Sustainable Cities and Society 89 (2023) 104348

Contents lists available at ScienceDirect

Sustainable Cities and Society

journal homepage: www.elsevier.com/locate/scs

The spatially varying effects of built environment characteristics on the integrated usage of dockless bike-sharing and public transport

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A R T I C L E I N F O

Keywords:
Dockless bike-sharing
Integrated usage
Built environment
Sustainable city
Multiscale geographically weighted regression

A B S T R A C T

The dockless bike-sharing (DBS) system offers a flexible feeder mode for connecting to public transport. Using multi-source big data, this study employs a multi-scale geographically weighted regression to analyze the effects of built environment characteristics on the integrated usage of DBS and public transport. Different modes of public transport (i.e., bus and subway) are further considered to explore these effects by defining two scenarios in Beijing, namely the bike-bus scenario and the bike-subway scenario. The results show that the number of points of interest around public transport stations (e.g., education and culture places, leisure services, and residential and accommodation services), length of main road, and length of cycle path significantly affect the integrated usage in the two scenarios. However, population density, number of workplaces, and number of shopping and eating places only play a vital role in the integrated DBS and bus system. Access to bus stops significantly impacts the integration of DBS and the subway. In addition, the effects of these built environment characteristics on the integrated usage are diverse in different areas. These findings can be utilized to create a bike-friendly environment to encourage a connection between DBS and public transport.

1. Introduction

Dockless bike-sharing (DBS) has become a mode of transport in many countries, such as China (Ji, Ma, Yang, Jin & Gao, 2018; Soriguera & Jiménez-Meroño, 2020; Wang et al., 2022). Unlike motorized transportation modes, DBS has many advantages, including energy efficiency and environmental protection, health benefits, the possibility of door-to-door travel, lower cost, etc. (Li, Krishna Sinniah & Li, 2022; Macioszek & Cieśla, 2022). However, it also has some disadvantages, such as sensitivity to weather conditions, exposure to road accidents, and dependence on the condition of the cycling infrastructure (Kubaľák, Kalašová & Hájnik, 2021). Considering the relationship with other modes of public transport, bikes in urban transportation systems serve two main functions (Campbell & Brakewood, 2017). One is to encourage people to use bikes instead of public transport for short-distance travel (Liu et al., 2020b). The other is bike-transit integration, where the bike is used as a feeder mode to/from a public transport station (Zhao & Li, 2017). Integrating DBS and public transport (e.g., bus and subway) is widely regarded as an important way to improve the efficiency of public transport and solve the first- and last-mile problem (Lee, Choi & Leem, 2016). In the past decade, bike-transit integration has had a remarkable growth in many countries, representing one of the most important future directions in the bike-sharing domain (Fishman, 2016). Therefore, it is essential to understand how commuters use the combined mode to motivate the use of bikes as a mode of transport.

There are many studies on determinants of the integrated usage of DBS and public transport from multiple perspectives, including several main categories: individual and socioeconomic attributes (Chen, Chen, Chen & Cheng, 2021; Ji et al., 2017; Zhao & Li, 2017), land use (Guo, Yang, Lu & Zhao, 2021; Lin et al., 2018), and transport infrastructure (Böcker, Anderson, Uteng & Throndsen, 2020; Griffin & Sener, 2016). First, individual-level features, such as socioeconomic factors (e.g., age, gender, income, and home location), personal attitude factors (e.g., environmental awareness), and perceptual factors (e.g., perceived comfort and traffic safety), are associated with the use frequency of DBS (Wang et al., 2022). Second, the effects of land use on DBS-public transport integration have been widely identified. According to Ji et al. (2018), many governmental, commercial, and industrial land uses

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https://doi.org/10.1016/j.scs.2022.104348
Received 8 May 2022; Received in revised form 12 November 2022; Accepted 9 December 2022
Available online 10 December 2022

are significantly associated with integrated uses. Considering pedestrian crowding, Chen, van Lierop and Ettema (2020) discovered that areas with more restaurants are less attractive for cycling. In addition, the integrated usage is also related to the surrounding transport infrastructure. Xu et al. (2019) found that a dense road network is positively associated with more bike trips. Longer bicycle lanes tend to attract more DBS trips and their integrated trips with the metros (Liu, Ji, Feng & Shi, 2020a; Zhao, Ke, Lin & Yu, 2020).

In recent years, the built environment has been recognized as a significant determinant of the travel model. Establishing a bike-friendly environment requires a better understanding of the relationship between the built environment and bike usage (Lin et al., 2018). Studies that examine these topics have flourished, demonstrating the importance of such effects. For example, Zhang, Thomas, Brussel and Van Maarseveen (2017) employed a multiple linear regression model to examine how built environment factors (e.g., station attributes and accessibility, cycling infrastructure) affect the use of public bikes at the station level. More recently, Guo and He (2020) applied a series of negative binomial regressions to investigate the effect of the built environment on the integrated use of DBS and the metro. They found that a higher employment/job density could improve commuting demand and thus increase bike-sharing and metro usage. Orvin and Fatmi (2021) further developed a latent segmentation-based logit model to examine the reasons for choosing DBS. They confirm the effects of socio-demographic characteristics, travel attributes, transportation infrastructure attributes, and neighbourhood characteristics. In addition, Cheng, Jin, Wang, Lee and Witlox (2022) used a generalized additive mixed modeling approach to investigate the relationship between bikeshare-metro integrated use and the built environment attributes of station catchment areas.

Combining DBS and public transport is beneficial not only to the transport system and the natural environment, but also to users and organizers of transportation (Macioszek & Kurek, 2020). Previous studies lay a foundation for an in-depth analysis of how the built environment affects DBS usage. However, it is unclear how built environment characteristics affect the integrated usage of DBS and public transport (Cheng et al., 2022). Moreover, few studies have examined the spatially varying effects of built environment characteristics on the integrated usage, especially considering the spatial heterogeneity. The differences in the natural conditions and socioeconomic development of various regions lead to spatial differences in the integrated usage levels. Therefore, revealing the spatial heterogeneity of the effect of the built environment on the usage of DBS connected to public transport is of great significance to the city's governance in relation to low-carbon transport. In addition, the possible different effects of the built environment on the bike integrated with different modes of public transport (bus or subway) have not been sufficiently investigated. To fill the above research gaps, this study analyzes the effects of the built environment on the integration of public transport and DBS with an emphasis on exploring the spatial heterogeneity of these effects. The built environment characteristics are extracted from multi-source big data. We further create two scenarios, namely the bike-bus scenario and the bike-subway scenario, to explore these effects in Beijing using a multi-scale geographically weighted regression. The findings of this study can help policy-makers to develop a bike-friendly built environment that improves the seamless connection between DBS and public transport.

This study makes three main contributions. First, a more thorough characterization of the built environment is presented using multi-source big data such as bike-sharing trip data and points of interest data. Second, the spatially varying effects of the built environment on the integrated usage of DBS and public transport are explored by applying a multi-scale geographically weighted regression. Third, two scenarios, namely the bike-bus scenario and the bike-subway scenario, are further created to investigate the different effects of the built environment on the bike integrated with different public transport modes.

The rest of this study is organized as follows. Section 2 presents the study area and the data. Section 3 introduces the methodology used in this study. The results and discussion are given in Section 4 and Section 5, respectively. Finally, the conclusions are presented in Section 6.

2. Study area and data collection

2.1. Study area

The study area of this study focuses on Beijing, which is the capital of China and one of the biggest cities in the country. As shown in Fig. 1, Beijing is located on the North China Plain. The population of Beijing is more than 20 million and covers an area of 16,411 km^2 (Chai, Guo, Xiao & Jiang, 2021). In June 2015, the first DBS system appeared on the campus of Peking University in Beijing and then obtained large popularity in other regions of Beijing (Chen et al., 2020). Due to no strict policy supervision during the early stages, DBS in Beijing experienced explosive growth in 2017 and 2018 (Wang & Sun, 2022). In recent years, considering some negative impacts, such as oversupply, vandalism, and improper parking, the Beijing government has formulated a series of regulations and rules to overhaul and standardize the DBS market. Currently, there are about 950,000 shared bikes in Beijing (Beijing Municipal Commission of Transport, 2022). Many exclusive cycle paths have been built in Beijing, which provides an excellent opportunity to promote bike-public transport integration. This also makes Beijing a good case to investigate the relationships between the built environment and the integrated usage of DBS and the bus or subway. Since there is less bike-sharing used outside the Fifth Ring Road (Song, 2020), the region within the Fifth Ring Road in Beijing was further selected as the study area.

2.2. Data collection

The data used in this study are as follows:

(1) DBS trip data. The DBS trip data during the period of November 11 to 26, 2019 were obtained from the Beijing Engineering Laboratory of BD Navigation & LBS Technology. The dataset includes 4.35 million trip records and provides the following information: area code, bike ID, start time, end time, and the latitude and longitude of each bike. We first removed the trips which are out of the study area by setting longitude and latitude boundaries. Then, all invalid data such as repeated records, missing important information, and position errors were removed. Finally, there are 1.18 million trip records for further analysis.
(2) Road network data. The road network data used in this study were obtained from the OpenStreetMap (OSM) (http://www.openstreetmap.org/). Data acquisition for the OSM is multi-faceted, including amateurs and volunteers, surveyors and staff at federal agencies, and professionals of geographic information systems. The road types are divided into highways, primary roads, secondary roads, tertiary roads, cycle paths, special roads, footways, steps, and so on (Zhang, Li, Wang, Bao & Tian, 2015).
(3) Population data. The population data were collected from the WorldPop dataset (https://www.worldpop.org/). The WorldPop dataset provides global gridded population data with a resolution of 100 m for each year 2000–2020. Compared with other population grid datasets, this population data has high accuracy and resolution in China (Bai, Wang, Wang, Gao & Sun, 2018).
(4) Public transport stations data. The public transport stations in this study consist of subway stations and bus stops. These data were extracted using the application programming interface (API) of Amap (https://lbs.amap.com/). The data include the geographical coordinates of each transport stop. Since there are too many bus stops in Beijing, we obtained many sites with a high

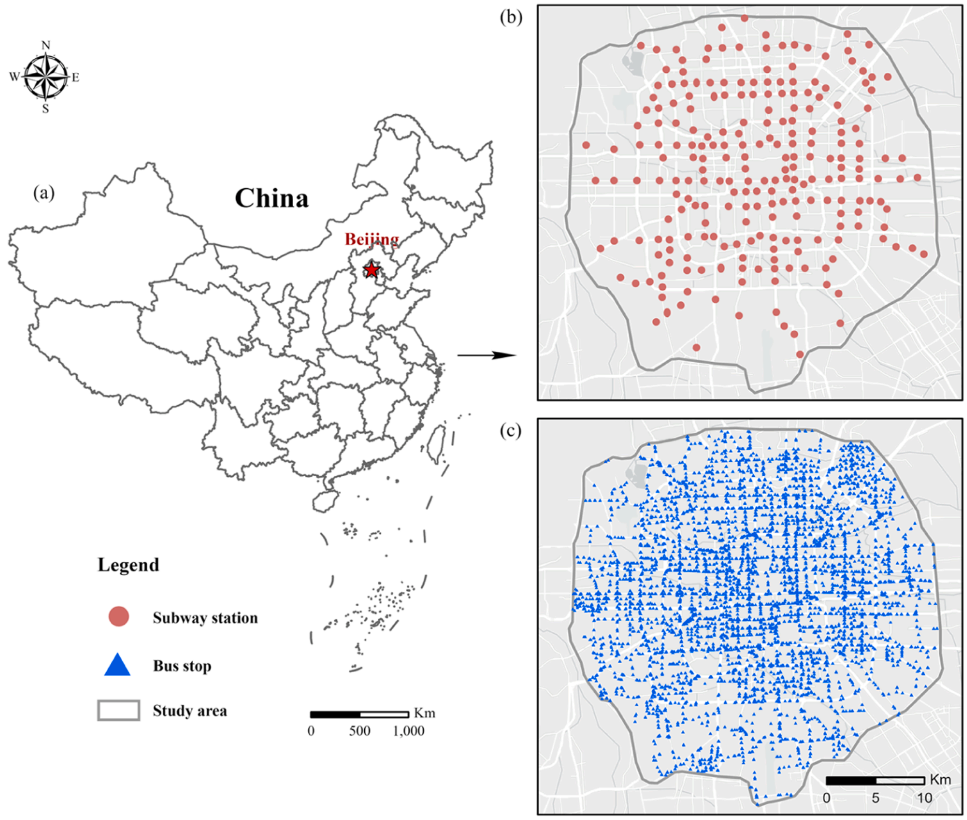

Fig. 1. Study area. (a) location of Beijing in China, (b) the spatial distribution of subway stations, and (c) the spatial distribution of bus stops.

density of bus stops as comprehensive bus stops. The process includes three steps. First, a density map of bus stops is obtained using the location data of bus stops and the density analysis tools in the ArcGIS 10.5 software (ESRI Inc., Redlands, CA, USA). Second, the value of the density map is further divided into five categories (i.e., very low, low, medium, high, and very high) based on the natural breaks (Jenks) classification method, representing the different density levels. Finally, the sites classified as medium to very high density are extracted as comprehensive bus stops.

(5) Point of interest (POI) data. The POI data were also obtained from the Amap. Each POI's latitude and longitude are included in the data. This study selects seven categories POIs, including workplaces, education and culture places, shopping and eating places, leisure services, financial services, government agencies, and residential and accommodation services (see Table 1).

Table 1
Categories of POIs (Zhou et al., 2022).

POI category	Detailed description
Workplaces	Office buildings, Industrial parks
Education and culture places	Research institution, University, School, Museum, Library
Shopping and eating places	Shopping center, Convenience store, Snack bar, Restaurant
Leisure services	Zoo, Scenic zone, Park
Financial services	Banks, Automated teller machine
Government agencies	Government agency, Social organization
Residential and accommodation services	Apartment, House, Dormitory, Hotel

3. Methodology

3.1. Calculation of the integrated usage

In general, the integration of DBS and public transport has two patterns: (1) cycling to the public transport station (i.e., access integration) and (2) cycling from the public transport station (i.e., egress integration). Through access integration (Pattern 1) and egress integration (Pattern 2), DBS can work as a feeder mode (Guo & He, 2021). Fig. 2 shows an integrated "DBS + public transport" trip for commuting.

The integrated usage of DBS and public transport (e.g., bus and subway) is calculated by a big data-based approach. First, the relative location of bikes to public transport stations is identified by spatially matching the real-time position data of DBS with the fixed location of public transport stations. Then, in line with Wu, Lu, Lin and Yang (2019) and Guo et al. (2021), the integrated usage is measured by the counts of the use of DBS in the buffer of a public transport station (see Fig. 3). Here, a fundamental assumption is that bike trips in close proximity to public transport stations can be considered as the integrated usage (Guo et al., 2021). According to Ji et al. (2018), over 90% of transfer trips are finished within 300 m. Therefore, a 300 m buffer is created for each public transport station to judge whether a DBS trip can be considered as an integrated usage.

3.2. Ordinary least squares regression (OLS)

The OLS model is always applied to analyze the relationships between a set of independent variables and a dependent variable. It estimates the global statistic that assumes a stationary and constant relationship over space, so the estimated parameters are the same for the entire study area (Tu & Xia, 2008). In this study, the OLS model is used as the base model and can be described as follows (Chien, Carver & Comber, 2020):

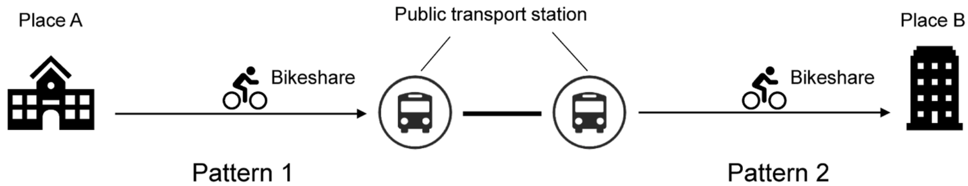

Fig. 2. An integrated "DBS + public transport" trip.

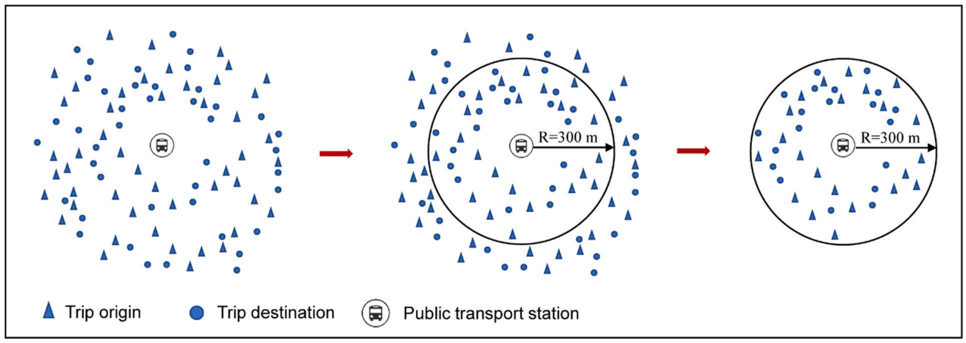

Fig. 3. The process of identifying the integrated usage.

$$y_i = \beta_0 + \sum_{j=1}^{m} \beta_j x_{ij} + \varepsilon_i \tag{1}$$

where y_i denotes the dependent variable, x_{ij} denotes the j-th independent variable, m is the number of independent variables, β_0 denotes the estimated intercept, β_j indicates the regression coefficient for the j-th independent variable, and ε_i denotes the random error term.

3.3. Multi-scale geographically weighted regression

It is frequently observed that the OLS model suffers from two common effects in spatial data: spatial autocorrelation of observation and process spatial heterogeneity (Anselin, 2010). To overcome such an issue, a geographically weighted regression (GWR) is developed, highlighting a non-stationary relationship between the independent variables and the dependent variable (Brunsdon, Fotheringham & Charlton, 1996). Although the GWR can be a significant improvement, a uniform bandwidth specified in a standard GWR may not be appropriate in situations where different independent variables operate over different spatial scales and thus have unique spatial relationships with the dependent variable (Chien et al., 2020). Consequently, a multiscale geographically weighted regression (MGWR) is further developed. An individual bandwidth is determined in a MGWR model for each independent variable. It allows the scales of the relationship between the independent variables and the dependent variable to vary spatially, as described in Eq. (2) (Fotheringham, Yang & Kang, 2017).

$$y_i = \beta_{bw0}(u_i, v_i) + \sum_{j=1}^{m} \beta_{bwj}(u_i, v_i) x_{ij} + \varepsilon_i \tag{2}$$

where $\beta_{bw0}(u_i, v_i)$ indicates the local intercept of i th observation, $\beta_{bwj}(u_i, v_i)$ indicates the parameter of the j-th independent variable x_{ij}, ε_i indicates the random error term, and (u_i, v_i) indicates the spatial location of i th observation. In this study, the built environment factors are the independent variables, and the integrated usage of DBS and the bus or subway is the dependent variable.

3.4. Measurement of the variables

This study aims to analyze the built environment's effects on the integrated usage of DBS and public transport. Considering different modes of public transport (i.e., bus and subway), the integrated usage can be described as bike-bus trips and bike-subway trips, respectively. It represents the usage frequency of bikes as a feeder mode to/from subway stations or bus stops. The dependent variable is the integrated usage of DBS and the bus or subway. Especially, the integrated usage is divided into two parts based on workdays and weekends. In addition, this study selects independent variables from five dimensions to describe the built environment comprehensively according to previous studies and data availability, including density, diversity, road service, transportation facility, and bike infrastructure, as shown in Table 2 (Cervero, Sarmiento, Jacoby, Gomez & Neiman, 2009; Guo et al., 2020; Wu, Kim & Chung, 2021; Zhang et al., 2017; Zhao, 2014; Zhao & Li, 2017). There is no multicollinearity problem among the independent variables since the variance inflation factor is all below 7.5 (Wu, 2020). The integrated usage of DBS and the bus or subway is obtained by calculating the total number of valid uses of bikes within a 300 m buffer of each public transport stop (Ji et al., 2018). In addition, the variables related to numbers are all calculated within a 1.5 km buffer of each public transport station. The size of this buffer is obtained by considering an acceptable cycling distance. The 1.5 km range is appropriate for both the bike-bus scenario and the bike-subway scenario. Bike-sharing studies have shown that most bicycle trips are short (e.g., within 1.5 km) (Yang et al., 2018). Liu, Ji, Feng and Timmermans (2020b) and Hu, Chen, Jiang, Sun and Xiong (2022) indicated that 1.5 km is a more reasonable range for analyzing the integrated use of bike-sharing and subway system. As for the integration of bike-sharing and bus, Basu and Ferreira (2021) demonstrated that bike-sharing has the most significant impact on reducing car dependence when the distance to bus station is within a reasonable distance (e.g. 1.5 km).

3.5. Evaluation index

Four evaluation indexes are employed to assess the relative performance of the two models, including residual sum of squares (RSS), corrected Akaike information criterion (AICc), R-squared value (R^2), and adjusted R-squared value (Adjusted R^2) (Fotheringham et al., 2017; Jia & Zhang, 2021; Wang & Lu, 2021). The AICc evaluates the quality of each model, and a smaller AICc implies optimal parsimony and predictive accuracy for the model (Zeng et al., 2016). RSS indicates the sum

Table 2
Summary statistics of variables.

Variable	Description	Mean	SD	Min	Max
Dependent variables					
Bike-bus trips on workdays	Average bike-bus trips on workdays	130.43	336.78	0	730
Bike-bus trips on weekends	Average bike-bus trips on weekends	107.98	277.97	0	3743
Bike-subway trips on workdays	Average bike-subway trips on workdays	90.68	219.75	0	1656
Bike-subway trips on weekends	Average bike-subway trips on weekends	76.39	187.91	0	1619
Built environment					
Density					
Population density (people/km^2)	Number of people per square kilometer	12,500.05	550.87	1000.53	20,500.56
Diversity					
Workplaces	Number of workplaces	726.62	644.51	0	3698
Education and culture places	Number of education and culture places	452.31	354.06	1	1737
Shopping and eating places	Number of shopping and eating places	1077.25	806.62	13	3896
Leisure services	Number of leisure services	166.36	124.49	0	627
Financial services	Number of financial services	125.71	131.46	2	744
Government agencies	Number of government agencies	320.21	246.57	0	925
Residential and accommodation services	Number of residential and accommodation services	521.36	434.01	5	1988
Road service					
Main road (km)	Length of main roads	10.17	6.77	1.66	18.61
Transportation facility					
Subway stations	Number of subway stations	3.14	1.80	1	9
Bus stops	Number of bus stops	32.37	13.72	8	61
Bike infrastructure					
Cycle path (km)	Length of cycle paths	15.01	7.11	2.06	28.45

of the squared residuals in the model. R^2 and Adjusted R^2 evaluate the goodness of fit for the model accounting for a number of predictors and observations.

$$RSS = \sum_{i=1}^{n} (z_i - \widehat{z}_i)^2 \tag{3}$$

$$AICc = 2nln(\widehat{\sigma}) + nln(2\pi) + n\frac{n + tr(S)}{n - 2 - tr(s)} \tag{4}$$

$$R^2 = \frac{\sum_{i=1}^{n} (\widehat{z}_i - \overline{z})^2}{\sum_{i=1}^{n} (z_i - \overline{z})^2} \tag{5}$$

$$Adjusted\ R^2 = \left\{1 - \left[\frac{(1 - R^2)(n - 1)}{n - m - 1}\right]\right\} \tag{6}$$

where z_i indicates the observed value, $\widehat{z}_i$ indicates the estimated value, $\overline{z}$ indicates the mean value of observation, n indicates the number of data points, m indicates the number of independent variables, $\widehat{\sigma}$ indicates the estimated standard deviation of the error, $tr(S)$ indicates the trace of the hat matrix S, and S is the function of bandwidth.

Table 3
Model comparison between the OLS and the MGWR.

Models	RSS	AICc	R^2	Adjusted R^2
OLS				
Bike-bus_workday	380.98	1623.44	0.47	0.47
Bike-bus_weekend	397.53	1654.49	0.45	0.44
Bike-subway_workday	181.78	799.24	0.49	0.47
Bike-subway_weekend	189.53	814.14	0.46	0.45
MGWR				
Bike-bus_workday	256.32	1434.61	0.64	0.61
Bike-bus_weekend	287.57	1498.93	0.61	0.57
Bike-subway_workday	103.42	664.03	0.71	0.67
Bike-subway_weekend	98.93	658.27	0.72	0.68

Note: Residual sum of squares (RSS), Corrected Akaike information criterion (AICc), R-squared value (R^2), and adjusted R-squared value (R^2).

4. Results

4.1. Model comparison

The OLS model and the MGWR model are compared using four indexes: RSS, AICc, R^2, and Adjusted R^2, as shown in Table 3. The four indexes give a measure of model performance. Lower values of RSS and AICc and higher values of R^2 and Adjusted R^2 show better model fit.

In addition, the results of the OLS model show that the Koenker and Jarque-Bera statistics are statistically significant (P_value<0.005). It means there is statistically significant heteroscedasticity or non-stationarity in the global regression model, and the model's residuals are not normally distributed. Theoretically, the residuals must be independent of each other and distributed randomly in space (Fotheringham, Yue & Li, 2019). It can be found that the residuals from the MGWR model exhibit no spatial correlation (Moran's I index = 0.009; P_value>0.005), while the residuals from the OLS model are spatially correlated (Moran's I index = 0.245; P_value < 0.005).

As stated above, the OLS model is ineffective for analyzing the effects of the built environment on the integration of DBS and the bus or subway. However, the MGWR model can be regarded as a power tool, and the statistical performance of MGWR is better than that of OLS.

4.2. MGWR analysis

Two scenarios, namely the bike-bus scenario and the bike-subway scenario, are used to investigate the effects of the built environment characteristics on the integrated usage of DBS and the bus or subway, respectively.

4.2.1. Bike-bus scenario

The statistics are summarized in Table 4 for local parameter estimates in the bike-bus scenario obtained by the MGWR model, which shows the percentage of significant coefficients ($P \leq 0.1$), and the percentage of significant positive or negative coefficients to significant coefficients.

The results show that population density, workplaces, education and culture places, shopping and eating places, leisure services, residential and accommodation services, and main road are all significant on both workdays and weekends. But the cycle path is only significant on workdays. The main reason may be that there is more demand for commuting trips on workdays, which makes bike-sharing necessary as a

Table 4
The percentage of significant coefficients in the bike-bus scenario.

Variable	Bike-bus_workday			Bike-bus_weekend		
	$P \leq 0.1$ (%)	+ (%)	- (%)	$P \leq 0.1$ (%)	+ (%)	- (%)
Intercept	48.25	0.85	99.15	42.06	0.00	100.00
Population density	75.46	0.00	100.00	88.45	0.00	100.00
Workplaces	18.35	100.00	0.00	20.41	100.00	0.00
Education and culture places	50.93	100.00	0.00	47.01	100.00	0.00
Shopping and eating places	22.89	0.00	100.00	17.11	0.00	100.00
Leisure services	100.00	0.00	100.00	100.00	0.00	100.00
Financial services	0.00	0.00	0.00	0.00	0.00	0.00
Government agencies	0.00	0.00	0.00	0.00	0.00	0.00
Residential and accommodation services	17.73	0.00	100.00	21.44	0.00	100.00
Main road	92.99	0.00	100.00	99.38	0.00	100.00
Cycle path	79.18	100.00	0.00	0.00	0.00	0.00
Subway stations	0.00	0.00	0.00	0.00	0.00	0.00

feeder mode (Guo & He, 2020). For example, Xu et al. (2019) found two significant peak periods on workdays (i.e., 8 a.m. - 9 a.m. and 7 p.m. - 9 p.m.), while weekends show a relatively more static trend. Considering that the effects of the significant variables are almost similar on workdays and weekends, this study focuses mainly on the significant variables on workdays. Fig. 4 shows the spatial variation of local parameters on workdays. As shown in Fig. 4, a positive parameter estimate would represent a positive effect of explaining variables on the integrated usage, whereas a negative parameter estimate would reflect the negative effect. In addition, the gray color indicates areas where the variable doesn't significantly influence the integrated usage of DBS and the bus (at the 90% confidence level). The classification range of coefficient values is demarcated based on the natural breaks (Jenks) classification method provided by the ArcGIS 10.5 software (ESRI Inc., Redlands, CA, USA). The natural breaks (Jenks) classification method is a data classification method designed to determine the best arrangement of values into different classes (Stefanidis & Stathis, 2013).

In terms of population density, this variable negatively influences the integrated usage of DBS and the bus in central and northern Beijing. But there is no significant association in the south of Beijing (see Fig. 4(a)). A similar pattern can be seen in the spatial distribution of population density in Beijing. There is a higher population density in northern Beijing than in southern areas (He, Xu & Li, 2020). Wu et al. (2021) highlighted that bikes are not necessarily more common in areas with a high density of people. Crowded streets and high volumes of traffic may make cycling less attractive. As shown in Fig. 4(b), the local coefficient estimates for workplaces are significant in about 18% of the region, and it associates positively with the integrated usage of DBS and the bus. This effect only occurs in the northwest parts of Beijing. These areas have many public parks. One possible reason is that people who go to work may cycle through parks to avoid traffic and wait for traffic lights (Zhao & Li, 2017).

Previous studies found that DBS trips positively correlate with bike stations near the university (Rixey, 2013; Wang, Akar & Chen, 2018). Our findings support it but only in half of the region (see Fig. 4(c)). The number of education and culture places in the north of Beijing is far greater than that in the south of Beijing. Fig. 4(d) shows the local parameter estimates for shopping and eating places. It has a significant negative impact in just over 20% of the region, and in each case shopping and eating places associates negatively with the integrated usage. The primary reason might be that the areas with a high density of commercial land use (e.g., restaurants and shopping malls) are less attractive for cycling due to pedestrian crowding (Chen et al., 2020). In addition, the local coefficients of leisure services are significantly negative across the whole region (see Fig. 4(e)), showing a relatively robust relationship between leisure services and the integrated usage.

The local estimates for residential and accommodation services are significantly negative in the northeast of Beijing (17.73% of the study area), as shown in Fig. 4(f). This result supports the previous findings reported by Shen, Zhang and Zhao (2018). They pointed out that a negative association between public residential and bike usage may indicate that the residential areas are usually located in high accessibility areas. In relation to the main road and cycle path, the local

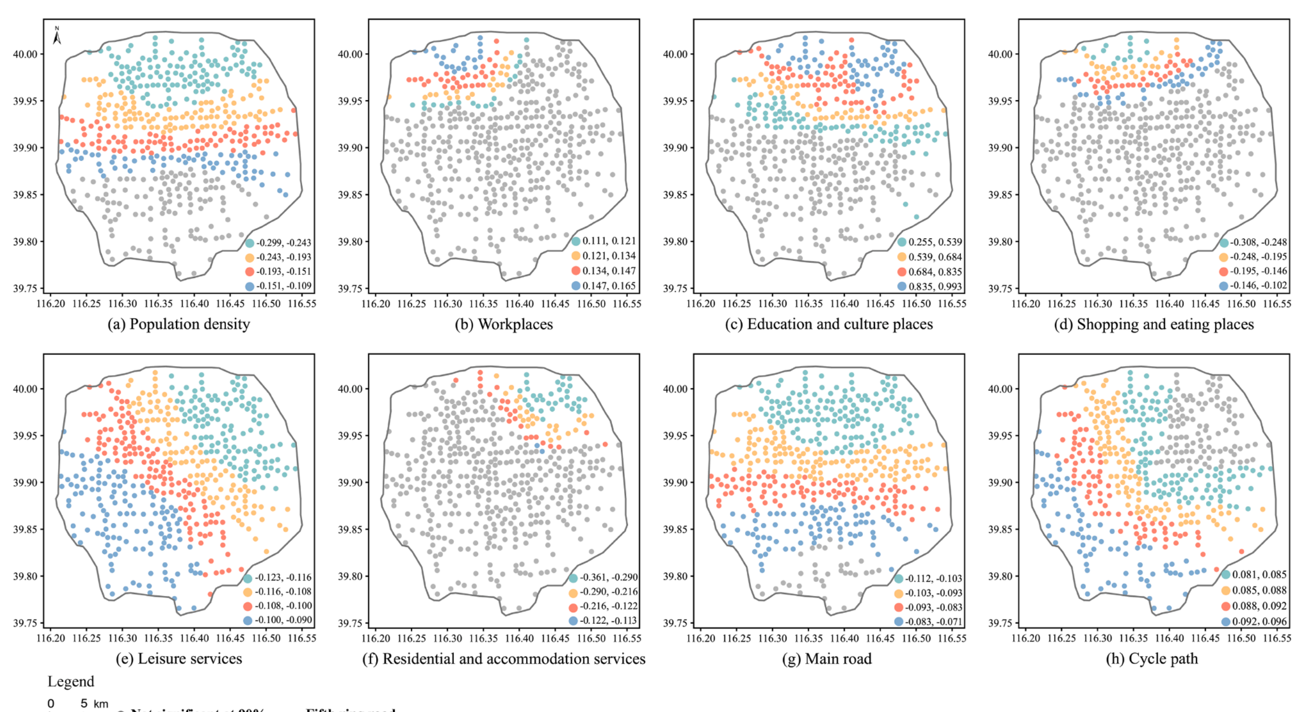

Fig. 4. The spatial distribution of local coefficients on workdays in the bike-bus scenario.

coefficients of main road are significantly negative in most regions (see Fig. 4(g)). As mentioned in Zhao and Li (2017), road length is positively associated with the likelihood of driving. This is because a larger number of roads promote motorized travel, such as driving. In addition, the cycle path positively impacts the integrated usage, as shown in Fig. 4(h). More cycle paths generally lead to higher cycling rates (Krizek & Roland, 2005). It indicates that a comfortable and safe cycling condition can motivate people to participate in the DBS system. It should be noted that the cycle path in the northeast of Beijing has no significant effect. The main reason may be that the commuting distance in these areas is longer than that in other areas. Bike use is significantly lower due to the much longer commuting distances (Yang & Zacharias, 2016).

4.2.2. Bike-subway scenario

Table 5 shows the percentage of significant coefficients ($P \leq 0.1$) in the bike-subway scenario, and the percentage of significant positive or negative coefficients to significant coefficients is also given. The results show that population density, workplaces, shopping and eating places, financial services, and government agencies are all insignificant in the bike-subway scenario, showing strong evidence that these variables have little impact on the integrated usage of DBS and the subway. Education and culture places, main road, cycle path, and bus stops play a significant role in the integrated usage on both workdays and weekends. However, leisure services and residential and accommodation services are significantly associated with the integrated usage on workdays but not on weekends.

Similarly, the spatial variation of the local parameter on workdays is further illustrated in Fig. 5. The local parameters of education and culture places are positive in most areas (See Fig. 5(a)), indicating that a higher number of education and culture places are associated with high integrated usage. Fig. 5(b) shows that local parameter estimates of leisure services across the entire study area are significant negative relationships and are very uniform (-0.174 – -0.179). Most scenic areas in Beijing would not allow shared bike parking, which reduces bike-sharing usage.

Residential and accommodation services have a different spatial effect on the integration of DBS and the subway (see Fig. 5(c)). In the western part of Beijing, the parameter estimates of residential and accommodation services are significantly negative, while some areas in the east have significant positive parameter estimates. On the one hand, residences are related to commuting trips, which makes DBS necessary as a feeder mode (Guo & He, 2020). On the other hand, overcrowded residential areas may cause congested traffic, and uncomfortable riding conditions may reduce integrated usage (Zhao, 2014). In addition, residential areas are usually located in high accessibility areas, which may reduce the potential demand for the integrated usage (Shen et al., 2018).

Table 5
The percentage of significant coefficients in the bike-subway scenario.

Variable	Bike-subway_workday			Bike-subway_weekend		
	$P \leq 0.1$ (%)	+ (%)	- (%)	$P \leq 0.1$ (%)	+ (%)	- (%)
Intercept	62.61	27.08	72.92	56.52	34.62	65.38
Population density	0.00	0.00	0.00	0.00	0.00	0.00
Workplaces	0.00	0.00	0.00	0.00	0.00	0.00
Education and culture places	96.52	100.00	0.00	100.00	100.00	0.00
Shopping and eating places	0.00	0.00	0.00	0.00	0.00	0.00
Leisure services	100.00	0.00	100.00	0.00	0.00	0.00
Financial services	0.00	0.00	0.00	0.00	0.00	0.00
Government agencies	0.00	0.00	0.00	0.00	0.00	0.00
Residential and accommodation services	26.09	68.33	31.67	0.00	0.00	0.00
Main road	63.04	0.00	100.00	50.87	0.00	100.00
Cycle path	100.00	100.00	0.00	100.00	100.00	0.00
Bus stops	100.00	0.00	100.00	100.00	0.00	100.00

Fig. 5(d) shows the spatial distribution of the local parameter estimates associated with the main road. Previous studies have suggested a negative relationship between the length of main road and the integration of DBS and the subway (Faghih-Imani, Eluru, El-Geneidy, Rabbat & Haq, 2014; Zhang et al., 2017). Here we support these findings in most areas. The length of the cycle path positively impacts the bike-subway integration across the entire study area (see Fig. 5(e)). Cycling rates are directly affected by bike infrastructure. A greater number of cycle paths can increase bike usage (Guo & He, 2020). In terms of bus stops, this variable has a significantly negative effect on the integration of DBS and the subway in Beijing, as shown in Fig. 5(f). The availability of feeder bus services encourages people to choose buses as a transfer mode rather than bikes (Rietveld & Daniel, 2004).

5. Discussion

Bike-sharing is faster than walking and greener than other modes of transportation (Cheng et al., 2022; Zhou, Zhao, Cheng & Min, 2019). It offers a convenient feeder mode for connecting to public transport and is considered as an efficient solution to the first- and last-mile problem (Guo & He, 2020; Ma, Zhang, Li, Wang & Zhao, 2019). This study explores the effects of built environment attributes on the usage frequency of bikes as a feeder mode to/from subway stations or bus stops. At present, few platforms record bike-sharing and public transport usage simultaneously. Therefore, information about the symbiotic usage of bike-sharing and urban transit is hardly available (Guo et al., 2021). Moreover, questionnaire surveys are costly and challenging to implement (Ma, Ji, Yang, Jin & Tan, 2018). Also, due to the small sample size and restricted spatial coverage of survey data, exploring the spatially varying effects of the built environment on the integrated usage of DBS and public transport is difficult. Fortunately, big data (e.g., DBS trip data and POI data) allow us to identify the integrated usage. In this study, we recognize the relative location of bikes to public transport stations by spatially matching the real-time position data of DBS with the fixed location of public transport stations. A basic assumption is that DBS trips in close proximity to public transport stations can be regarded as the integrated usage (Guo et al., 2021; Wu et al., 2019). More available data about the symbiotic usage of DBS and public transport may improve the accuracy of the model's results.

Numerous empirical studies have shown the influence of the built environment on the bike–transit integration (Griffin & Sener, 2016; Guo & He, 2020). We further explore the spatially varying effects of the built environment on the integrated usage of DBS and public transport. Especially, the bike-bus scenario and the bike-subway scenario are created to identify the different effects when considering the type of public transport (i.e., bus and subway). A well-designed built environment with the proximity of certain POIs supports cycling for commute purposes (Kerr et al., 2016; Moudon et al., 2005). The effects of urban roads (e.g., cycle paths and main roads) on the integration of DBS and public transport have also been highlighted in previous studies (Guo et al., 2021; Lin et al., 2018; Zhao & Li, 2017). Our findings further show that five variables, including education and culture places, leisure services, residential and accommodation services, main road, and cycle path, significantly affect the integrated usage in two scenarios. However, population density, workplaces, and shopping and eating places only play a vital role in integrating DBS and the bus. Rietveld and Daniel (2004) indicated that easy-to-access bus stops encourage people to choose buses as a transfer mode rather than bikes. Here, we support these findings in the bike-subway scenario, which shows that the number of bus stops negatively impacts the integration of DBS and the subway. Furthermore, the effects of these built environment characteristics on integrated usage vary in different areas. This implies that different policies and measures should be devised for different regions to

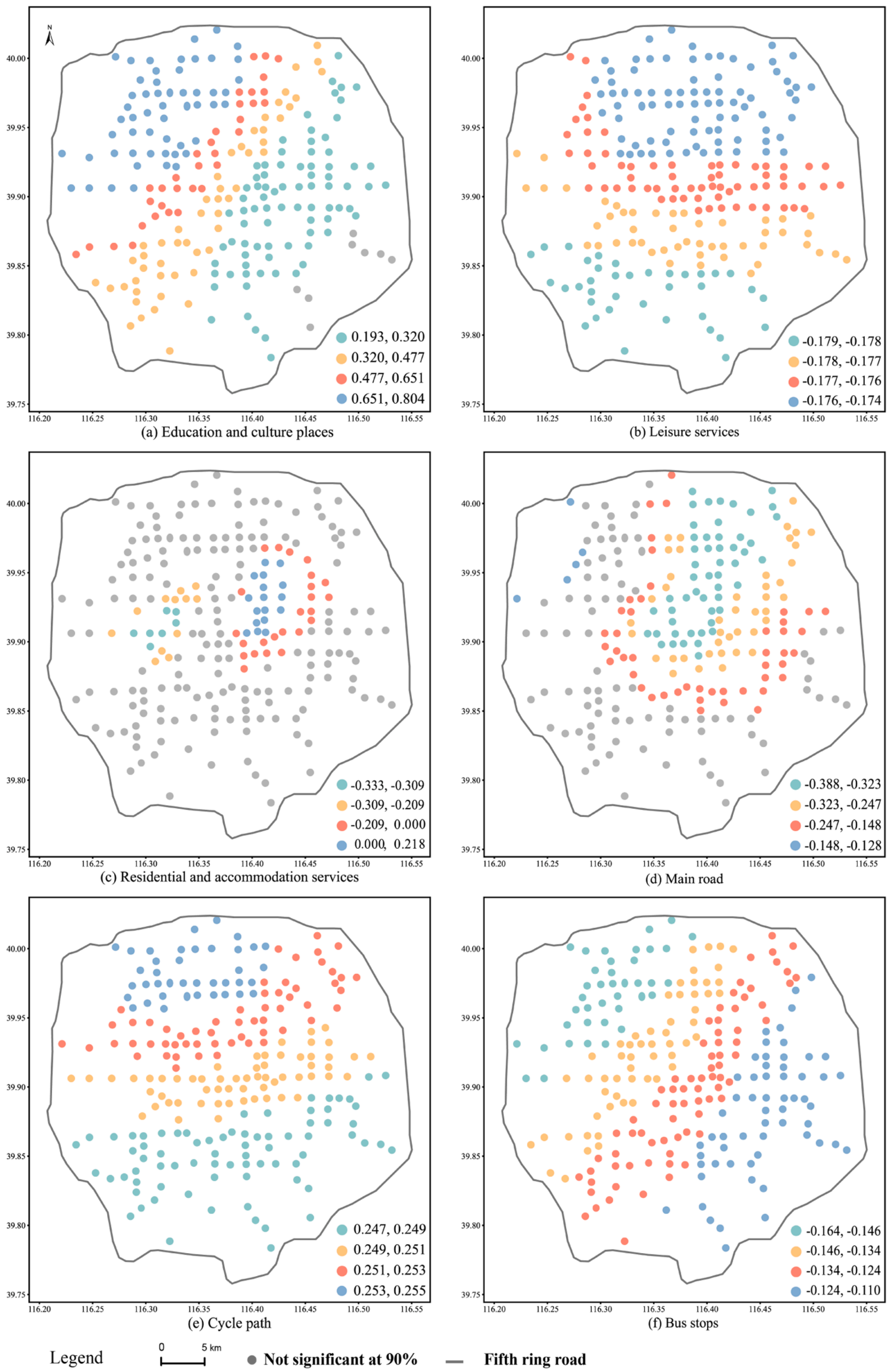

Fig. 5. The spatial distribution of local coefficients on workdays in the bike-subway scenario.

support the integration of DBS and public transport.

6. Conclusions

A more precise understanding of the built environment's influence on the integrated usage of DBS and public transport is essential for improving integration efficiency. This study applies a multi-scale geographically weighted regression to analyze the effects of built environment characteristics on the integrated usage of DBS and public transport considering the spatial heterogeneity. To distinguish different public transport modes such as bus and subway, two scenarios, including the bike-bus scenario and the bike-subway scenario, are created in Beijing to further explore these effects. The results show that the number of points of interest around public transport stations (e.g., education and culture places, leisure services, and residential and accommodation services), length of main road, and length of cycle path significantly influence the integrated usage in both two scenarios. Population density, number of workplaces, and number of shopping and eating places only play a vital role in integrating DBS and the bus, while access to bus stops significantly impacts the integration of DBS and the subway. Moreover, the effects of these built environment variables on the integrated usage of DBS and public transport are diverse in different areas. The findings of this study can be used to create a bike-friendly environment to encourage a connection between bikes and public transport.

Based on the results of this study, we propose several policy suggestions on how to promote the integration of DBS with public transport. As for bike-sharing operators, it is common to redistribute bikes by driving trucks in accordance with their experience (Wang & Kim, 2018). This is ineffective and inconvenient. Real-time relocation of DBS depends on identifying hotspot regions for the integrated use. It is suggested that priority should be given to places near education and workplaces to satisfy commuters' demands. In addition, many Chinese cities are currently experiencing a disorderly parking problem (Lu, An, Hsu & Zhu, 2019; Zhang, Chen & Liu, 2019). Our findings show that there should be a limit to the number of DBS placed in areas with a high density of commercial land use (e.g., restaurants and shopping malls).

Governments play an essential role in promoting the integrated usage. In recent years, the Chinese government has enacted several policies and planning, e.g., Guidelines on Encouraging and Regulating the Development of Internet Bicycle Rental, in which the integration of DBS and public transport is explicitly encouraged (Guo et al., 2021). For the government, providing a perfect network of cycle paths is paramount according to our results. It is worth noting that many of Beijing's exclusive cycle paths are illegally occupied by cars (Zhao & Li, 2017). Therefore, future policies should pay attention to improving the cycling environment and protecting the road space for cyclists. Moreover, some related measures (e.g., adding cycling signs and removing road obstacles) may be helpful to promote the integrated usage. In sum, although the geographical disparity in the built environment that affects the integrated usage varies across the city, solutions can be found by coordinating efforts among many interest groups, such as bike-sharing operators and governments.

This research can be further improved. First, socioeconomic attributes and individual attitudes, which also are important determinants of cycling transfer rates, are neglected in this study due to a shortage of data. Exploring the influence of these variables on bike trips in different regions would deepen the understanding of the DBS system. Second, longer-term DBS trip data should be collected to analyze whether seasonal variations occur in transfer behavior. In addition, this study only examines the DBS system in Beijing, and other cities' DBS systems are not analyzed. Future studies may focus on these issues.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

This research was supported by grants from the National Natural Science Foundation of China (42201454, 42271471) and the China Postdoctoral Science Foundation (2022M710193).

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