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Investigating the Multiscale Impact of Environmental Factors on the Integrated Use of Dockless Bike-Sharing and Urban Rail Transit

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ABSTRACT

Dockless bike-sharing (DBS) is an effective solution to the "first and last mile" problem in urban transportation. It can be integrated with urban rail transit (URT) to provide passengers with more convenient travel services. This study focuses on the integrated use of DBS and URT in Shenzhen, utilising a multi-buffer zone approach to identify DBS data within URT station catchment areas. By employing ordinary least squares (OLS), geographically weighted regression (GWR) and multiscale geographically weighted regression (MGWR) models, the spatiotemporal heterogeneity of integrated use and its relationship with environmental factors surrounding URT stations were examined. The empirical findings highlight the superiority of the MGWR model in accurately explaining spatial relationships compared to the OLS and GWR models. Furthermore, the study reveals that the impact of built environment factors on integrated use varies during morning and evening peak periods, as well as in terms of access and egress. Specifically, factors such as catering, shopping, companies, residential buildings, bus stops, minor roads, transfer stations and population density were found to influence the integrated use of DBS and URT. These findings not only contribute to the promotion of the DBS-URT integration but also promote the overall development of urban transportation.

KEYWORDS

bike-sharing; urban rail transit; multiscale geographically weighted regression; environmental factors.

1. INTRODUCTION

Urban rail transit (URT), as an efficient and fast public transportation mode, has become an important component of modern urban transportation construction. It can not only alleviate urban road traffic congestion and improve the traffic efficiency, but also reduce the air pollution and noise pollution, and enhance environmental quality [1, 2]. However, due to the fixed routes of URT, its coverage is limited, and URT stations are often located on urban trunk roads or commercial centre areas, which also leads to the first and last mile problem. The problem is particularly prominent in some cities, especially in densely populated city centre [3, 4].

To solve this problem, dockless bike-sharing (DBS) has become a popular travel mode. The emergence of DBS not only fills the gap between URT and residential areas, but also makes travel more convenient for passengers [5]. Dockless bike-sharing, as a convenient short-distance travel mode, has the advantages of flexibility, convenience and low cost, which allow users to use them anytime and anywhere. It can not only save time and cost, but also provides passengers with a free and fast solution for first and last mile [6, 7].

Previous studies have shown that environmental factors have significant impacts on the usage of dockless bike-sharing [8–12]. And most studies have focused on discussing the usage of bike sharing in the entire area rather than around the URT stations. Furthermore, they analysing the factors affecting the DBS-URT integration mainly used traditional model regression (e.g., OLS model, GWR model), and rarely consider the relationships among different factors at multiple scales. It will lead to a neglect of spatial heterogeneity among different factors. Therefore, investigating the impacts of the environment around URT stations on the DBS-URT integration is important for sustainable development and optimization of transportation systems.

In summary, this study is based on the DBS data in Shenzhen, China in 2021, and employs the multiscale geographically weighted regression (MGWR) model to investigate the impact of the surrounding environment of URT stations on the DBS-URT integrated use. Specifically, this study addresses three questions: (1) Are there differences in the effects of different environmental factors around the station on the integrated use during different time periods (e.g. morning peak and evening peak)? (2) How do different environmental factors around the station affect the access-/egress-integrated use? (3) How does the impact of different environmental factors around the station on integrated use vary spatially? The remaining structure of the study is as follows. Section 2 reviews the relevant literature on bike-sharing, bike-sharing-metro integration and influential factors on bike-sharing-metro integration. Section 3 describes the study area, data sources and the attachment area of the integration. It also introduces theoretical foundations of different models, lists the selected environmental variables and conducts spatial autocorrelation analysis. Section 4 presents the spatial heterogeneity between environmental factors and the integrated use by different models. Based on the results of the model regression, the best model is determined to analyse the spatiotemporal impact of the surrounding environment of URT stations on the DBS-URT integration.

2. LITERATURE REVIEW

In this section, we reviewed three aspects and introduced the background, techniques and methods of this study. Firstly, we introduced the research progress of bike-sharing in the past. Secondly, we reviewed the recent studies on bike-sharing connected to urban rail transit. Lastly, we summarised the least progress in studying the impact of the surrounding environment of rail transit on bike-sharing ridership and discussed the corresponding research models and methods.

2.1 Bike-sharing

In recent years, bike-sharing has gradually become one of the important transportation modes in cities, attracting the attention of numerous scholars, and related research has shown a rapid development trend. This includes research on the usage patterns and user characteristics of shared bikes, research on the spatial distribution and service range of shared bikes, and research on the factors influencing the demand for shared bike travel. For example, Cao et al. [13] extracted the main features of the cycling flow from the origin and destination data of shared bicycles based on singular value decomposition. Zhou et al. [14] conducted an analysis of the travel characteristics of bike-sharing from four aspects: distribution, spatial features, riding features and turnover rate. Lin et al. [15] employed the gradient boosting decision tree model to investigate the relationship between environment and dockless bike-sharing demand. The results demonstrated that factors including subway ridership, bus ridership, hour, residence density and office density had significant impacts on travel demand. Robert et al. [16] examined the determinants of bikeshare station usage using a fine-grained approach. Zhang et al. [17] employed a multiple linear regression model to analyse the impact of construction environment variables on bicycle demand. Chen et al. [18] proposed an optimization model for the free-floating bike-sharing rebalancing problem and improved the NSGA-II algorithm to discuss the rationality of bicycle parking areas. Ji et al. [19] applied a binary logistic model to explain the effects of travel characteristics and built environment factors on the usage patterns of shared bikes and concluded that work-related, residential and transportation-related points of interest promote the usage patterns of the two bike-sharing systems.

2.2 Bike-sharing-metro integration

The integration of urban rail transit and bike-sharing has become one of the important measures to solve the last-mile problem in urban transportation. Researchers have extensively studied this integration mode to improve the convenience, sustainability and efficiency of urban transportation. Gao et al. [7] proposed a spatiotemporal visualization analysis method for the passenger flow of public bicycle rental stations connecting with subway systems. Kuang and Wu [8] proposed a new method to establish the attraction area of subway stations based on travel origin-destination and a bike clustering method considering subway stations based on travel characteristics. Fan and Zheng [20] constructed a framework to distinguish metro-complementing and metro-substituting trips based on the difference-in-difference identification strategy, which showed that the complementary relationship between metro and bike-sharing is stronger than the substitution. Li et al. [21] analysed the temporal usage and the relationship with points of interest of dockless bikes near metro stations. Lin et al. [22] proposed methods to process bike trajectories and generate the bike catchment areas of metro stations. The results showed that the bike catchment areas are positively associated with metro service, frequent morning trips, diverse users and large distances to the city centre and terminal stations, but negatively associated with the density of metro stations. Liu et al. [23] developed a photovoltaic gradient booster model to investigate the influence of various factors on the demand for two types of electric bicycles charging stations in metro stations, promoting the integration of electric bicycles and subway transportation. Li et al. [24] analysed the reasons for the imbalance in bike sharing supply by comparing the travel patterns of bikes during weekdays and weekends. Liu et al. [25] evaluated the consistency between regional functions and mobility characteristics by integrating shared bikes and land use near subway stations, and the research results reconfirmed the relationship between land use and mobility characteristics.

2.3 Influential factors on bike-sharing-metro integration

The integrated use of dockless bike-sharing and urban rail transit can provide more efficient and friendly travel experiences for users. As a result, many studies have begun to focus on the factors that influence the integrated use and explore relevant conclusions through methods such as data analysis and model building. For example, Liu et al. [26] used an ordered logistic regression model to examine the significant factors that influence groupings of metro-bikeshare passengers. They found that education, individual income, travel purpose, travel time on the metro, workplace location and bike lane infrastructure were significant impacts on metro-bikeshare passengers. Zhao and Li [27] used a multi-level logistics model to investigate the determinant of urban residents' use of bikes as a transfer mode for the metro and found that the transportation distance between the home and the station is the most important factor affecting whether people ride bike-sharing bikes. Cheng et al. [28] used quantile regression to explore the relationship between the built environment and the integration of free-floating bike-sharing and urban rail transit and revealed temporal differences in the relationship between the built environment and integrated use. Gao et al. [29] performed K-means clustering on the source-sink network of shared bikes around metro stations and used a geographic detector to explore the reasons for spatial differences. Guo and Sylvia [11] evaluated the synergistic effects between dock-less bike-sharing and metro commuting and how they are influenced by urban built environment factors, through objective and perceptual indicators. Ma et al. [30] used ordinary least squares (OLS) model and spatial error model (SEM) to reveal the impact of social population factors, travel-related factors and built environment factors on the activity space of dockless bikes around metro stations. They found that the SEM model was significantly better than the OLS model in terms of model fitting. Guo et al. [31] developed a multilevel negative binomial model to explore the influence of building environment characteristics on the integrated use of dockless bike-sharing and metro under different conditions. Li et al. [8] used ordinary least squares (OLS) model and geo-graphically weighted regression (GWR) model to investigate how built environment and social population characteristics affect the use of dockless bikes and found that the explanatory power of the GWR model was higher.

To summarise, previous research on the factors affecting the bike-sharing integration has mainly employed ordinary least squares (OLS) model, traditional geographically weighted regression (GWR) model, negative binomial regression model and logistic regression model, etc. Although these models have yielded significant insights, they still have limitations in addressing the spatial heterogeneity of the independent variables. To address these gaps in knowledge, this study aimed to employ the multiscale geographically weighted regression (MGWR) model to explore the factors affecting the integration under time-segmented conditions (i.e. access and egress in morning and evening peak) in Shenzhen, China. The MGWR model can effectively clarify the relationship between independent and dependent variables at different spatial scales and handle the spatial autocorrelation among variables. Additionally, it can select the optimal spatial scale to achieve the best fitting performance [32–34]. The findings of this study can provide valuable in-sights for optimising the construction of bike-sharing in cities and guiding urban transportation planning and management policies, thereby better meeting the travel needs of citizens, promoting sustainable urban economic development and improving their quality of life.

3. MATERIALS AND METHODS

3.1 Study area

Shenzhen is one of the four first-tier cities in China and the core of the Guang-dong-Hong Kong-Macau Greater Bay Area. Located on the eastern bank of the Pearl River Delta, it shares a river border with Hong Kong. As of 2021, Shenzhen had a population of 17.68 million and an area of 1997.47 km^2. The study area contains nine urban districts (Futian, Luohu, Nanshan, Yantian, Baoan, Longgang, Longhua, Pingshan, Guangming) and one functional area, the Dapeng New District, as shown in *Figure 1*.

Urban rail transit (URT) is the most popular public transportation choice among Shenzhen's citizens, accounting for 40% of public transport trips. Shenzhen URT system comprises 11 operating lines with a total length of 419 kilometres and 288 stations, with an average daily passenger flow of 5.97 million in 2021 [28]. The URT lines mainly cover the central areas of the city, such as Nanshan, Futian and Luohu, which are relatively developed in terms of commercial organization, entertainment facilities and living services.

In December 2011, the first public bicycle transportation system was launched in Shenzhen. It featured 36,950 announced bicycles and attracted 216,000 registered users, providing citizens with a convenient green travel option. However, the introduction of dockless bike-sharing (DBS) in September 2016 had a significant impact on the public bicycle market, leading to the suspension of multi-regional public bicycle systems. By 2021, Shenzhen had installed approximately 390,000 DBS bikes, 27.7 million registered users and an average daily cycling volume of 1.38 million [35]. The rapid development of DBS has better met the needs of citizens for the last "one-kilometre" connection and short-distance travel, playing a positive role in alleviating urban traffic congestion and building a green travel system.

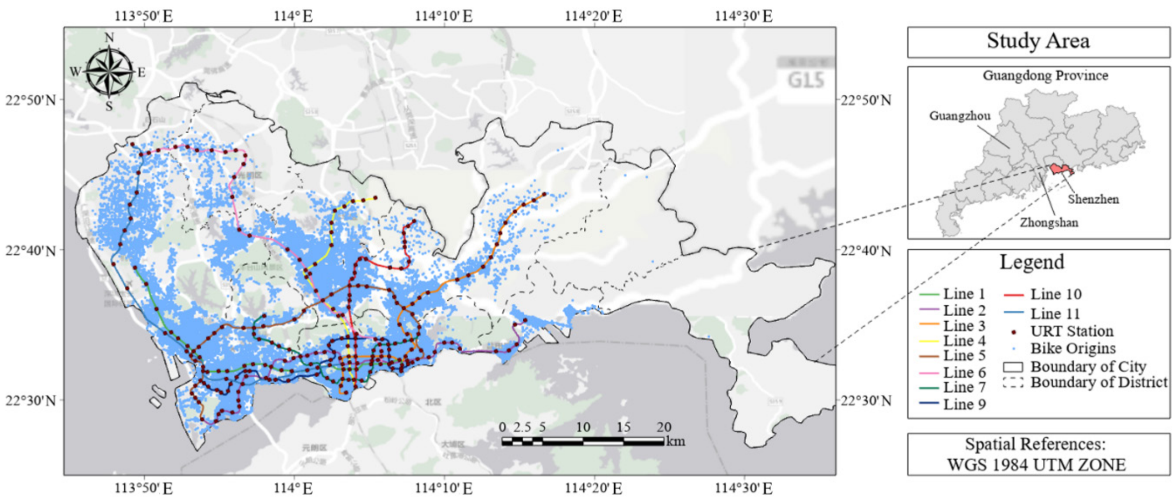


Figure 1 – Study area and the distribution of DBS

3.2 Data source

The DBS data used in this study were provided by the data open platform of Shenzhen municipal government. The dataset includes user ID, start time, end time, start location (longitude and latitude) and end location, covering 7 days from 31 March to 6 April 2021, with a total of 4,216,172 cycling records, as shown in *Table 1*. To obtain more accurate results, we considered the cycling process within 60 seconds to 7200 seconds (2 hours) as a valid record and eliminated invalid data outside of this time domain. Ultimately, 4,138,494 cycling records were obtained. As shown in *Figure 1*, the DBS origins and destinations were mostly distributed in seven districts: Nanshan, Futian, Luohu, Longgang, Longhua, Guangming and Baoan.

Table 1 – Structure of DBS data

User ID	Start time	End time	Start longitude	End longitude	Start latitude	End latitude
26cd5b18d********	6:00	6:04	114.1041214	114.1111117	22.56191655	22.56381287
efd6c4e61********	14:45	14:58	113.9050134	113.8929629	22.56977017	22.57008241
2f3a94fbfa********	18:45	18:53	114.022614	114.0141847	22.5525833	22.55098779
1d3df34c2********	23:00	23:04	114.0581909	114.0546952	22.5093104	22.50924813

According to traffic restrictions in Shenzhen and other literature references, the morning peak is defined as 7:00–10:00 and the evening peak as 17:00–20:00 [36]. As this study aims to analyse the behaviour of the integration of DBS and URT, the period of the DBS data refers to the operating time of Shenzhen URT [37]. It means that only DBS data from 6:00 a.m. to 11:00 p.m. are considered.

The POI data was collected from Amap (also known as Gaode Map) web service in 2022, using the application programming interface (API). Amap API provides developers with programmatic access to various geographic data services [38]. These data provide 12 categories of locations that may be useful or interesting to users, such as catering, shopping, company, residential building, etc.

The road data for different regions within Shenzhen were obtained from Open Street Map (OSM). The required road types within the regions were extracted from OSM and were categorised into major and minor roads. The lengths of these two types of roads were calculated accordingly. The population density data were obtained from the WorldPop dataset (https://www.worldpop.org/), with a spatial resolution of 1 km × 1 km. The population data for different age and gender groups within each region of Shenzhen were sourced from the 7th National Population Census in 2020.

3.3 Measuring the variables

In this study, we classified the variables into dependent and independent variables. The dependent variables were categorised into four types based on time periods and access/egress, including the average morning and evening DBS-URT access-/egress-integrated use. The average integrated use is formula as follows:

Average integrated use (trips/hour) = Total integrated use (trips) / time period (hour) (1)

Previous studies usually determined the buffer range for connectivity based on the URT station centre, which led to lower accuracy in extracting integrated cycling data. In this studay, we created multi-ring circular buffer zones with the entries and exits of the URT stations as the centre, increasing the range of circular radius from 10 metres to 150 metres in steps, as shown in *Figure 2*. We extracted and statistically analysed the cycling data distributed within each buffer zone and calculated the corresponding increase in cycling frequency in each buffer zone. Combined with the catchment range defined in previous studies, we finally selected the 100-metre radius buffer zone around the entries and exits of each URT station as the integrated ridership.

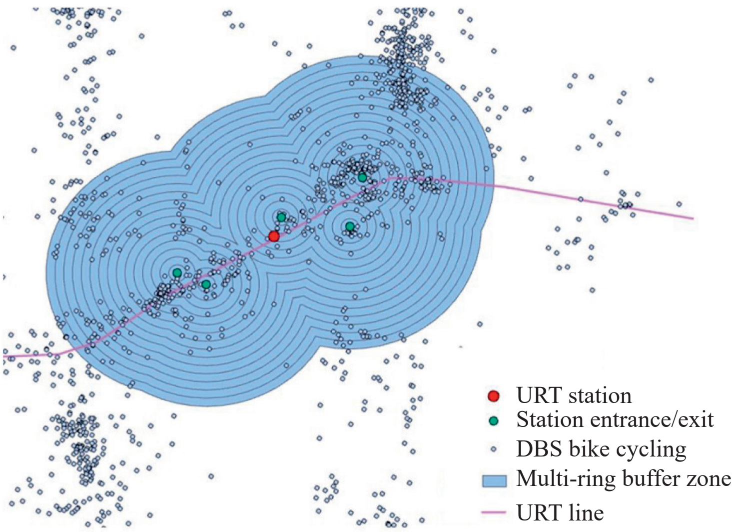


Figure 2 – DBS access use with the multi-ring buffer zone around each entry and exit of Cuizhu URT station

The independent variables are divided into five categories, including land use, public transport infrastructure, road facilities, dummy variables and socio-economic elements. These variables were extracted within an 800-meter radius centred on URT stations. The land use variables were integrated using the POI data, including 12 categories: catering, shopping, company, healthcare, sports & recreation, education, residential building, attraction, finance, life service, car service and hotel.

We hypothesise that different land use types will attract more users compared to a single type, leading to a higher demand for the integrated cycling [13]. Therefore, we added the entropy index of 12 land use types to measure whether the proportion of different land use types has an impact on the integrated use [39, 40]. It can be calculated as follows:

$$E = -\frac{\sum_{i=1}^{n}((P_{ij} / P_j) \cdot \ln (P_{ij} / P_j))}{\ln (n)} \tag{2}$$

where E represents land use mix entropy, which ranges from 0 to 1. The value of E is 0 when there is only one pattern of land use within an 800 m buffer of the station, and 1 when the proportions of different land use patterns are equal; P_{ij} indicates the proportion of the i^{th} land use pattern within the j^{th} station zone; N_j denotes the number of land use patterns within the j^{th} station zone.

The variables related to public transportation facilities include the number of bus stops, parking lots and URT stations within the buffer zone. Buses, as another mode of transport that connects with URT, compete with DBS to some extent. Cars, as the most popular choice for travel, affect the connection of DBS indirectly. And if there are multiple URT stations in the buffer zone, users will consider using the line for transfers directly, which may result in a decrease in the integration.

Regarding road facilities, we take the length of main and minor roads as two variables into account. In Shenzhen, main roads connect the city centre, urban areas, transportation hubs and administrative districts, with high traffic capacity and a design speed of over 40km/h. Minor roads are the roads that connect small-scale areas such as communities and residential areas or branch roads that connect main roads, with poorer conditions and a design speed below 40 km/h.

In addition, we also consider two dummy variables: whether a URT station is a transfer station and whether it is in the suburbs, as well as three socio-economic factors: population density, gender ratio (percentage of males) and age ratio (percentage of people under 35). Transfer stations provide different URT line services, resulting in higher passenger flow compared to regular stations. The distribution of URT lines and stations is relatively sparse in suburban areas and the supply of surrounding DBS is lower, which will affect the integrated use. Population density is one of the important indicators for evaluating the traffic attraction and passenger flow of URT stations. It can explore potential integrated use demands. Gender refers to the percentage of males in the buffer zone. Age relates to the percentage of people under 35 years old. The descriptive statistics of these variables are shown in *Table 2*.

Table 2 contains 23 independent variables and it is essential to check for multicollinearity among them when using the model for regression. To eliminate multicollinearity, we will utilise the variance inflation factor (VIF) as a detection indicator. The formula for calculating the indicator is as follows.

$$VIF(i) = \frac{1}{1 - R_i^2} \tag{3}$$

where R_i^2 is the coefficient of determination of the linear regression model established by taking the i^{th} independent variable as the dependent variable and other independent variables as the independent variables. The larger the $VIF(i)$, the higher the correlation between the i^{th} independent variable and other independent variables, indicating a more severe multicollinearity. If $VIF(i)>10$, it indicates the presence of a severe multicollinearity problem. According to the multicollinearity test results in *Table 3*, we have excluded these variables from the model, namely: life service, education and hotel.

Table 2 – Descriptive statistics of the variables

Variables	Description	Mean	Std.	Min	Max
Dependent variables					
Morning access-integrated use (MAU)	Number of access use within URT catchment areas at the morning peak (trips/hour)	50.09	42.79	2.75	229.61
Evening access-integrated use (EAU)	Number of access use within URT catchment areas at the evening peak (trips/hour)	58.95	64.19	2.00	454.64
Morning egress-integrated use (MEU)	Number of egress use within URT catchment areas at the morning peak (trips/hour)	59.09	56.69	4.50	386.68
Evening egress-integrated use (EEU)	Number of egress use within URT catchment areas at the evening peak (trips/hour)	49.14	38.36	2.96	207.89
Land use					
Entropy index	Entropy of land use patterns in the 800 m buffer of the station	0.721	0.0620	0.407	0.854
Catering	Number of restaurants	450.726	310.852	1	1389
Shopping	Number of malls, supermarkets, etc.	613.579	539.826	5	2857
Company	Number of companies and enterprises, etc.	318.184	294.243	11	1962
Healthcare	Number of hospitals, clinics, etc.	80.853	52.843	0	241
Sports & Recreation	Number of sports stadiums	61.437	41.539	0	239
Education	Number of universities, libraries, etc.	51.716	45.587	0	271
Residential building	Number of buildings, residential houses	110.895	62.013	4	351
Attraction	Number of sports stadiums, cinemas, etc.	10.674	14.693	0	130
Finance	Number of banks, ATM, etc.	48.963	54.418	1	313
Life Service	Number of facilities for life service	312.853	194.858	6	1034
Car Service	Number of facilities for car service	57.068	48.752	1	387
Hotel	Number of hotels	51.716	45.587	0	271
Public transport infrastructures					
Bus stop	Number of bus stops	151.068	76.319	4	377
Parking lot	Number of parking lots	18.263	7.436	5	48
Metro station	Number of metro stations	1.742	0.930	1	5
Road facilities					
Major road	Length of major roads in the 800 m buffer of the station (km)	10.856	6.149	0	29.276
Minor road	Length of minor roads in the 800 m buffer of the station (km)	17.061	7.672	1.672	49.513
Dummy variables					
Transfer station	1 for transfer station, 0 for regular station	20.526% transfer station, 79.474% regular station			
Suburban	1 for suburban, 0 for downtown	37.368% suburban, 62.632% downtown			
Socio-economic elements					
Population density	Number of people in the 800 m buffer of the URT station (thousand people / km^2)	28.729	20.993	2.161	115.955
Gender (% male)	Percentage of males (%)	53.53%	2.15%	50.95%	58.55%
Age (% under 35)	Percentage of people under 35 (%)	55.69%	3.37%	49.63%	63.34%

Notes: Std. = standard deviation.

Table 3 – The multicollinearity test results

Variables	p	VIF	Variables	p	VIF	Variables	p	VIF
Catering	0.002	8.753	Entropy index	0.490	2.261	Population density	0.447	2.086
Company	0.867	3.390	Major road	0.947	2.288	Gender (% male)	0.439	5.764
Shopping	0.008	5.161	Minor road	0.556	1.448	Age (% under 35)	0.104	5.133
Suburban	0.400	6.897	Bus stop	0.005	2.010	Transfer station	0.006	1.302
Finance	0.001	3.465	Parking lot	0.038	2.429	Residential building	0.600	4.342
Attraction	0.342	1.234	Healthcare	0.251	6.883	Sports & Recreation	0.007	5.070
Hotel	0.110	41.047	Metro station	0.228	1.782	Life Service	0.341	19.076
Education	0.061	44.203	Car Service	0.081	1.517			

3.4 Methodology

The Geographically Weighted Regression Model

According to the research conducted by Anselin et al., the global ordinary least squares (OLS) model is considered the starting point for spatial regression analysis at a global scale [41]. However, the global OLS model fails to provide a clear explanation of the spatial relationship between DBS usage and built environment variables. To address this limitation, the Geographically Weighted Regression (GWR) model is introduced [42]. GWR is an extension of the global linear regression model that allows for the investigation of spatial heterogeneity in geographic variables [33, 43]. The GWR is formulated as follows:

$$y_i = \sum_{j=1}^{k} \beta_{ij}(u_i, v_i)x_{ij} + \varepsilon_i \tag{4}$$

where for the i^{th} location, y_i represents the integrated use of DBS, x_{ij} denotes the j^{th} independent variables. β_{ij} is the j^{th} local parameter. The coordinates of the centroid of location i are represents by (u_i, v_i), and ε_i denotes the error term. The parameter estimator can be presented in matrix form:

$$\hat{\beta}_i = [X^T W_i X]^{-1} X^T W_i y \tag{5}$$

where X represents the matrix of independent variables, Y denotes the vector of dependent variables and W_i is the weight matrix associated with spatial locations.

Generally, compared with the OLS model, the GWR model has two main advantages. Firstly, the GWR model considers the spatial dependence effect of adjacent locations since nearby areas are often more similar. When analysing these areas using the GWR model, it violates the assumption of homoscedasticity [44]. Secondly, the GWR model can adjust the size of the study area to keep it stationary. If the study area is large, different parts of the study area may have different characteristics. The OLS model cannot reflect these non-stationary conditions since it estimates a fixed set of regression coefficients for the entire study area [45].

The Multiscale Geographically Weighted Regression Model

The Multiscale Geographically Weighted Regression (MGWR) model is an enhanced version of the Geographically Weighted Regression (GWR) model, proposed by Fotheringham in 2017 initially [46]. MGWR is used to address the relationships among multiple variables in spatial data. Unlike GWR model, which can only handle a single response variable, MGWR model is more refined in addressing the relationships among multiple variables in spatial data by modelling response variables as a model to better capture the interaction relationships between them. The MGWR model can automatically select the optimal bandwidth size based on the characteristics of the data, reducing the interference of human factors and improving the accuracy of the model [47, 48]. It considers the heterogeneity and autocorrelation characteristics at different scales, enabling it to adaptively adjust parameters at different scales. Moreover, it can establish nonlinear relationships by introducing kernel functions and other methods to explore the nonlinear relationships in spatial data. This makes the MGWR model more capable of modelling complex spatial data relationships and capturing spatial heterogeneity. The MGWR model can be mathematically represented as follows:

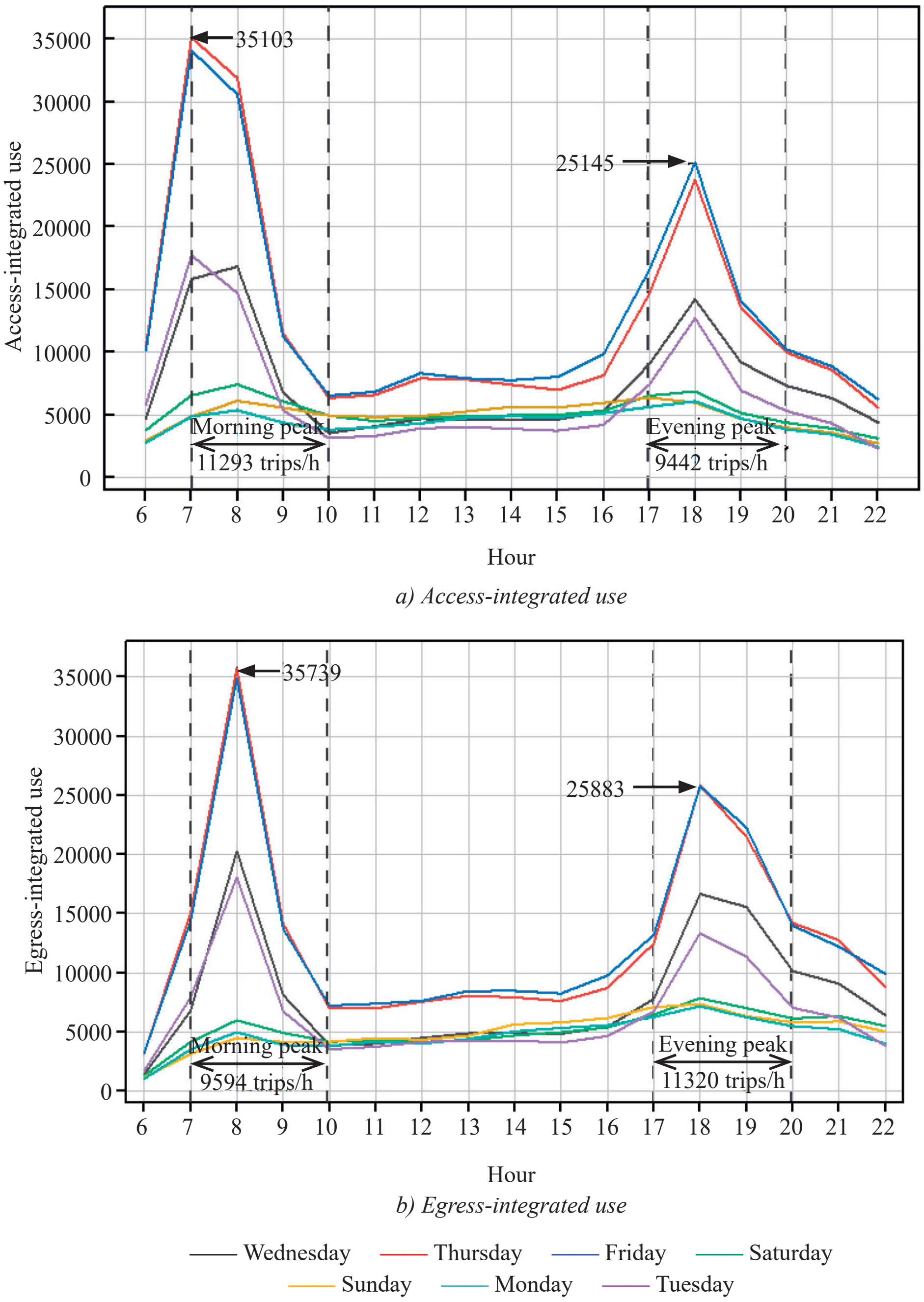
$$y_i = \sum_{j=1}^{n} \sum_{k=1}^{K} \beta_{jk}(u_{ij}) x_{ij,k} + \varepsilon_i \tag{6}$$

where y_i is the observed value of the dependent variable, $x_{ij,k}$ represents the observed value of the k^{th} independent variable at spatial location j^{th} for the i^{th} observation. $\beta_{jk}(u_{jk})$ is the coefficient of the k^{th} independent variable at j^{th} spatial location, u_{ij} is the distance between the i^{th} observation and the j^{th} spatial location and ε_i is the error term. The MGWR model can adjust the coefficients locally at different spatial locations, which allows it to capture spatial heterogeneity more accurately in spatial data.

4. RESULTS AND ANALYSIS

4.1 Temporal and spatial variation of DBS-URT use

Figure 3 displays the access-/egress-integrated use of the catchment area of URT stations within a week. Overall, it shows a clear peak trend in the morning and evening on weekdays, indicating that the integrated



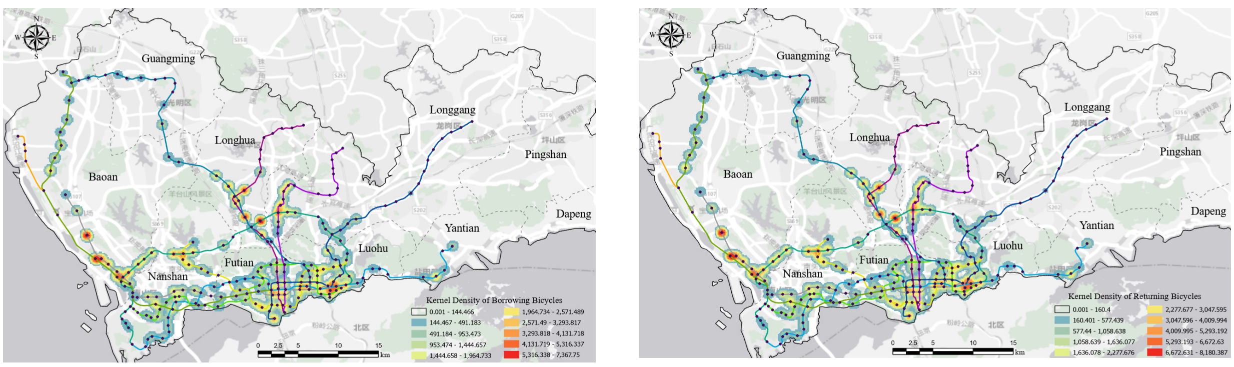
a) Access-integrated use

b) Egress-integrated use

Figure 3 – Temporal distribution of DBS use in URT catchment area

bikes are mostly used for commuting, which is consistent with previous research [28, 49]. Descriptive results show that the average usage of DBS-URT bikes for accessing during the morning peak period is 28.9% higher than that during the evening peak period, with the highest level of access usage at around 7:00 a.m., reaching 3.5103 trips/h. On the other hand, the average usage of DBS-URT bikes for egressing during the morning peak period is 7.6% lower than that during the evening peak period, with the highest level of egress usage at around 8:00 a.m., reaching 3.5739 trips/h. This suggests that most users arrive at the URT stations at 7:00 a.m. for transfer behaviour by cycling DBS, and the users who leave the URT stations by transferring to DBS at 8:00 a.m. account for a large proportion. However, the usage of integrated bikes reached its maximum for both access and egress on Friday, with 22.0633 trips and 22.2427 trips, respectively. This is presumably since people tend to stay at home or travel further away on weekends. In contrast, the usage of integrated bikes on Monday, as a working day, was relatively low this week. After checking the calendar for 5 April 2021, in Shenzhen, we found that it was Tomb-Sweeping Day, which led to the lowest trips this week, reaching 7.5327 trips.

Figure 4 presents the spatial distribution of the access-/egress-integrated use of DBS within a 100-meter buffer zone using kernel density analysis. Based on the statistical analysis, the pattern of DBS usage for access and egress is roughly similar. Firstly, the number of bikes in the suburbs is significantly lower than that in the central urban areas, such as Luohu and Futian Districts, which have dense URT stations. The density of transfer cycling is generally higher in areas with dense URT stations, compared to those in the suburbs with sparse URT stations. The lack of URT stations in suburban areas forces residents to ride long distances to reach the stations, leading to lower awareness of DBS bikes for transfer. Conversely, the central urban area has a high density of URT stations, leading to more DBS-URT transfer and cycling around the stations. Secondly, there are hotspots of DBS transfer in non-central urban areas, such as Baoan Station on Line 1, Longhua Station on Line 4, and other employment and commercial centres. For instance, Baoan Station is surrounded by the Baoan Centre, attracting many office workers who choose to use DBS to travel to the nearest URT station from their workplace, thereby improving the utilization rate of DBS in this area. However, in the south of Longhua District, where the pressure of high rent in the centre forces more office workers to purchase houses in suburbs closer to the city with more convenient transportation, the transfer volume is higher than in other areas.



a) Access-integrated use *b) Egress-integrated use*

Figure 4 – Kernel density of DBS use in URT catchment area

As of 2021, there were a total of 239 URT stations in Shenzhen. Based on the access-/egress-integrated use of DBS in the catchment area in Figure 4, some URT stations, such as the Airport station, Shenyun station and other stations located at important transportation hubs or suburban parks, had relatively low daily demand using DBS for transfer, with less than 144 vehicles per day. To eliminate errors caused by this data and improve the effectiveness of results, these stations were excluded, resulting in a final sample of 190 stations.

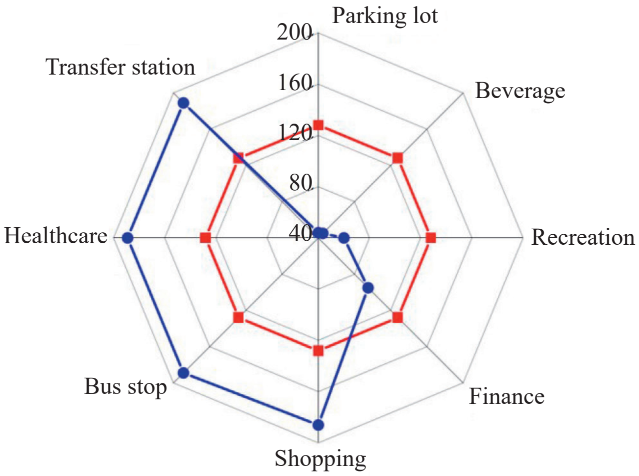
4.2 Model comparison

After conducting a thorough review of the literature, we found that commonly used indicators for evaluating geographical regression models include goodness of fit, parameter significance, multicollinearity and residual analysis. In this study, we utilised three types of indicators to evaluate the performance of the regression models: Akaike Information Criterion (AIC), R-squared (R^2) and Residual Sum of Squares (RSS) [50, 51]. AIC is used to balance the fit of the model with its complexity, with lower values indicating better performance. R^2 measures the extent to which the model explains the variation in the data, with values closer to 1 indicating better explanatory power. RSS is used to measure the fit of the model, with lower values indicating a better fit.

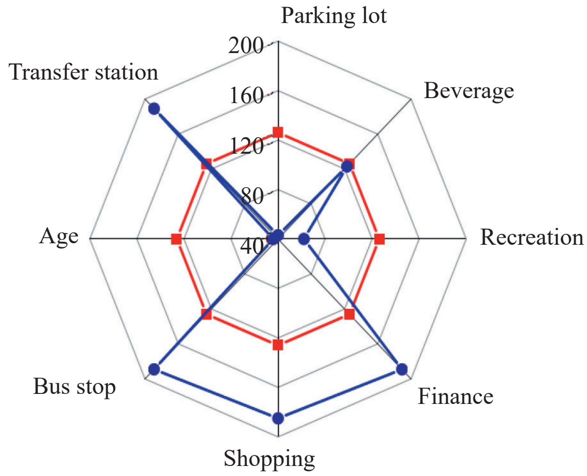
As shown in *Table 4*, both the GWR and MGWR models outperform the OLS model when analysing the usage of DBS in terms of the three indicators. This result is consistent with previous research [33]. The reason for this is that the two models account for spatial heterogeneity and spatial autocorrelation, which solves the problem of spatial non-stationarity that the OLS model cannot handle, resulting in more accurate regression results. The table also indicates that the MGWR model performs better than the single GWR model for the four dependent variables, with a proportion of decrease in AIC and RSS values ranging from 11.61% to

Table 4 – Comparison of the goodness of fit for the proposed models

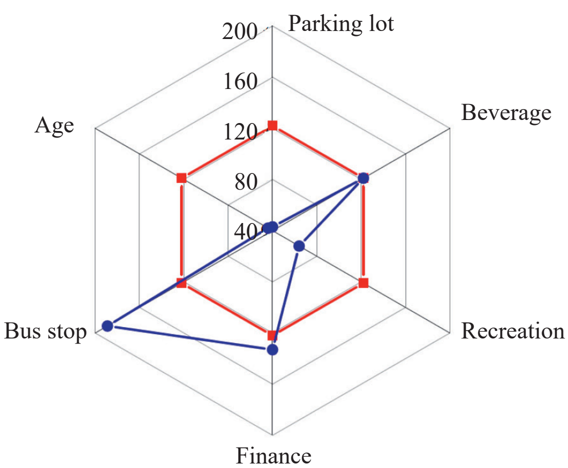
Model	MAU			MEU			EAU			EEU		
	AIC	R2	RSS	AIC	R2	RSS	AIC	R2	RSS	AIC	R2	RSS
OLS	481.4	0.415	111.2	482.3	0.412	111.7	472.3	0.442	105.9	494.2	0.374	118.9
GWR	411.8	0.718	53.54	383.7	0.759	45.72	373.6	0.777	42.41	450.5	0.591	77.76
MGWR	338.2	0.826	33.11	339.1	0.817	34.68	320.4	0.825	33.18	387.3	0.753	46.95



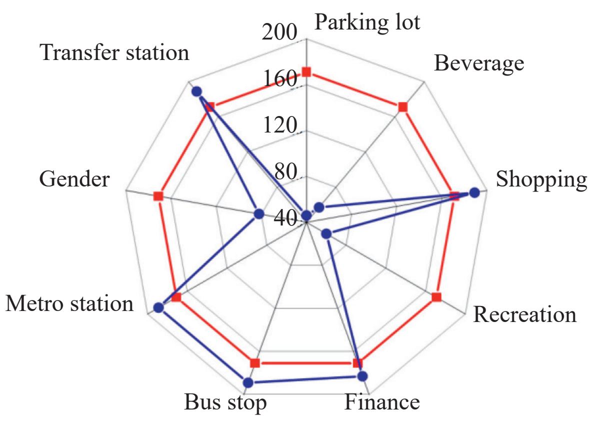
a) Morning access-integrated use



b) Morning egress-integrated use



c) Evening access-integrated use



d) Evening egress-integrated use

GWR MGWR

Figure 5 – Comparison of bandwidths for significant variables between the GWR and MGWR models

17.86% and 21.76% to 39.61%, respectively. In addition, the increase in R^2 ranges from 6.18% to 27.41%. These findings suggest that the fitting performance of the MGWR model is significantly better than that of the single GWR model. The MGWR model can provide an optimal bandwidth for different independent variables by considering changes in the scale of the influence between variables, ultimately leading to better results. Therefore, subsequent analysis will only present the model results of the MGWR.

Figure 5 reveals that that the bandwidth of independent variables in the GWR model is uniform, indicating that the spatial influence scale of each independent variable has not been considered. In contrast, the MGWR model considers the spatial heterogeneity of independent variables by adaptively adjusting the bandwidth based on the influence scale of each in dependent variable at each spatial location. This approach can better capture the spatial relationships among independent variables and improve the fitting performance of the MGWR model.

For the four types of dependent variables, namely the number of parking lots, catering and recreation, their bandwidths are close to the regional scale, indicating that they have a regional-scale impact on DBS ridership within a specific geographic area. The bandwidth of bus stop density is larger and closer to the sample size, indicating a relatively uniform and similar spatial influence, which means a smaller spatial heterogeneity.

For morning access-integrated use, the number of transfer stations, healthcare and shopping have relatively large bandwidths with small heterogeneity. The bandwidth length of finance density is close to the regional scale, indicating its spatial impact is local. For morning egress-integrated use, the number of transfer stations, shopping and finance have relatively small bandwidths, indicating that their impacts on DBS usage are more localised and specific. Age affects the overall use of bicycles at the regional scale.

For evening access-integrated use, the number of significant variables is lower than the other three usage segments, indicating that the usage during the evening peak period is less affected by surrounding environmental factors. For evening egress-integrated use, the number of metro stations, transfer stations, shopping and finance have global-scale impacts on DBS integrated use, while gender has a regional-scale impact on DBS integrated use.

4.3 Analysis of spatial influence at multiple scales

Table 5 presents the regression results of the MGWR model for the relationship between the integrated use of DBS-URT and multiple factors during the two peak periods of station entry and exit. The estimated mean and significance of explanatory variables vary with travel purpose and urban spatiotemporal structure for different riding behaviours.

Figure 6 displays the regression results of the MGWR model for the relationship between the number of catering establishments near URT stations and the integrated use of DBS with URT for commuting during the morning and evening peak periods. The results demonstrate a significant positive correlation between the number of catering establishments and DBS-URT access integrated use in the morning peak, while a significant negative correlation exists between the number of catering establishments and DBS-URT egress integrated use in the evening peak. The coefficient distributions for morning access integrated use and evening egress integrated use are presented in *Figures 6a and 6d*, respectively.

The figures reveal that during the morning peak period, high coefficient values for access integrated use are concentrated around URT stations in urban areas such as Futian, Luohu and Nanshan. It indicates that the presence of numerous catering establishments in these areas prompts individuals to use DBS as a connecting mode of transport after having breakfast, facilitating their access to URT. This choice alleviates morning commute congestion issues, establishing a positive correlation between access-integrated use and the number of catering establishments. Conversely, the coefficient values for evening egress integrated use are comparatively lower, indicating a negative correlation. It suggests that during the evening peak period, individuals prefer direct homeward travel rather than utilising DBS for transfers at catering establishments near URT stations. The availability of various transportation options, such as private cars or direct metro transfers, contributes to this preference. Consequently, the negative correlation between egress integrated use and the number of catering establishments signifies a tendency towards more direct and diverse commuting options during the evening.

Table 5 – Modelling results of multiscale geographically weighted regression

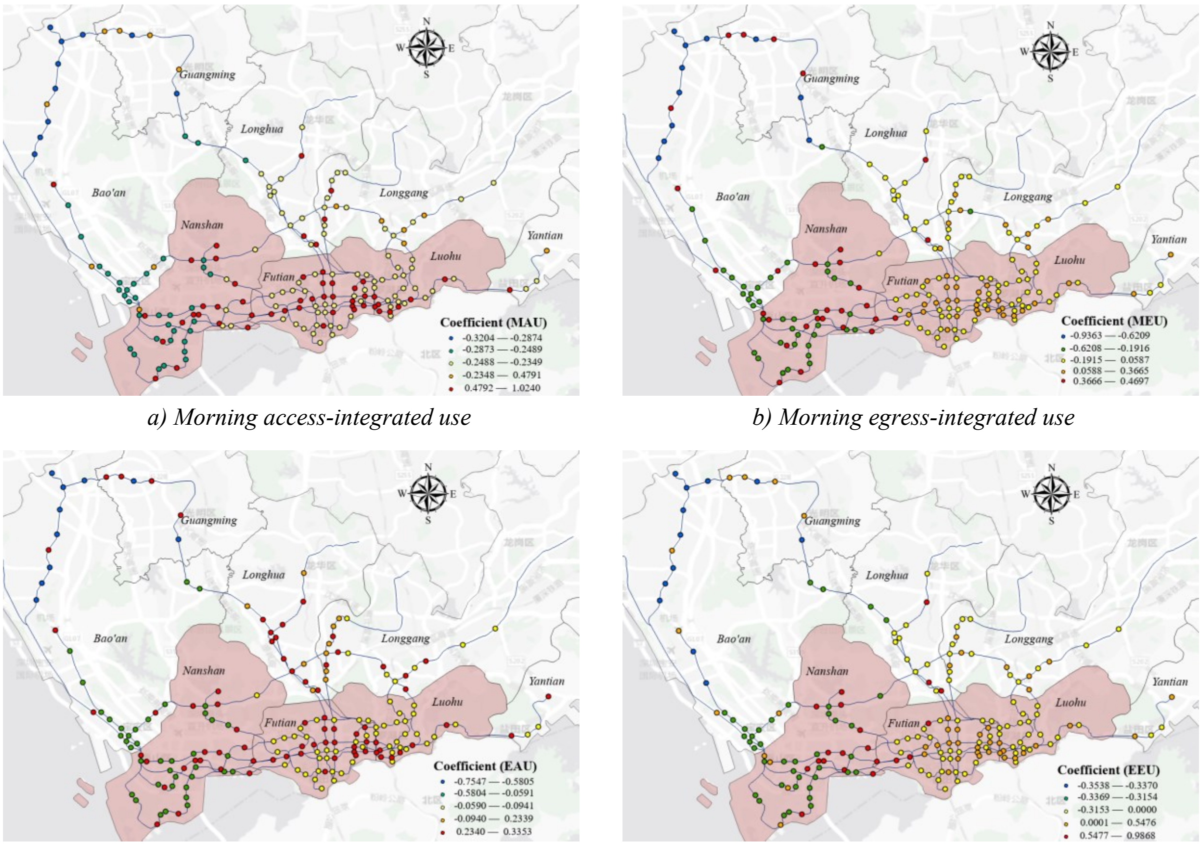
Variable	Morning				Evening			
	Access use (MAU)		Egress use (MEU)		Access use (EAU)		Egress use (EEU)	
	coef.	p	coef.	p	coef.	p	coef.	p
Intercept	-0.151	0.352	-0.160	0.159	-0.110	0.606	-0.151	0.131
Land use								
Entropy index	0.354	0.182	0.208	0.102	0.207	0.328	0.274	0.106
Catering	0.043	0.049**	-0.007	0.319	0.084	0.370	-0.034	0.048**
Shopping	-0.184	0.185	-0.025	0.457	0.060	0.061*	0.145	0.089*
Company	-0.190	0.064*	-0.058	0.438	0.049	0.586	-0.246	0.206
Healthcare	-0.011	0.311	0.067	0.498	0.049	0.526	0.017	0.222
Sports & Recreation	0.158	0.172	0.049	0.736	0.006	0.741	0.226	0.149
Residential building	0.106	0.083*	-0.004	0.714	-0.016	0.644	0.085	0.015**
Attraction	-0.079	0.285	0.068	0.406	0.002	0.619	-0.066	0.524
Finance	0.000	0.237	0.048	0.391	0.000	0.752	-0.055	0.535
Car Service	0.094	0.119	0.049	0.322	0.056	0.351	0.048	0.299
Public transport infrastructures								
Bus stop	-0.050	0.086*	-0.055	0.067*	-0.051	0.093*	-0.078	0.078*
Parking lot	0.158	0.245	0.148	0.196	0.132	0.186	0.193	0.195
Metro station	-0.068	0.258	-0.126	0.268	-0.073	0.432	-0.105	0.226
Road facilities								
Major road	-0.057	0.281	-0.088	0.357	-0.057	0.358	-0.067	0.431
Minor road	0.072	0.063*	0.049	0.141	0.050	0.079*	0.073	0.163
Dummy variables								
Transfer station	0.388	0.163	0.473	0.007***	0.395	0.005***	0.608	0.002***
Suburban	0.208	0.425	0.275	0.197	0.249	0.096*	0.362	0.113
Socio-economic elements								
Population density	0.606	0.372	0.702	0.137	0.752	0.084*	1.101	0.062*
Gender (% male)	0.010	0.256	0.273	0.329	0.180	0.216	0.008	0.103
Age (% under 35)	-0.154	0.365	-0.046	0.550	-0.097	0.561	-0.301	0.373

*Note: *** $p<0.01$, ** $p<0.05$, * $p<0.01$*

Impacts of urban land use

In the morning peak, there is a positive correlation between residential building and access-integrated use, while in the evening peak, there is a positive correlation between residential building and egress-integrated use. This suggests that people in areas with a higher proportion of residential land use are more likely to choose DBS bikes as their intermodal transportation mode. DBS bikes are widely distributed in this area, relatively low in cost and suitable for short-distance travel. Therefore, commuters may choose to ride DBS bikes for short trips during the morning rush hour from their residence to the subway station and during the evening rush hour from the subway station to their residence.

When there are multiple companies located in the attachment, the results show a negative correlation between the number of companies and the access-integrated use in the morning peak. This implies that an increase in the number of companies in the attachment leads to a lower usage of DBS by commuters for ridership. One reason for this is that areas with a higher concentration of companies are typically focused on



a) Morning access-integrated use *b) Morning egress-integrated use*

c) Evening access-integrated use *d) Evening egress-integrated use*

Figure 6 – Spatiotemporal effects of estimated coefficients associated with catering

office use, with a lower proportion of residential land. Additionally, some offices are in suburban areas, making it inconvenient for most commuters to use DBS bikes to transfer to subway stations during the morning peak. As a result, most commuters do not choose to ride DBS bikes to the subway station during this period, which contrast with the impact caused by residential building.

For shopping, a positive correlation exists between shopping and access, egress integrated use in the evening peak. The URT stations near shopping areas serve as transportation hubs for people to ride DBS bikes around the station. On the one hand, consumers can take the metro to stations near the shopping areas and then ride to nearby malls. On the other hand, there may be more traffic congestion near shopping areas during the evening peak period. So, riding DBS bikes to the URT stations will become a way to avoid congestion and reach the URT station quickly, thereby increasing the comprehensive usage.

Impacts of traffic facilities

For public transportation facilities, the number of bus stops around metro stations is negatively correlated with the DBS-URT integrated use, indicating that an increase in bus stops may lead to a decrease in the usage of integrated DBS bikes. On the one hand, an increase in bus stops around metro stations may spread out users who choose DBS bikes as a means of access and egress the metro, making them more likely to choose buses instead of bikes. On the other hand, it may lead to an increase in road traffic flow, making cycling more dangerous and uncomfortable. In addition, it may also affect the conditions for bike access and egress, for example, the setting of bus stops may occupy bike lanes, reducing the convenience and safety of cycling. These results are consistent with previous studies [49].

For road facilities, minor roads have a positive impact on the DBS integrated use as a transportation mode for metro connections. Main roads are usually the roads with high traffic flow in the city. As a connecting transportation mode, DBS bikes travelling on main roads will slow down, leading to an increase in the cost of connecting transportation. Furthermore, metro stations are often located on major roads in the urban area and passengers can take the metro or bus without using DBS bikes for transfers. However, minor roads can provide more convenient cycling conditions for riders, such as smaller traffic flows and lower speed limits, which will present a safer and more comfortable cycling experience. When minor roads set efficient bike lanes or DBS parking facilities, they can make important conditions and attract more riders to use bikes as a mode for transfers.

Impacts of other elements

For other elements, when a metro station is a transfer station, it has a significant positive impact on the DBS integrated use (excluding MAU). If that is the case, it usually has more passengers getting on and off, meaning more travellers need a mode of transport to reach their destinations or to transfer from other locations to the metro station. In this case, DBS bikes become a more attractive option. As shown in *Table 4*, the population density around metro stations in the evening peak is correlated with the integrated use positively. The catchments with higher population densities usually have more passengers commuting or travelling in short distances, which will increase their likelihood for using DBS bikes to transfer with URT. Besides, high-density attachments may have more traffic congestion and parking problems, which also make people more likely to choose DBS bikes as a metro access mode to avoid these issues.

5. CONCLUSIONS

DBS is a promising mode of transportation for urban sustainable development, which is gaining popularity in cities worldwide. Integration of DBS and URT provides new opportunities for sustainable transportation, efficiently solving the "last mile" problem and benefiting society. This study, based on DBS data in Shenzhen, uses multiple spatial regression models to explore the multiscale spatiotemporal relationships between environmental factors around URT stations and integrated use. The main findings of this study can be summarised as follows:

1) Temporally, the integration of DBS and URT reaches two peak usage periods during the morning and evening rush hours on workdays. During the morning peak period, transfer behaviour for commuting purposes is more frequent, with an access use 28.9% higher than that during the evening peak period, and an egress use 7.6% lower than that during the evening peak period. Spatially, areas with dense employment and commercial centres attract more users to utilise DBS as a transfer tool for URT, while the usage of connecting bicycles in remote suburban areas shows a cold spot distribution pattern.
2) The MGWR model and GWR model can both solve the problem of spatial non-stationarity in the OLS model. However, the GWR model has limitations in under-standing spatial heterogeneity and multiple comparisons. In contrast, the MGWR model considers the effects of spatial heterogeneity and the differences of variable scale, which can better characterise spatial relationships and improve prediction accuracy. Therefore, the MGWR model is more reliable and effective than the other two models when analysing the relationships between the environmental factors and DBS-URT integrated use.
3) The number of catering establishments, residential buildings and minor roads is positively correlated with the MAU, while the number of companies and bus stops is negatively correlated. The overall correlation between the MEU and environmental factors is relatively weak, with a negative correlation with the quantity of bus stops and a significantly positive correlation with whether the station is a transfer station. The EAU shows a positive correlation with the quantity of shopping, minor roads, whether the area is suburban, whether the station is a transfer station, and population density, but a negative correlation with the quantity of bus stops. Factors that are positively correlated with EEU include shopping, residential buildings, population density and whether the station is a transfer station, while factors that are negatively correlated include catering establishments and bus stops.

The in-depth analysis of multiscale relationship between environmental factors and the integrated use can help managers better understand the usage needs and preferences of city residents for DBS as a transfer mode between DBS and URT. This can facilitate the development of more precise transportation planning and policies, thus improving the efficiency and sustainable development of urban transportation. Additionally, since the integrated use can be categorised as access and egress and the usage level varies dynamically between peak and off-peak periods, our research results can be used to adjust the DBS supply dynamically according to different time periods. Finally, we can allocate DBS bikes according to the characteristics of different facilities around URT stations to promote the transfer between DBS and URT and better solve the "first mile" and the "last mile" problem.

This study still has some limitations. The integration data we used were divided into only two time periods: the morning and evening peak, without considering the differences between weekdays and weekends. There is also room for improvement in the method used to extract connection data, which may result in error that does not reflect the use of DBS as a transfer tool. In terms of environmental factor analysis, we did not consider the impact of natural factors such as terrain on DBS integration travel. Therefore, future research needs to explore further on this basis.

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探究环境因素对无桩共享单车和城市轨道交通综合使用的多尺度影响

摘要：
无桩共享单车（DBS）是城市交通中“最后一公里”问题的有效解决方案。它可以与城市轨道交通（URT）相结合，为乘客提供更便捷的出行服务。本研究关注深圳市DBS和URT的综合利用，采用多缓冲区方法在URT站点的覆盖范围内识别DBS数据。通过采用普通最小二乘（OLS）、地理加权回归（GWR）和多尺度地理加权回归（MGWR）模型，研究了综合利用的时空异质性及其与URT站点周围环境因素的关系。实证结果表明，与OLS和GWR模型相比，MGWR模型在准确解释空间关系方面具有优势。此外，研究揭示了建成环境因素在早晚高峰期以及出入口方面对综合利用的影响存在差异。具体而言，餐饮、购物、公司、居住建筑、公交车站、次干道、换乘站和人口密度等因素被发现对DBS和URT的综合利用产生影响。这些发现不仅有助于促进DBS-URT的综合使用，还促进了城市交通的整体发展。

关键词：
共享单车；城市轨道交通；多尺度地理加权回归；环境因素