Research Article

Evaluation of Dockless Bike-Sharing Transfer Services around Metro Stations considering Spatial Heterogeneity

Jieshuang Dong,1 Shawen Chen,1 Wenxiang Li,1 Yiwei Zhou,1 and Hongyun Si2

1Business School, University of Shanghai for Science and Technology, Shanghai 200093, China
2School of Public Administration and Policy, Shandong University of Finance and Economics, Jinan 250014, China

Correspondence should be addressed to Wenxiang Li; liwx@usst.edu.cn

Received 27 April 2022; Accepted 12 May 2022; Published 30 May 2022

1.Introduction

As the backbone of urban public transportation, the metro plays a key role in urban travel. However, metro lines and stations are fixed and the service scope is limited. Therefore, it is necessary to improve the attractiveness and accessibility of the metro for travelers. With the rapid development of mobile Internet technology, dockless bike-sharing is emerging as one of the most popular transfer modes for metros. It can easily connect the access trips to metro stations or egress trips from metro stations, which offers more flexibility and convenience for travelers. It also extends the service range of metro stations compared to walking. Therefore, dockless bike-sharing can effectively ease passengers' “last mile” travel difficulties and can help cities better manage the transition to low-carbon urban transport [1, 2].

Existing studies about dockless bike-sharing mainly focus on the analysis of the characteristics of bike-sharing, including the users, ridership, travel distance, and parking problems. Some studies also analyzed the relationship between bike-sharing and the metro. Most of them only explored the influencing factors of bike-sharing transfer ridership for the metro, such as built environment, weather, and travel characteristics. However, the spatially varying effects of these factors were rarely analyzed in their studies. In addition, there are few quantitative evaluations on the bike-sharing transfer services around metro stations. As there are significant spatial differences in the bike-sharing ridership, a fair evaluation of bike-sharing transfer services for each metro station is difficult. Therefore, this study aims to solve two main problems: (1) How do the effects of the influencing factors on bike-sharing transfer ridership vary...
across space? and (2) How to evaluate the bike-sharing transfer services around metro stations considering spatial heterogeneity?

The contributions of this study are threefold. First, the transfer trips between bike-sharing and metros are identified based on a catchment method with varying radii. Second, spatially varying relationships between bike-sharing transfer ridership and built environments are analyzed using a geographically weighted regression (GWR) model. Third, a benchmark method is proposed based on the GWR model to evaluate the transfer services of different metro stations with spatial variation. Therefore, this study can help the government and operators put forward differentiated policies for different regions to facilitate better integration of dockless bike-sharing and metros.

The rest of the paper is organized as follows. Section 2 presents a literature review of bike-sharing and spatial heterogeneity. The data processing and preliminary analysis are presented in Section 3. The methods are described in Section 4. Section 5 analyzes and discusses the results. The last section provides a summary of key findings and some policy suggestions.

2. Literature Review

2.1. Related Research on Bike-Sharing. At present, the research on bike-sharing mainly focuses on the usage, characteristics of bike-metro transfer ridership, and their influencing factors. Schoner et al. [3] applied the network science model based on the nonmotor vehicle infrastructure maps of 74 different cities in the United States, and the results showed that there was a positive correlation between the amount of bike-sharing and the amount of nonmotor vehicle infrastructure. Subsequently, Cherry et al. [4] analyzed the riding data and user statistics of bike-sharing and concluded that there was a significant relationship between the user demand for bike-sharing and the existing transportation system. Chen et al. [5] found through research that nearly 50% of metro passengers are more inclined to use bike-sharing to complete the transfer with the metro. From the perspective of space, Gu et al. [6] studied the overall temporal and spatial characteristics of bike-sharing around metro stations. The results showed that there were significant differences in the use characteristics of bike-sharing around metro stations in different areas. Chen et al. [7] studied by classification model and found that the possibility of bike-sharing connecting to the metro station was about 21.9%. Ma et al. [8] used the cubic regression model to study the connection distance of bike-sharing around metro stations and used an independent sample t-test and one-way analysis of variance (ANOVA) to explore access and egress transfer characteristics in demographic groups. Guo et al. [9] used a series of negative binomial regressions to examine the effect of the built environment on the integrated use of bike-sharing and the metro. To further explore the causes of the aforementioned laws, scholars carried out research on the built environment, socio-demographic attributes, transportation infrastructure, weather conditions, and other aspects. Li et al. [10] proposed that employment density could affect the bike-metro transfer ridership. Dense workplaces indicate that commuting in this region accounts for a high proportion of trips, attracting more commuters to use bike-sharing as a tool to connect to the metro. Givoni et al. [11] found that the age of travelers is a key factor affecting the bike-metro transfer ridership. The research results show that young people ride more frequently than old people. Imani et al. [12] analyzed the reasons affecting the bike-metro transfer ridership in Montreal using 4-month travel data and found through multilevel statistical modeling that road network structure and bicycle infrastructure had a significant impact on the demand for bike-sharing. Gebhart et al. [13] found that the usage of bike-sharing was positively correlated with a moderate temperature (15–32°Celsius), and negatively correlated with the temperature outside the range.

Although there are a lot of studies on bike-sharing, most of them focus on the characteristics of bike-sharing and its relationship with the metro. However, the spatial variation of transfer ridership between bike-sharing and the metro has been rarely examined. In addition, there is still a lack of evaluation of bike-sharing transfer services around metro stations considering the spatial heterogeneity.

2.2. Related Research on Spatial Heterogeneity. Spatial heterogeneity is mainly used to explain spatial variation and reflect the instability and complexity of spatial distribution. The application of spatial heterogeneity is first in ecology research, which is an important characteristic of ecological system and the main attribute of a biological system. Ecologists can conduct quantitative analyses on the function of the ecosystem according to different spatial scales. Li and Reynolds [14] proposed that spatial heterogeneity refers to the variability and complexity of a system or its attributes in space. Lin et al. [15] studied the spatial heterogeneity characteristics of land subsidence in different geological units using Moran's I and analyzed the key factors affecting land subsidence using geographical detectors. The research methods of spatial heterogeneity have been found by more and more scholars, which are also widely used in the field of transportation. Based on a large number of traffic data, Xie and Yan [16] constructed a spatial model of urban road network morphology and traffic state to analyze the spatial heterogeneity of urban road networks. Sun et al. [17] used the spatial lag model, and the influence mechanism of spatial factors around public bicycle stations is discussed. Qian and Ukkusuri [18] used the GWR model to depict the spatial visual features of the regression coefficients of each variable in space and finds that the GWR model has a better fitting degree by comparing it with the ordinary least square method. Yang et al. [19] used semiparametric geographically weighted regression (S-GWR) model to explore the spatial variation relationship of bike-sharing passenger flow. Yang et al. [20] compared the goodness of fit of the general least square method and the mixed GWR model to study the spatial heterogeneity of factors affecting the choice of travel mode at intersections. Li et al. [21] used the GWR model to explore the influencing factors and spatial variations of
transfer distances between dockless bike-sharing systems and metros.

In summary, the GWR model is a widely adopted method to explore spatial heterogeneity. It allows for spatially varying relationships between a dependent variable and its independent variables. Therefore, it could be used as a benchmark model for the evaluation of bike-metro transfer services in different metro stations with spatial variation.

3. Data Preparation

3.1. Study Area. As an international metropolis, Shanghai has the largest metro network. By the end of 2020, there are 18 lines in operation, with a total length of 729 kilometers, 430 metro stations, and 729 kilometers of metro lines built, ranking first in China. At the same time, the emerging dockless bike-sharing is all over the streets and alleys in Shanghai, especially around the metro stations. To explore the bike-sharing transfer services for the metro, the study area is focused on the metro stations in Shanghai, as shown in Figure 1.

3.2. Data Sources and Preprocessing

3.2.1. Data Sources

(1) Mobike Trip Data. The data on bike-sharing are mainly selected from Mobike trip data in Shanghai, which are recorded from August 1 to August 31, 2016. The data include 1,023,603 bike-sharing orders of 306,936 unique bikes and 17,688 unique users. The data fields consist of an order ID, bike ID, user ID, start time, start location, end time, end location, and longitude and latitude of the cycling track.

(2) Metro Data. The data of Shanghai metro lines and stations are from Amap, including 14 metro lines and 313 stations. Metro station passenger flow data are derived from metro smart card data, which contain inbound and outbound records of all metro stations from August 1, 2016, to August 31, 2016, including card ID, metro station name, metro line, date, time, and price.

(3) Built Environment Data. Built environment factors are often defined by words starting with “D”. Cervero and Kockelman [22] proposed the initial “3 Ds”, which are defined as density (such as population and job density), diversity (such as land-use mix, and jobs-housing balance), and design (such as road and intersection density). Subsequently, the main built environment factors were extended to “5 Ds” by including destination accessibility and distance to transit [23]. In this study, the POI data, population data, and road network data are used to calculate “5 Ds” built environment indicators [24]. POI data are collected through the application programming interface (API) of Amap Web service, and the total number of POI is 665,953, including the names, addresses, categories, latitude, and longitude of specific locations. The population data are from China’s sixth census. The Open Street Map (OSM) is used to extract the road network of different road types, including expressways, primary roads, and cycleways.

3.2.2. Data Preprocessing. For the Mobike trip data, we first delete the unnormal trips with riding time over 1 h or riding distance over 10 km. According to related literature [25, 26], the travel pattern of bike-sharing during peak hours of weekdays can better reflect commuting characteristics. Compared with the morning peak, the bike-sharing ridership in the evening peak is larger and the period is longer [21], which can provide better statistical significance for regressions. Therefore, we select the bike-sharing trips during the evening peaks on 23 weekdays in August 2016 since the evening peak traffic is more representative.

To identify the bike-sharing transfer trips around the metro station, a catchment method is proposed. It should be noted that this study cannot validate each identified bike-sharing transfer trip due to the lack of true transfer trip data. However, the most possible transfer trips can be extracted by determining a reasonable radius of the catchment. Many studies have explored the catchment radius for bike-metro integration ranging from 100 m to 500 m [27, 28]. To determine the best radius of the catchment, we create circular buffer zones with radiiuses from 10 m to 300 m increasing by 10 m. Then the bike-sharing trips with origins and destinations (ODs) within these catchments are extracted, as shown in Figure 2. For each catchment, we calculate the ridership of bike-sharing and the increment from every 10-meter expansion of the catchment radius. The screening results are shown in Figure 3. It is obvious that the greater the radius, the higher the ridership of bike-sharing within the catchment. It can also be found that the increment in the ridership of bike-sharing peaks at 140 m which represents a threshold of the radius. It indicates that the bike-sharing transfer demand is decreasing when the distance from the metro station is larger than 140 m. Therefore, this study finally uses a catchment with a radius of 140 m. Then, the bike-sharing trips with ODs in this catchment are identified as the transfer trips. Furthermore, the bike-sharing transfer ridership around each metro station can be calculated.

For the metro smartcard data, we merge the repeated data and separate the data of ridership in and out of metro stations. Then we extract the data during the evening peak (17:00–20:00) on 23 weekdays and count the inbound and outbound passengers of each metro station to calculate the metro ridership.

For the built environment data, we delete the records with positions outside the boundary of Shanghai and merge the records with similar names and locations. Then we classify the built environment data into indicators of “5Ds”, which consist of density, design, diversity, distance to transit, and destination accessibility. According to previous studies [29, 30], a 2 km service radius of each metro station is usually regarded as the range for the calculation of the built environment around the metro station. Therefore, we calculate...
the “5Ds” built environment indicators within a 2 km buffer of metro stations.

The processing process is shown in Figure 4.

3.3. Evaluation Object and Variable Selections

3.3.1. Evaluation Object Selection. Based on the analysis of the bike-sharing trip data, the daily bike-sharing transfer ridership of different metro stations during the evening peak is visualized in Figure 5. It shows a significant spatial variation in the bike-sharing transfer ridership of different metro stations [31]. The transfer ridership reflects the connection between bike-sharing and metros, providing a reference for operators to better balance the supply and demand for shared bikes. The smaller the difference between supply and demand, the better the transfer service of bike-sharing is provided. Therefore, this study takes transfer ridership as the evaluation basis to measure the transfer service of bike-sharing around different metro stations. To reduce the randomness of evaluation, this study only selects the metro stations whose average daily bike-sharing transfer ridership is more than 4 as the object for transfer services evaluation. As a result, there are 208 metro stations left, and the unselected stations are marked in gray in Figure 5.

3.3.2. Variable Selection. The transfer ridership reflects the number of bike-sharing connected to the metro, which can better evaluate the situation of bike-sharing transfer
services around the metro station. Therefore, this study takes transfer ridership as the dependent variable for regression. Many studies on influencing factors of bike-sharing mainly concentrated on the built environment, transport, population, weather, and so on. Based on previous studies [32, 33], we select several indicators related to transport and the built environment as the independent variables. The transport variable is the average daily metro ridership at each metro station, which determines the potential users of bike-sharing. The built environment variables include eight indicators of the "5 Ds". Specifically, the bus stop density presents the indicator of the distance to transit; cycleway density presents the indicator of design; distance from CBD presents the indicator of destination accessibility; percentages of various POIs present the indicator of diversity; the population density and job density present the indicator of density. All the independent variables may affect the transfer ridership of bike-sharing. The descriptive statistics results of all variables are shown in Table 1.

Although the aforementioned explanatory variables may have effects on transfer ridership, not all of them are significant and appropriate for regression. If unrepresentative variables are added to the regression model, the
correctness of other variables in the model may be affected. In addition, if the correlation between independent variables is too high, information overlap will occur, leading to a multicollinearity problem. Therefore, the exploratory regression tool of ArcGIS is used to further select the independent variables [34].

Exploratory regression analysis is to establish all possible combinations of different variables under specific index
conditions through data mining [35]. Variables without significance and stability are filtered one by one according to the significance output table. Meanwhile, a multicollinearity test is performed to calculate the variance inflation factor (VIF) of independent variables (as shown in Table 1), and independent variables with VIF larger than 7.5 were filtered. Finally, the remained independent variables are average daily metro ridership, population density, and cycleway density.

4. Methodology

4.1. Spatial Autocorrelation Test. Before GWR model analysis, it is necessary to understand the spatial distribution characteristics of variables without theoretical assumptions. Spatial autocorrelation is to judge the spatial dependence of attribute values in the whole research area. Moran’s I, Getis’ G, and Geary’s C are indexes representing spatial correlation analysis, among which Moran’s I index is the most commonly used. Moran’s I determine whether there is spatial correlation by measuring the similarity of attribute values of adjacent sample points in space, which can be expressed as follows:

\[ I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} (x_i - \bar{x})^2} (i \neq j), \]  

where \( n \) is the number of metro stations, \( \bar{x} \) is the mean of \( x \), and \( w_{ij} \) is the spatial weight between stations \( i \) and \( j \).

The values of Moran’s I usually range from −1 to +1. Moran’s \( I > 0 \) means positive correlation, and the larger the value is, the higher the spatial positive correlation degree of unit attribute values is. Moran’s \( I < 0 \) means negative correlation, and the smaller the value is, the lower the spatial positive correlation degree of unit attribute values is. Moran’s \( I = 0 \) means there is no spatial autocorrelation.

The Z-score is used to indicate the statistical significance of Moran’s I index and can be calculated as follows:

\[ Z = \frac{I - E(I)}{\sqrt{VAR(I)}}, \]  

where \( E(I) \) and \( VAR(I) \) are the expected value and variance of Moran’s I, respectively.

4.2. Geographically Weighted Regression. Spatial heterogeneity is different from spatial correlation, which is a reason to explain spatial variation. Spatial heterogeneity mainly reflects the instability and complexity of spatial object distribution. If expressed by a linear regression model, the regression coefficient of variables is independent of spatial location. Therefore, an extended form of linear regression, the GWR model is introduced. The model expression is as follows:

\[ y_i = \beta_0 (\mu_i, \nu_i) + \sum_{k=1}^{n} \beta_k (\mu_i, \nu_i) X_{ik} + \epsilon_i, i = 1, 2, \ldots, n, \]  

where \( y_i \) is the dependent variable; \( (\mu_i, \nu_i) \) is the spatial position coordinate; \( \beta_k (\mu_i, \nu_i) \) is the regression parameter; \( \epsilon_i \) is the random error.

The least-square method is used to estimate the parameters, and the formula is as follows:

\[ \hat{\beta} (\mu_i, \nu_i) = (X^T W (\mu_i, \nu_i) X)^{-1} X^T W (\mu_i, \nu_i) Y, \]  

where \( \hat{\beta} \) is the estimated coefficients of independent variables, \( X \) and \( Y \) are the vector matrices of the independent and dependent variables, respectively, and \( W \) is the spatial weighted matrix. They can be expressed as follows:
transfer ridership is higher than the benchmark, indicating that shared bikes around this metro station are sufficient for the expected bike-sharing transfer demand. Therefore, the difference between the actual ridership and the benchmark can be a criterion for evaluating the quality of bike-sharing transfer service around different metro stations.

Since the benchmark varies from station to station, the absolute differences between the actual values and the benchmark values are incommensurable for different metro stations. Therefore, a relative evaluation index based on the difference value is proposed to evaluate the bike-sharing transfer services for different metro stations [36]. It is calculated by the ratio between the difference and benchmark value, as follows:

\[ TR_i = \frac{e_i}{\bar{y}_i} \times 100\% \]

where \( TR_i \) represents the relative evaluation index. The higher the \( TR_i \) is, the better the bike-sharing transfer service is.

5. Results and Discussion

5.1. Model Performance Evaluation. To evaluate the performance of the GWR in this study, a regression using ordinary least squares (OLS) is also conducted for comparison. The results of the OLS and GWR models are shown in Table 2. According to the \( R^2 \), the explanation degree of the OLS model is only 20.7%, which is relatively low. The possible reason is that OLS did not take into account the spatial heterogeneity of influencing factors, leading to poor performance of the model when explaining global regression. However, the \( R \) square of GWR is 0.832, which is significantly higher than that of the OLS model. In addition, the AICc value of GWR is also smaller than that of the OLS, indicating significant superiority of the GWR model.

To further examine the local performance of the GWR model, the condition number and local \( R^2 \) are visualized in Figure 6. In terms of local collinearity, no condition is less than 0, greater than 30, or set to “null”, indicating that there is no local multicollinearity and the correlation results are reliable. In terms of Local \( R^2 \), the higher the value is, the better the fitting effect of the model is. As can be seen from the figure, the value in most areas is over 0.4, and the value in Pudong District is greater than that in Huangpu District, indicating that Pudong District has a higher explanatory ability than Huangpu District. As for the residual autocorrelation test, the residual is in a discrete state, indicating that the possible spatial autocorrelation in the model is avoided after adopting the GWR model.

In conclusion, the GWR model has passed the tests of local collinearity, local goodness of fit, and residual autocorrelation. In this case, the transfer ridership can be considered as a benchmark value to evaluate the transfer services of bike-sharing from the perspective of spatial heterogeneity.
Table 2: GWR performance evaluation.

| Models | AICc     | $R^2$  | Adjusted $R^2$ |
|--------|----------|--------|----------------|
| OLS    | -283.121 | 0.207  | 0.195          |
| GWR    | -487.212 | 0.832  | 0.762          |

Figure 6: Continued.

(a)
5.2. Spatial Heterogeneity Analysis. To make the results more intuitive, the regression coefficients of the model are visualized for each metro station. If the value is greater than 0, the independent variable has a positive effect on the transfer ridership of bike-sharing; if it is less than 0, it has a negative effect; if it is equal to 0, it has no effect. Then, the spatially varying effect of each influencing factor is analyzed hereafter.

5.2.1. Spatially Varying Effect of the Metro Ridership on Bike-Sharing Transfer Ridership. The regression coefficients of the metro ridership are visualized by the color of each metro station in Figure 7. It shows that the coefficients range from \(-0.099\) to \(2.396\) with colors from light to dark, indicating a spatially varying effect of the metro ridership on bike-sharing transfer ridership. From the perspective of influence direction, the effect of metro ridership is generally positive, except for a few stations in the periphery. It indicates that the more metro ridership, the more transfer ridership in most cases. From the perspective of influence degree [37], the metro ridership in the north Yangpu district has the largest coefficient which shows the promotion effect of metro ridership on the transfer ridership is more significant in this district.

5.2.2. Spatially Varying Effect of the Population Density on Bike-Sharing Transfer Ridership. The regression coefficients of the population density are visualized by the color of each metro station in Figure 8. It shows that the coefficients range from \(-0.523\) to \(1.03\) with colors from light to dark, indicating a spatially varying effect of the population on bike-sharing transfer ridership. From the perspective of influence direction, the effect of population density is negative in the north of Hongkou District, Yangpu District. However, the population density has a positive effect on the transfer ridership in other districts. From the perspective of influence degree, the positive effect of population density on the transfer ridership is especially larger in the Baoshan District which is sparsely populated. It shows that the population growth in this district may increase bike-sharing transfer ridership more significantly, compared with other districts.

5.2.3. Spatially Varying Effect of the Cycleway Density on Bike-Sharing Transfer Ridership. The regression coefficients of the cycleway density are visualized by the color of each metro station in Figure 9. It shows that the coefficients range from \(-1.962\) to \(0.61\) with colors from light to dark, indicating

\[\text{Figure 6: GWR performance evaluation: (a) GWR condition number and (b) GWR local R}^2.\]
Figure 7: Spatially varying effect of the metro ridership on bike-sharing transfer ridership.

Figure 8: Spatially varying effect of the population density on bike-sharing transfer ridership.
a spatially varying effect of the cycleway density on bike-sharing transfer ridership. In terms of the influence direction, the cycleway density has a positive effect on bike-sharing transfer ridership in the western and northern parts of Shanghai. Whereas in the rest parts of Shanghai, the cycleway density has an inhibitory effect on the transfer ridership. In terms of the influence degree, the effects of cycleway density are usually larger in the periphery. For example, the regression coefficient of cycleway density at Gongfu Xincun station of Line 1 in the Baoshan District is the largest, up to 0.61, indicating that the change in cycleway density has a significant impact on the transfer ridership.

5.3. Bike-Sharing Transfer Services Evaluation. According to the aforementioned method [38, 39], the evaluation of bike-sharing transfer services is based on the difference between the bike-sharing transfer ridership and its benchmark for different metro stations. Considering the spatial heterogeneity in bike-sharing transfer ridership and its influencing factors, the spatially varying benchmarks can be derived from the GWR model for different metro stations. Based on equation (7), the relative evaluation index ($TR_i$) of each metro station is calculated and visualized in Figure 10. The metro stations in blue are those with actual bike-sharing transfer ridership above the benchmark, which are also identified as the good ones. While the metro stations in red are those with actual bike-sharing transfer ridership below the benchmark, which are also regarded as the bad ones. The darker the color, the greater the deviation from the benchmark. Therefore, the evaluation results of bike-sharing transfer services for different metro stations are also presented in Figure 10. The closer the color of a metro station to dark blue, the better the bike-sharing transfer services for the station. On the contrary, the closer the color of a metro station to dark red, the worse the bike-sharing transfer services for the station.

To be more specific, we select the top 5 metro stations with the best and worst transfer services of bike-sharing, as shown in Table 3. These 10 metro stations show the largest relative deviation between the transfer ridership and benchmark value. The top 5 metro stations with the best transfer services of bike-sharing are mainly on Line 2, Line 7, and Line 9. Three of them are online 7, and the largest is the Jinxiu Road station. The evaluation indexes of all these stations are greater than 100%, indicating that the bike-sharing transfer ridership of these stations is more than twice their benchmark. The top 5 metro stations with the worst transfer services of bike-sharing are mainly on Line 2, Line 6, Line 8, and Line 12. The actual values of bike-sharing transfer ridership for these stations are all below the benchmark values. For example, Century Park station has
the lowest $TR_i$, which is $-1,369.395\%$, indicating that transfer service of bike-sharing at this station deviates most from the average level. Therefore, more actions should be taken to improve the bike-sharing transfer services for these stations, such as providing more bike-sharing around these metro stations.

To further evaluate the bike-sharing transfer services around metros stations in different districts, the average $TR_i$ of metros in each district is calculated and visualized in Figure 11. According to the color of the district, we can derive the overall score of bike-sharing transfer services in the district. The darker the color of a district, the better the transfer services in this district. It shows that the districts with average $TR_i$ larger than 0 are the Xuhui District, Minhang District, and Huangpu District. The average score of the Xuhui District is 7.427%, with the darkest color in Figure 11, indicating that bike-sharing transfer services are generally better than expected in the Xuhui District. While the bike-sharing transfer services in Yangpu District, Qingpu District, and Pudong District are generally worse than the benchmarks. For example, the average score of Pudong District is $-700.453\%$, with the lightest color, indicating that the transfer services of bike-sharing in this area should be further improved. It provides a reference for the governments to develop a differentiated policy to optimize the connection between dockless bike-sharing and metros.
6. Conclusion and Implications

Based on multisource data on the bike-sharing, metro, and the built environment, this study evaluates the bike-sharing transfer services around metro stations considering spatial heterogeneity. First, we identify the bike-sharing transfer trips through a catchment method and calculate the bike-sharing transfer ridership for each metro station. Second, the possible explanatory variables for transfer ridership are calculated, including the metro ridership and some built environment features of the metro station. Then, we use a GWR model to explore the spatially varying effects of these explanatory variables on the bike-sharing transfer ridership. On this basis, the prediction of the GWR model is regarded as a benchmark to evaluate the bike-sharing transfer services. A relative evaluation index is proposed based on the difference between the actual bike-sharing transfer ridership and its benchmark value for each metro station. Finally, we analyze and discuss the results derived from the aforementioned data and methods. The main findings are as follows:

Figure 11: Evaluation of bike-sharing transfer services in different districts.
(1) The performance of the GWR model is much better than that of the OLS model for the same variables in this study, indicating a significant spatial heterogeneity in the transfer ridership of bike-sharing. The $R^2$ square of the GWR model is 0.832, compared with 0.207 of the OLS model.

(2) The main factors affecting the transfer ridership of bike-sharing are metro ridership, population density, and cycleway density. The regression coefficients of these variables vary from station to station, showing spatially varying effects on the transfer ridership. The coefficients of metro ridership range from −0.099 to 2.396 with larger values in the north Yangpu district. The coefficients of population density range from −0.523 to 1.03 with larger values in the Baoshan District. The coefficients of cycleway density range from −1.962 to 0.61 with larger values at Gonggu Xincun station of Line 1 in the Baoshan District.

(3) Given the benchmark derived from the GWR model and the relative evaluation index, the bike-sharing transfer services of different metro stations in different districts are comparatively evaluated. The metro stations with the best and worst transfer services of bike-sharing are Jinxiu Road station and Century Park station, and their TR are 227.750% and −1369.395% respectively. Overall, the bike-sharing transfer services are better in Xuhui District, Minhang District, and Huangpu District, and worse in Pudong District and Qingpu District.

Based on these findings, some policy implications and suggestions can be provided for the government and operators. First, the government should termly evaluate the levels of the bike-sharing transfer services around metro stations based on the method proposed in this study. Second, the government could identify the metro stations or districts where the bike-sharing transfer services are below the average level (benchmark) and carry out some specific measures to improve them. Third, the operators should increase the supply of shared bikes around the metro stations with deficient bike-sharing transfer services. Last, all future policies on the integration of dockless bike-sharing and metros should consider the spatial heterogeneity in bike-sharing transfer ridership and its influencing factors.

There are also some limitations in this study. First, only the data from one bike-sharing company, that is, Mobike, is analyzed in this study, which cannot paint the whole picture of the bike-sharing market in Shanghai. If more data from other companies are available in the future, a validation study should be conducted to make our results more convincing and universal. Second, this study mainly analyzes the influences of transport and built environment factors on the bike-sharing transfer ridership. Other influencing factors, such as weather, prices, and user attributes, should also be considered in future studies. Finally, the method proposed above is only tested in the city of Shanghai, so the results may only reflect the bike-sharing transfer services in Shanghai. It is necessary to validate the applicability of the methods and findings for other cities in the future.

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

Conflicts of Interest
The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments
This study was sponsored by the National Natural Science Foundation of China (grant no. 52002244); Shanghai Chenguang Program (grant no. 20CG55); Shanghai Pujiang Program (grant no. 2020PJ(C083); Humanities and Social Science Foundation of the Ministry of Education of China (grant no. 21YJC630117); and Natural Science Foundation of Shandong Province, China (grant no. ZR2021QG053).

References
[1] W. Li, L. Bao, Y. Li, H. Si, and Y. Li, “Assessing the transition to low-carbon urban transport: a global comparison,” Resources, Conservation and Recycling, vol. 180, Article ID 106179, 2022.
[2] Y. Yang, Z. Yuan, J. Chen, and M. Guo, “Assessment of oscillating value method based on entropy weight to transportation energy conservation and emission reduction,” Environmental engineering and management journal, vol. 16, no. 10, pp. 2413–2423, 2017.
[3] J. E. Schoner and D. M. Levinson, “The missing link: bicycle infrastructure networks and ridership in 74 US cities,” Transportation, vol. 41, no. 6, pp. 1187–1204, 2014.
[4] A. A. Campbell, C. R. Cherry, M. S. Ryerson, and X. Yang, “Factors influencing the choice of shared bicycles and shared electric bikes in Beijing,” Transportation Research Part C: Emerging Technologies, vol. 67, no. 4, pp. 399–414, 2016.
[5] L. Chen, A. J. Pel, X. Chen, D. Sparing, and I. A. Hansen, “Determinants of bicycle transfer demand at metro stations,” Transportation Research Record: Journal of the Transportation Research Board, vol. 2276, no. 1, pp. 131–137, 2012.
[6] T. Gu, I. Kim, and G. Currie, “Measuring immediate impacts of a new mass transit system on an existing bike-share system in China,” Transportation Research Part A: Policy and Practice, vol. 124, no. 8, pp. 20–39, 2019.
[7] C. Jingxu, C. Xuewu, W. Wei, and F. Baol, “The demand analysis of bike-and-ride in rail transit stations based on revealed and stated preference survey,” Procedia - Social and Behavioral Sciences, vol. 96, no. 2, pp. 1260–1268, 2013.
[8] X. Ma, Y. Jin, and M. He, “Measuring bikeshare access/egress transferring distance and catchment area around metro stations from smatcard data,” Information, vol. 9, no. 11, p. 289, 2018.
[9] Y. Guo and S. Y. He, “Built environment effects on the integration of dockless bike-sharing and the metro,” Transportation Research Part D: Transport and Environment, vol. 83, Article ID 102335, 2020.
[10] S. Li, D. Lyu, G. Huang et al., “Spatially varying impacts of built environment factors on rail transit ridership at station level: a case study in Guangzhou, China,” Journal of Transport Geography, vol. 82, Article ID 102631, 2020.
[11] M. Givoni and P. Rietveld, “The access journey to the railway station and its role in passengers’ satisfaction with rail travel,” *Transport Policy*, vol. 14, no. 5, pp. 357–365, 2007.

[12] A. Faghih-Imani, N. Eluru, A. M. El-Geneidy, M. Rabbat, and U. Haq, “How land-use and urban form impact bicycle flows: evidence from the bicycle-sharing system (BIXI) in Montreal,” *Journal of Transport Geography*, vol. 41, no. 2, pp. 306–314, 2014.

[13] K. Gebhart and R. B. Noland, “The impact of weather conditions on bikeshare trips in Washington, DC,” *Transportation*, vol. 41, no. 6, pp. 1205–1225, 2014.

[14] H. Li and J. F. Reynolds, “On definition and quantification of heterogeneity,” *Oikos*, vol. 73, no. 2, pp. 280–284, 1995.

[15] L. Guo, H. Gong, F. Zhu et al., “Analysis of the spatiotemporal variation in land subsidence on the beijing plain, China,” *Remote Sensing*, vol. 11, no. 10, p. 1170, 2019.

[16] Z. Xie and J. Yan, “Kernel density estimation of traffic accidents in a network space,” *Computers, Environment and Urban Systems*, vol. 32, no. 5, pp. 396–406, 2008.

[17] Y. Sun, D. Tong, and C. Cao, “How urban built environment affects the use of public bicycles: A case study of nanshan district of shenzhen,” *Acta Scientiarum Naturalium Universitatis Pekinensis*, vol. 12, no. 6, pp. 11–24, 2018.

[18] X. Qian and S. V. Ukkusuri, “Spatial variation of the urban taxi ridership using GPS data,” *Applied Geography*, vol. 59, pp. 31–42, 2015.

[19] H. Yang, Y. Zhang, L. Zhong, X. Zhang, and Z. Ling, “Exploring spatial variation of bike sharing trip production and attraction: a study based on Chicago’s Divvy system,” *Applied Geography*, vol. 115, Article ID 102130, 2020.

[20] H. Yang, T. Xu, and D. Chen, “Direct modeling of metro ridership at station level: a study based on mixed geographically weighted regression,” *Canadian Journal of Civil Engineering*, vol. 47, no. 3, pp. 96–106, 2019.

[21] W. Li, S. Chen, J. Dong, and J. Wu, “Exploring the spatial variations of transfer distances between dockless bike-sharing systems and metros,” *Journal of Transport Geography*, vol. 92, Article ID 103032, 2021.

[22] R. Cervero and K. Kockelman, “Travel demand and the 3Ds: density, diversity, and design,” *Transportation Research Part D: Transport and Environment*, vol. 2, no. 3, pp. 199–219, 1997.

[23] R. Ewing and R. Cervero, “Travel and the built environment: a synthesis,” *Transportation Research Record: Journal of the Transportation Research Board*, vol. 1780, no. 1, pp. 87–114, 2001.

[24] I. Mateo-Babiano, R. Bean, J. Corcoran, and D. Pojani, “How does our natural and built environment affect the use of bicycle sharing?” *Transportation Research Part A: Policy and Practice*, vol. 94, pp. 295–307, 2016.

[25] Y. Tang, H. X. Pan, and Q. Shen, “Bike-sharing Systems in Beijing, Shanghai, and Hangzhou and Their Impact on Travel Behavior,” in *Proceedings of the Transportation Research Board 90th Annual Meeting*, Transportation Research Board, Washington, D.C., USA, January, 2011.

[26] W. Li, Z. Pu, Y. Li, and M. Tu, “How does ridesplitting reduce emissions from ridesourcing? A spatiotemporal analysis in Chengdu, China,” *Transportation Research Part D: Transport and Environment*, vol. 95, Article ID 102885, 2021.

[27] T. Ma, C. Liu, and S. Erdoğan, “Bicycle sharing and public transit,” *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2534, no. 1, pp. 1–9, 2015.

[28] Z. Wang, L. Cheng, Y. Li, and Z. Li, “Spatiotemporal characteristics of bike-sharing usage around rail transit stations: evidence from Beijing, China,” *Sustainability*, vol. 12, no. 4, p. 1299, 2020.

[29] J. Wang and X. Cao, “Exploring built environment correlates of walking distance of transit egress in the Twin Cities,” *Journal of Transport Geography*, vol. 64, pp. 132–138, 2017.

[30] T. Zuo, H. Wei, and A. Rohne, “Determining transit service coverage by non-motorized accessibility to transit: case study of applying GPS data in Cincinnati metropolitan area,” *Journal of Transport Geography*, vol. 67, pp. 1–11, 2018.

[31] X. Ma, X. Zhang, X. Li, X. Wang, and X. Zhao, “Impacts of free-floating bikesharing system on public transit ridership,” *Transportation Research Part D: Transport and Environment*, vol. 76, pp. 100–110, 2019.

[32] B. Flamm, “Determinants of bicycle-on-bus boardings: a case study of the greater cleveland rta,” *Journal of Public Transportation*, vol. 16, no. 2, pp. 67–84, 2013.

[33] W. Li, Z. Pu, Y. Li, and X. Ban, “Characterization of ridesplitting based on observed data: A case study of Chengdu, China,” *Transportation Research*, vol. 100, pp. 330–353, 2019.

[34] Y. Ji, X. Ma, M. Yang, Y. Jin, and L. Gao, “Exploring spatially varying influences on metro-bikeshare transfer: a geographically weighted Poisson regression approach,” *Sustainability*, vol. 10, no. 5, p. 1526, 2018.

[35] Y. Shen, X. Zhang, and J. Zhao, “Understanding the usage of dockless bike sharing in Singapore,” *International Journal of Sustainable Transportation*, vol. 12, no. 9, pp. 686–700, 2018.

[36] P. D. Allison, “Change scores as dependent variables in regression analysis,” *Sociological Methodology*, vol. 20, pp. 93–114, 1990.

[37] L. Cheng, J. De Vos, M. Yang, and F. Witlox, “Examining non-linear built environment effects on elderly’s walking: a random forest approach,” *Transportation Research Part D: Transport and Environment*, vol. 88, Article ID 102552, 2020.

[38] Y. Yang, K. He, Y.-p. Wang, Z.-z. Yuan, Y.-h. Yin, and M.-z. Guo, “Identification of dynamic traffic crash risk for cross-area freeways based on statistical and machine learning methods,” *Physica A: Statistical Mechanics and Its Applications*, vol. 595, Article ID 127083, 2022.

[39] D. Lei, X. Chen, L. Cheng, L. Zhang, S. V. Ukkusuri, and F. Witlox, “Inferring temporal motifs for travel pattern analysis using large scale smart card data,” *Transportation Research Part C: Emerging Technologies*, vol. 120, Article ID 102810, 2020.