On weekdays, high-value areas with positive regression coefficients were concentrated in residential areas in the old urban areas (e.g., *Shangxiajiu*, *Huangsha*, and *Taojin*), peri-urban villages (*Xiaozhou* Village), and dormitories in industrial areas (*Shiweitang*) on the urban fringe; high-value areas with negative regression coefficients were mainly distributed in high-end residential areas such as *Huajing* Estate and *Jinbi* Estate (Fig. 8). This was mainly because residents in old residential areas, city villages, and factory dormitories preferred to use sharing bicycles to travel to public transportation stations; however, residents in high-end residential estates had more diversified options and lower demand for

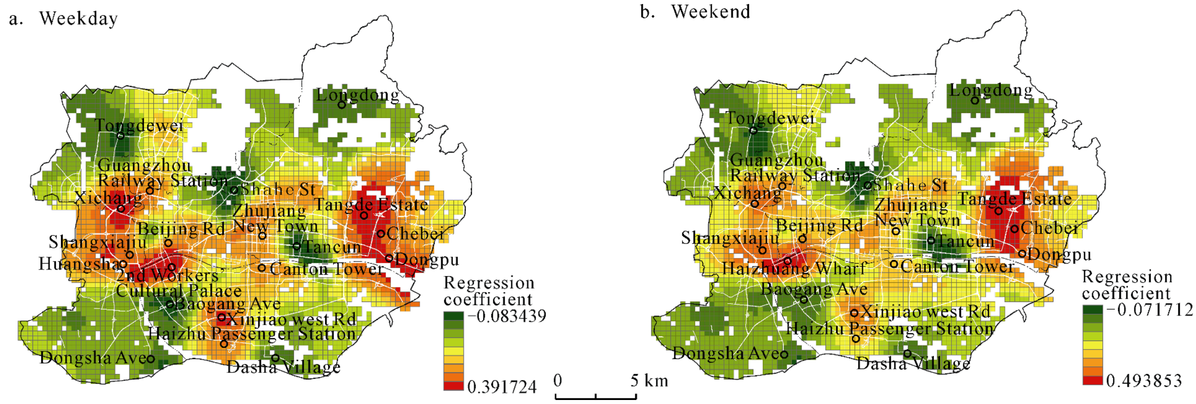


**Fig. 7** Impacts of density of public transport station POI on travel behaviours of sharing bicycles in the central urban area of Guangzhou on both weekday and weekend

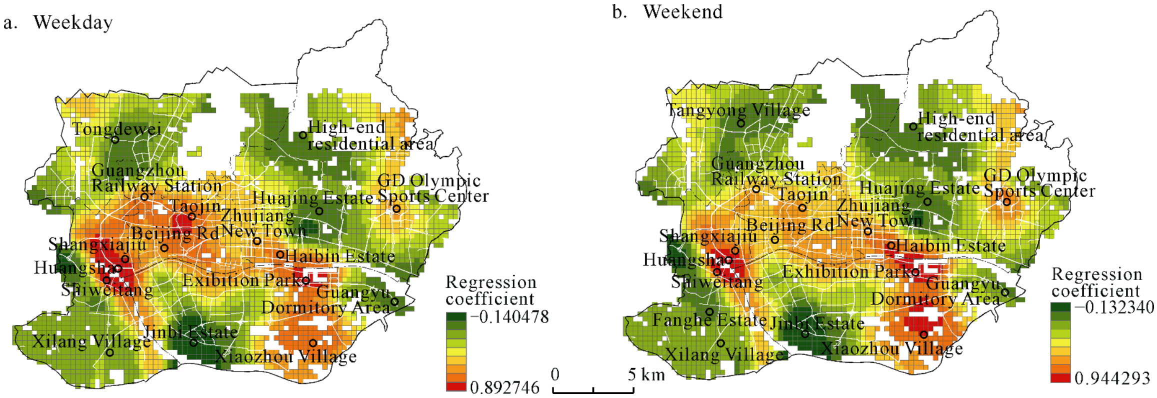


**Fig. 8** Impacts of density of residential POI on travel behaviours of sharing bicycles in the central urban area of Guangzhou on both weekday and weekend

sharing bicycles. Additionally, on the weekends, the regression coefficients of residential areas in the old urban area (e.g., areas around *Guangzhou* Railway Station and *Taojin)* declined. This may be because residents had higher time flexibility on the weekends, and old urban areas had a higher degree of functional mix. Thus, residents could easily reach their destinations without resorting to sharing bicycles, which might reduce the demand for them.

### *4.2.4 Impacts of other factors*

Compared to the aforementioned three factors, the effects of WD, RG, RCD, and MD on sharing bicycle travel were statistically insignificant, but they still carried a certain impact. The influence of WD on the travel behaviours of sharing bicycles showed a high degree of similarity during the weekdays and weekends. On weekdays, WD showed a significantly positive impact on sharing bicycle travel in areas characterised by dense employment opportunities, a heavy flow of people, and a friendly cycling environment; these areas included *Zhujiang* New Town, *Tancun*, *Pazhou* Creative Park, *Beijing* Road, the industrial area in South *Haizhu*, and the clothing wholesale market in South *Baiyun*. On weekends, WD had a lesser positive influence on sharing bicycle travel, while *Beijing* Road and *Zhujiang* New Town became negative influence zones mainly because the dense shopping flow on the weekends created an unfriendly cycling environment. The influence coefficient of WD was negative for sharing bicycle travel in *Fangcun* Tea Wholesale Market (Fig. 9); this was likely because of the low demand for sharing bicycles in the large-scale wholesale area.

RG had similar insignificant impacts on sharing bicycle travel during weekdays and weekends. As displayed in Fig. 10, high-value areas with a positive regression coefficient included *Hesha*, *Fangcun* Avenue West, *Tianpingjia*, *Guangshan* 2nd Road, *Tianhe* Children's Park, and *Xinzhou* Wharf. Although the RG of these areas was relatively minor, since they were located in the city fringe, bicycle supply was low; this resulted in fewer trips. Other high-value areas with positive regression coefficients included *Dongfeng* Road, *Shangxiajiu*, *Dongshankou*, and *Zhongda* Fabric Market. Although these areas had unfavourable RG conditions, the strong demand for travel led to a large number of bicycle trips. By contrast, *Beijing* Road, *Binjiang* West Road, *Tancun*, *Yuancun*, *Pazhou* Exhibition Centre, and *Tongdewei* were high-value areas with negative regression coefficients. These places enjoyed minor RGs and heavy flows of people, which created favourable conditions for sharing bicycle travel and satisfied the need for short-distance travel among bicycle users.

In terms of the positive impact on the bicycle travel, RCD on weekdays also showed a high degree of similarity to that on weekends. RCD on weekends had a slightly larger influence, thus indicating that citizens had more leisure time on the weekends, and consequently, a larger scope for travel. High-value areas with positive regression coefficients were mainly distributed in the *Wushan* University Area, Redtory Art Factory, *Pazhou* Exhibition Centre, *Lingnan* Flower Market, and *Guangzhou* Bio Island (Fig. 11). These areas were important travel destinations that tended to have cycling-friendly environments, beautiful scenery, or rich cultural and artistic significance; thus, they were suitable for entertainment and recreation, and cycling was the main means of transport.

MD also showed a high degree of similarity with regard to the impact of sharing bicycle travel on weekdays and weekends. MD on the weekends had a slightly larger scope of influence. On weekdays, the MD of *Zhongshan* Road, *Liede* Avenue, *Huangpu* Avenue, *Guangzhou* Avenue, *Keyun* Road, and *Xinjiao* Road had positive effects on sharing bicycle travel. These roads were major traffic routes connecting the residential and employment areas in Guangzhou, and they were spacious and friendly for cycling. As a result, the MD of these areas had significantly higher positive influences on sharing bicycle travel than that of other areas. The impacts of MD on sharing bicycle travel tended to weaken in areas that were situated away from the aforementioned major traffic routes. During weekends, MD had a lesser positive influence on sharing bicycle travel in new urban areas, including *Liede* Avenue and *Huangpu* Avenue, compared to that during weekdays. This might be due to the decline in the number of people going to work on the weekends. Additionally, the impacts of MD on bicycle sharing in the old urban areas were stronger on weekends than on weekdays, especially in *Beijing* Road and *Tangxi* Station (Fig. 12). The impacts of influencing factors of sharing bicycles' travel behaviours on both weekdays and weekends were compared in Table 5 to summarize their similarities and differences.

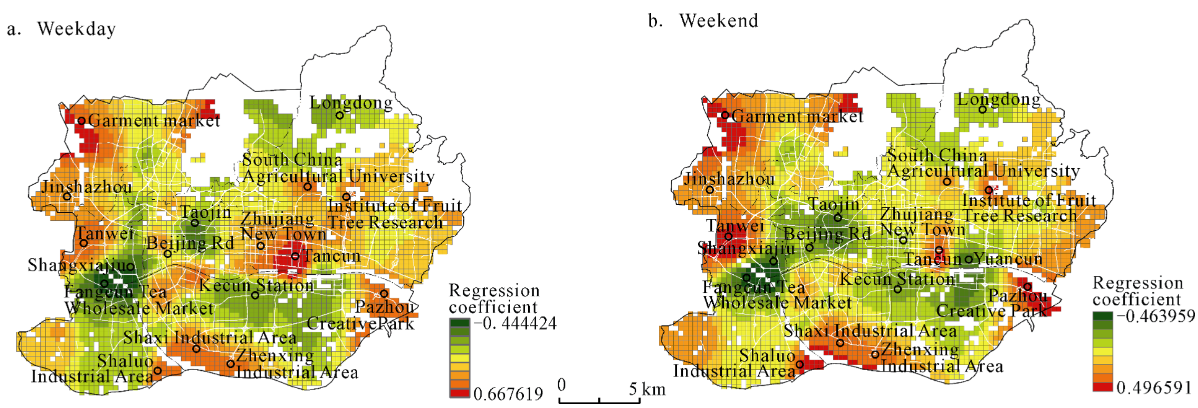


**Fig. 9** Impacts of density of work POI on travel behaviours of sharing bicycles in the central urban area of Guangzhou on both weekday and weekend

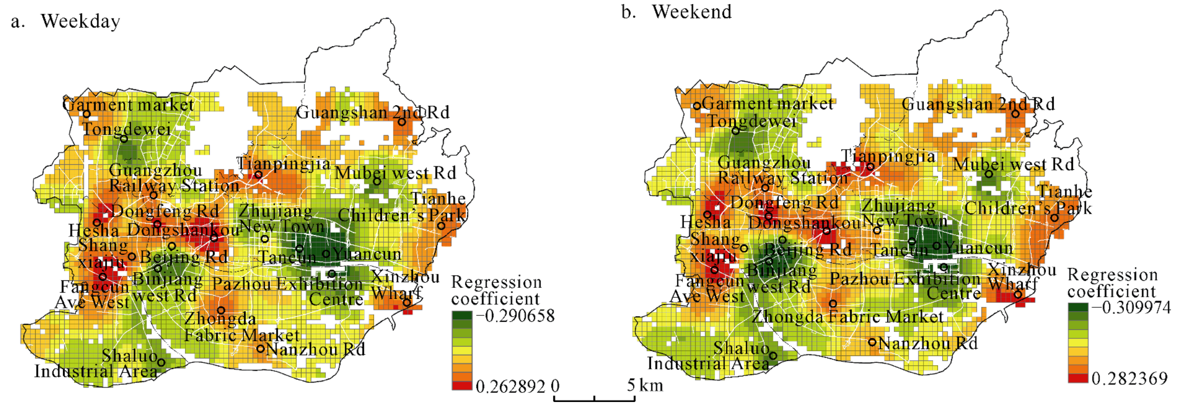


**Fig. 10** Impacts of road gradient on travel behaviours of sharing bicycles in the central urban area of Guangzhou on both weekday and weekend

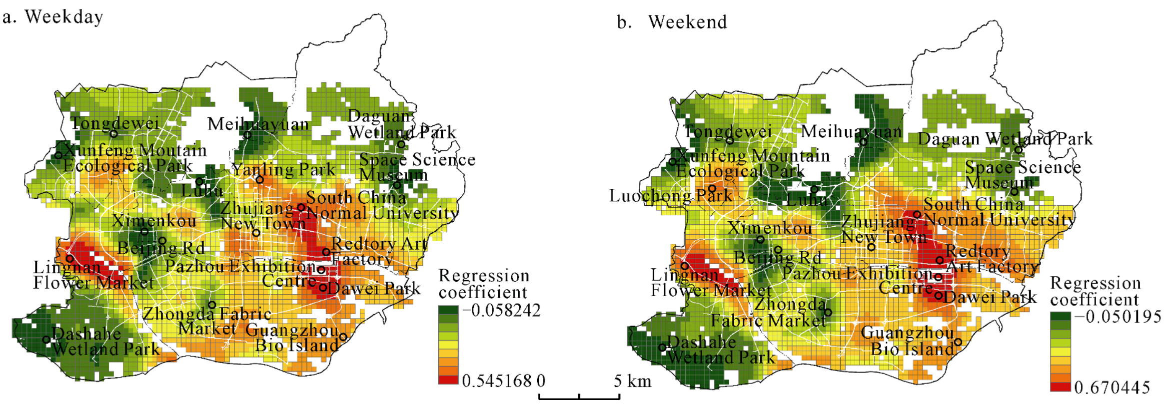


**Fig. 11** Impacts of density of recreational POI on travel behaviours of sharing bicycles in the central urban area of Guangzhou on both weekday and weekend

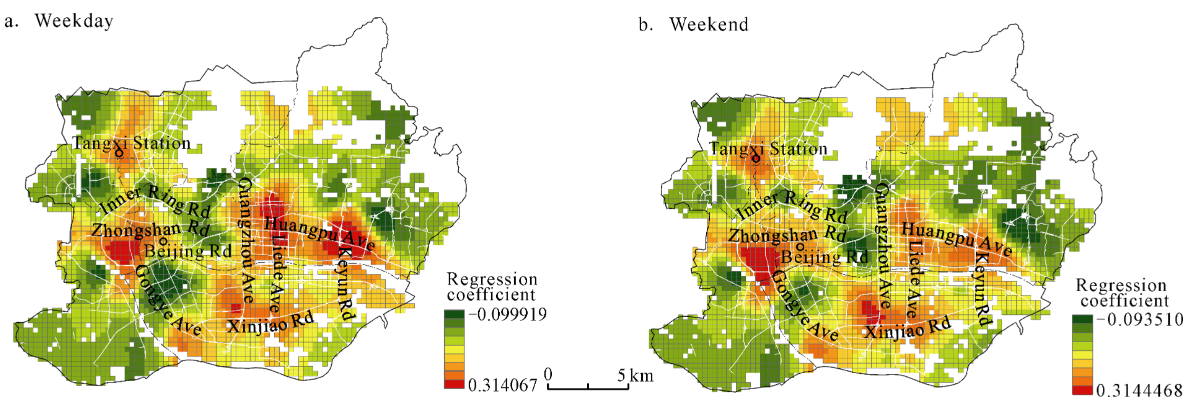


**Fig. 12** Impacts of motorway density on travel behaviours of sharing bicycles in the central urban area of Guangzhou on both weekday and weekend

**Table 5** Comparisons on the impacts of influencing factors of sharing bicycles' travel behaviours on both weekdays and weekends

| Variable types | Weekdays | Weekends |
|---|---|---|
| POIE | Positive impact: Commercial centres in the old urban area, such as *Beijing* Road, *Shangxiajiu*, Chen Clan Academy, *Jiangnanxi*, etc.<br>Negative impact: Areas with strong regulations for sharing bicycles (e.g. *Zhujiang* New Town), remotely located industrial areas and wholesale markets, large-scale exhibition areas, and parks where bicycles were forbidden. | Larger effect of positive influence compared to that on weekdays, especially in the *Wushan* University Area and *Tangxia* Creative Park. |
| PTSD | Positive impact: Traditional commercial areas around the West Inner Ring Road (*Xichang, Shangxiajiu, Huangsha*, 2nd Workers' Cultural Palace, *etc*.), industrial parks and residential areas around *Chebei* Road.<br>Negative impact: Areas around viaducts, industrial areas, and wholesale markets on the edge of the city. | Regression coefficient declined significantly in Guangzhou Avenue, compared to that on weekdays. |
| RSD | Positive impact: Residential area in the old city area (e.g. *Shangxiajiu*, *Huangsha*, *Taojin*), traditional villages (e.g. *Xiaozhou* village), and dormitories in the industrial area on the edge of the city (e.g. *Shiweitang*).<br>Negative impact: High-end housing estates in *Tianhe* District (e.g. *Huajing* Estate) and *Haizhu* District (e.g. *Jinbi* Estate). | Regression coefficient declined in the old city area (e.g. *Guangzhou* Railway Station, *Taojin*), while it rose in *Xiaozhou* village. |
| WD | Positive impact: Areas with high employment density, large population flow, cycling-friendly environments (e.g. *Zhujiang* New Town, *Beijing* Road), and industrial parks in south *Haizhu* district.<br>Negative impact: Wholesale markets on the edge of the city, etc. | Lesser scope of positive influence than on weekdays. *Beijing* Road and *Zhujiang* New Town becoming negative impact areas. |
| RG | Positive impact: on the edge of the city, low travel occurred in areas with few sharing bicycles despite a smooth road slope. High travel arose in areas with strong travel demand despite the steep roads (e.g. *Dongfeng* Road, *Shangxiajiu*, *Dongshankou*, and *Zhongda* Fabric Market).<br>Negative impact: High travel occurred in areas with smooth roads and dense population (e.g. *Beijing* Road, *Binjiang* West Road). | The effects were the same as on weekdays. |
| RCD | Positive impact: High travel occurred in areas with beautiful scenery, areas with a high concentration of universities and colleges, Redtory Art Factory, *Pazhou* Exhibition Centre, *Lingnan* Flower Market, and *Guangzhou* Bio Island.<br>Negative impact: Areas where sharing bicycles were forbidden (e.g. Space Science Museum, *Daguan* Wetland Park). | Larger scope of positive influence than on weekdays, especially in *Chebei* and *Dongpu* areas. |
| MD | Positive impact: Traffic arteries connecting the main residential area and the employment area, including *Zhongshan* Road, *Liede* Avenue, *Huangpu* Avenue, *Guangzhou* Avenue, *Keyun* Road, and *Xinjiao* Road.<br>Negative impact: Wholesale markets and industrial areas with disadvantaged locations. | Slightly lesser scope of positive influence than on weekdays. |

## 5 Conclusions

MICTs have penetrated everyday life in this era of smart societies, promoting the integration of online and offline services. Moreover, they have considerably transformed residents' daily activity spaces from physical spaces to a mixture of physical and virtual spaces, thus enriching residents' space selection for conducting daily activities. Space no longer indicates just a container; rather, it now manifests as a flow of various elements that are closely linked at different spatial levels. This has reshaped the concept of distance and space of flow. Noteworthily, traditional urban planning focuses more on optimising the allocation of space resources and improving the supply of built environment, while residents' actual needs are underestimated; this results in a variety of urban issues such as traffic jams. The emergence and use of individuals' activity-based big data has provided support for more humanistic explorations in the urban geography field (El-Assi et al., 2017). This research is a preliminary attempt in this field.

By using one week's travel data for Mobike, obvious morning and evening peaks were identified in the travel patterns of sharing bicycles on both weekdays and weekends in the Guangzhou central urban area. The old urban area, which had a high degree of mixed function, dense road networks, and cycling-friendly built environments, was the main travel activity area that attracted sharing bicycles on both weekdays and weekends. In contrast, the area with dense viaduct networks and unfriendly and unsafe cycling conditions was at the bottom of the list for all-day bicycle travel times. The new town area, which provided more employment opportunities (e.g., *Zhujiang* New Town and *Tianhe* Software Park) displayed higher travel density on weekdays and experienced significantly lower travel density on weekends. Compared to those during the morning peak periods, travel density peak areas for sharing bicycles during evening peak periods were more concentrated in core urban areas, possibly because sharing bicycles were dispatched at night.

This study found that among the built environment factors, POIE, PTSD, and RSD were revealed to be significant factors in terms of affecting residents' travel behaviours; this finding could provide evidence for selecting site locations for public transport stations and for urban spatial planning as well. Furthermore, beyond built environment factors, users' demand factors, including individuals' income, travel preferences, and policy factors such as governmental regulations also had certain influences on the travel behaviours of sharing bicycles, which remain to be further examined.

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