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Unraveling Spatial–Temporal and Interactive Impact of Built Environment on Metro Ridership: A Case Study in Shanghai, China

Qingwen Xue ¹ , Lingzhi Cheng ², Zhichao Li ³, Yingying Xing ², Hongwei Wang ⁴, Hongwei Li ⁵ and Yichuan Peng ^{2,*}

¹ College of General Aviation and Flight, Nanjing University of Aeronautics and Astronautics, Nanjing 211106, China; qingwenx@nuaa.edu.cn

² The Key Laboratory of Road and Traffic Engineering of Ministry of Education, Tongji University, 4800 Cao'an Road, Shanghai 201804, China; 2331710@tongji.edu.cn (L.C.); yingying199004@tongji.edu.cn (Y.X.)

³ College of Civil Aviation, Nanjing University of Aeronautics and Astronautics, Nanjing 211106, China; lizhichao@nuaa.edu.cn

⁴ Institute of High Performance Computing (IHPC), Agency for Science, Technology and Research (A*STAR), 1 Fusionopolis Way, Singapore 138632, Singapore; wang_hongwei@ihpc.a-star.edu.sg

⁵ College of Civil and Transportation Engineering, Hohai University, 1 Xikang Road, Nanjing 210098, China; lihongwei-2008@163.com

* Correspondence: yichuanpeng1982@hotmail.com

Abstract

Urban rail transit, as a green, environmentally friendly, safe, and efficient mode of transportation, plays a crucial role in urban sustainable development. However, the influencing mechanism of built environment factors on rail transit ridership still needs to be further investigated. Also, the interaction effects between these factors have not been considered. This study aims to explore the relationship and impact of built environmental factors on metro ridership. The research employs the Multiscale Geographically Weighted Regression (MGWR) model to analyze the temporal and spatial effects of built environmental factors on the rail transit ridership. The GeoDetector model is utilized to investigate the interactive effects of these factors on rail transit ridership. The Shanghai Metro ridership data and built environment data are applied to validate the model. Based on data analysis results, we found that Food & Beverages and Accommodation services, respectively, have the greatest impact on metro ridership on weekdays and weekends. Furthermore, the interaction effects between other variable and Land use diversity significantly enhance rail transit ridership, validating the promoting effect of land use diversity on metro ridership. By proposing recommendations for relevant urban planning and policy formulation, we can foster the sustainable development of urban rail transit.

Keywords: metro ridership; built environment factors; Multiscale Geographically Weighted Regression (MGWR); GeoDetector



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1. Introduction

In recent years, rapid urbanization has triggered a surge in private vehicle adoption, exacerbating traffic congestion, elevated carbon emissions, and environmental degradation globally [1]. As a sustainable mobility solution, urban rail transit systems—characterized by speed, efficiency, and low carbon footprint—have proven effective in mitigating traffic congestion [2]. Consequently, many countries have embraced the public transit priority

policy, spurring a surge in urban rail transit construction that is expanding from Western countries to emerging markets [3,4].

To optimize rail transit system planning, identifying determinants of ridership has become a focal research agenda in transportation and urban planning disciplines. Examining the correlation between rail transit ridership and built environment (BE) factors holds paramount importance across urban planning, rail transit design, and passenger flow management realms [5,6]. Consequently, numerous investigations have probed the links between urban rail transit ridership and BE factors employing diverse models. Regression-based Direct Ridership Models (DRMs) have been extensively utilized to scrutinize the influence of BE factors on rail transit ridership in metropolitan centers such as Seoul [7], Madrid [8], San Diego [9], Beijing [10] and Shanghai [11]. While DRMs are intuitive and offer strong explanatory ability, they assume that the observed values, such as passenger flow at each station, are independent of each other, implying that these values are spatially homogeneous. Nevertheless, Tobler's first law of geography asserts that all entities are interconnected, yet those in closer proximity exhibit a stronger relationship than those situated farther apart. In other words, geographical samples tend to be more similar in nearby locations compared to distant ones [12]. When the spatial autocorrelation occurs, the relationship between rail transit ridership and BE factors varies across different locations and is not uniform globally. To overcome this constraint, spatial statistical techniques like Geographically Weighted Regression (GWR) and Geographically and Temporally Weighted Regression (GTWR) have been employed in certain cases [7,13]. An et al. employed the Multiscale Geographically Weighted Regression (MGWR) model to examine the impact of the built environment on public transportation usage among commuters within Wuhan [14].

Despite many studies exploring the links between rail transit ridership and BE factors, two key research gaps remain. Primarily, while some studies have advocated for MGWR over OLS and GWR for exploring spatial heterogeneity [14,15], this model's rarity in studies on spatial-temporal BE impacts on metro ridership is evident. Secondly, prior research primarily focused on individual BE factor effects on rail transit ridership based on regression coefficients, sidelining interactive effects. To bridge these gaps, the MGWR model was applied to investigate the spatial-temporal BE impacts on metro ridership. It can better solve the heterogeneity influence level of different parameters to facilitate the deeper understanding of the metro ridership change. Moreover, the GeoDetector model was utilized to scrutinize interactive BE factor effects on metro ridership. The conclusions drawn can offer empirical backing to local governments on tailoring context-specific policies to enhance metro system utilization.

The subsequent sections of the paper are structured as follows. Section 2 entails a literature review, Section 3 covers data and variables introduction, Section 4 delves into modeling approaches, Section 5 discusses outcomes, and Section 6 summarizes the study and propounds policy insights.

2. Literature Review

2.1. Built Environment Factors

Abundant literature has demonstrated that passenger flows at rail transit stations are influenced by surrounding built environment factors. The influencing factors considered in existing research can be broadly grouped into three categories: (1) demographic variables, (2) land use diversity, and (3) transport integration and station characteristics [16].

Population density stands out as one of the most widely utilized variables within social-economic and demographic contexts [17–19]. In early studies, population density data primarily relied on governmental statistics due to limitations in data collection methods [8,20]. These sources were costly, slow to update, and often failed to accurately

reflect the actual distribution of populations. In recent years, the emergence of big data has facilitated the acquisition of real-time dynamic population distribution data through sources such as mobile phone signals [21] and social media data [22]. The effectiveness of these data sources has been proven in mapping dynamic population distributions at high resolutions in both spatial and temporal scales, a pivotal aspect for studying the impact of rail transit passenger flows [5].

In terms of land use, previous studies have traditionally categorized land use types into residential, commercial, and industrial sectors [3]. However, due to limitations in data collection methods, this classification of land use is rather rudimentary and fails to explore the impact of more detailed land use types closely related to travel purposes on passenger traffic flow. With the advancement of geographic spatial big data technologies, some studies have started utilizing open-source Points of Interest (POIs) data to estimate the quantities of different functional facilities and correlate them with passenger traffic flow [23,24]. Variables such as dining, leisure, sports, government institutions, accommodation services, tourist attractions, medical facilities, and educational institutions are increasingly being considered to comprehensively investigate the factors influencing metro ridership [11,14,23]. A wealth of research results indicates that conducting joint analysis of Points of Interest (POI) and travel purposes holds significant importance in studying factors influencing metro ridership, aiding in a comprehensive understanding of the determinants of metro ridership.

Regarding transport integration and station characteristics, most studies have taken into account the influence of variables related to transportation interchanges, including bus stations [20,25], parking lots [26,27], and high-speed rail stations. The majority of studies suggest that multimodal transportation integration has a positive impact on metro ridership. Additionally, in terms of station characteristics, road density [23,28] is often considered a key variable that correlates positively with urban rail transit passenger volume.

2.2. Models and Methods

Existing literature mainly employs two types of models: global regression models and local regression models. Taking Ordinary Least Squares (OLS) as an example, in global regression models, parameters are assumed to be constant, and computed coefficients do not exhibit significant spatial differences [29]. However, in real-world scenarios, estimates of the impact of factors on rail transit ridership may vary across different spatial units. To address this issue, some studies utilize GWR models and other local regression models to explore spatial variations [7,30,31]. GWR is a geographically based local regression method that considers spatial instability, showing spatial heterogeneity in parameter estimates, and has been proven to better fit data compared to global OLS model. GWR models assign a uniform search bandwidth to all independent variables, overlooking the various effects scales of different independent variables. With the development of the methodology, the extensions of GWR have been employed to address the spatiotemporal heterogeneity of variables, such as Geographically and temporally weighted regression (GTWR), Similarity and Geographically Weighted Regression (SGWR), and MGWR [32–34]. GTWR is a local linear regression model, which can consider both spatial and temporal non stationarity. The SGWR introduces the data attribute similarity into the conventional geographically weighted matrix to improve the model performance. Compared with GWR and the extensions, the MGWR can better solve the heterogeneity influence level of different parameters with allocating different bandwidth [35]. This is particularly crucial for metro ridership analysis where factors like population density might exert highly localized influences within a few hundred meters, while transportation connectivity or commercial development could have effects spanning several kilometers. The MGWR model facilitates varying

conditional relationships between the response variable and different predictor variables across different spatial scales, thus enabling a more tailored bandwidth selection. By allowing each variable to find its own optimal bandwidth, MGWR can capture both fine-grained local variations and broader regional patterns simultaneously, providing more accurate and nuanced insights into how different built environment factors influence metro ridership. Therefore, this model can further facilitate discussions on the spatial non-stationarity and scale effects of built environment on public transportation.

With respect to analyzing the nexus between rail transit ridership and built environmental aspects, preceding investigations have predominantly concentrated on individual factor impacts on metro ridership, hinged on regression coefficients, neglecting interaction ramifications. Rail transit ridership is influenced by multiple factors that may interact and have complex relationships, which should not be independently and simplistically explained for each factor. Therefore, by studying the interactions among influencing factors, a more comprehensive understanding of the spatiotemporal patterns of rail transit ridership can be achieved, providing more effective decision support for metro operation and planning to enhance system efficiency and service levels.

In studying the interaction effects among influencing factors, the team led by Jingfeng Wang proposed a novel statistical method: GeoDetector, which measures the degree of spatial differentiation, conducts significance tests, and performs attribution analysis [15,36]. This method has been widely applied in other fields such as research on factors influencing spatial distribution of soil heavy metals [37], the impact of natural factors on vegetation NDVI variations [38], evaluation of interactions affecting urban contraction [39], studies on determinants of housing prices [40], and health risk assessments [41]. However, there have been limited studies applying geographical detectors to analyze the interaction effects among influencing factors on rail transit ridership.

Existing investigations into metro ridership influencing factors have evolved from preliminary demographic approximations to incorporating real-time population distribution data through big data analysis, coupled with open-source POI datasets for granular analysis of functional facilities (e.g., catering, recreation, sports). Methodologically, enhanced regression modeling has progressively addressed spatial heterogeneity and scale effects. However, predominant focus remains on individual factor effects, with insufficient attention to interaction mechanisms among determinants, thereby overlooking their complex interdependencies. While GeoDetector has gained extensive traction in multidisciplinary applications, its implementation in deciphering interactive effects on metro passenger flow determinants warrants methodological extension and theoretical refinement.

3. Data

3.1. Study Area

Shanghai serves as a major financial and commercial center in East Asia. The Shanghai Metro is an urban rail transit system serving the city of Shanghai and the Shanghai metropolitan area in China. As of December 2023, the Shanghai Metro operates a total of 20 lines with 508 stations, covering a total operational distance of 831 km. The annual passenger volume in 2023 reached 3.661 billion. The substantial metro ridership may lead to issues such as congestion, delays, safety hazards, and increased management challenges. Therefore, it is of great importance to model and analyze the factors that influence metro ridership across various time periods and regions within Shanghai.

The pedestrian catchment area (PCA) entails the realm of influence surrounding a metro station delineated by the maximum walking range for pedestrians. Typically utilized as the fundamental spatial measure for scrutinizing metro ridership at the station level [3], the PCA features a 500 m radius that garners widespread acceptance among both metro

commuters and planners [42,43]. We collected and processed PCA for variables within 500 m of 272 metro stations in Shanghai, as shown in Table 1 below.

Table 1. Description and Statistics of Variables.

Variables			Description	Source	Mean	STD
Metro ridership	Weekday	Morning	Metro passenger flow at different time periods	SCD from Shanghai Metro during July of 2016	3887.88	3103.68
		Evening			3285.95	3000.55
		No Peak			1050.56	974.93
	Weekend	Morning			1293.28	1058.42
		Evening			1528.75	1655.19
		No peak			1030.43	1060.84
Transportation Service			Number of transportation services in each PCA	POI date of Gaode Map	124.62	100.82
Food & Beverages			Number of restaurants, coffee houses, dessert houses in each PCA	POI date of Gaode Map	409.20	411.83
Sports & Recreation			Number of sports stadiums, recreation center, theaters, cinemas in each PCA	POI date of Gaode Map	62.22	57.10
Population density			Population density in each PCA (thousands person per km ²)	Original data from WorldPop & measured in GIS	19.72	12.93
Commercial & Industrial place			Number of companies, financial institutions, and factories in each PCA	POI date of Gaode Map	66.32	78.30
Medical service			Number of medical services in each PCA	POI date of Gaode Map	17.43	19.50
Education			Number of schools and universities in each PCA	POI date of Gaode Map	5.94	9.03
Government agency			Number of government agencies in each PCA	POI date of Gaode Map	10.94	12.48
Accommodation service			Number of accommodation services in each PCA	POI date of Gaode Map	11.15	12.26
Scenic Spot			Number of Scenic Spots in each PCA	POI date of Gaode Map	3.73	8.55
Land use diversity			Land use diversity index	Original data from PCL (Peng Cheng Laboratory) & measured in GIS	0.48	0.21
Road density			Road density in each PCA (road length (km) per km ²)	Original data from OpenStreetMap & measured in GIS	28.78	12.56

3.2. Data Resource

We collected the July 2016 Shanghai Metro Smart Card Data (SCD) to validate the model. The SCD is collected when the cardholder enters and leaves the station to swipe

his/her card, recording their ID, the time, and place. The SCD data consists of the information as below.

$$\text{SCD} = \{\text{cardId}, \text{inDate}, \text{inTime}, \text{inStationId}, \text{outDate}, \text{outTime}, \text{outStationId}\}$$

The passenger flow during the morning peak, evening peak, and off-peak hours on weekdays and weekends are separately analyzed. We extracted nine built environment statistics from Amap, population density data from WorldPop, land use diversity data from PCL (Peng Cheng Laboratory), and road density data from OpenStreetMap. Table 1 offers detailed descriptions of the data.

4. Methodology

4.1. Multiscale Geographically Weighted Regression (MGWR)

The global model posits that the relationship between the response variable and the explanatory variables remains consistent and unchanged throughout the entire study area. GWR was formally introduced by Fotheringham in 1996. An approach entailing GWR revolves around a localized linear regression methodology founded on the portrayal of spatially varying associations, crafting a regression model delineating localized correlations at each site within the scrutinized region. It relaxes the steady-state assumption, allowing for a better explanation of the local spatial relationships and spatial heterogeneity of variables. The formula for GWR is presented as follows:

$$y_i = \sum_{j=0}^m \beta_j(u_i, v_i) x_{ij} + \varepsilon_i \quad (1)$$

where x_{ij} is the j -th predictor variable, $\beta_j(u_i, v_i)$ is the j -th coefficient, ε_i is the error term, and y_i is the response variable.

Compared to the classical GWR model, MGWR refines its bandwidth specificity by accommodating variable conditional relationships between the response variable and assorted predictor variables that shift across diverse spatial extents. This enhancement rectifies the limitation inherent in GWR, where the optimal bandwidth for all variables is confined to uniformity, rendering the spatial models birthed by this multi-bandwidth technique more authentic and advantageous. Hence, this analysis embraces the MGWR model to delve into the differentiation within space and varying spatial scales concerning passenger flow on the Shanghai Metro. The MGWR formula stands as follows:

$$y_i = \sum_{j=0}^m \beta_{bwj}(u_i, v_i) x_{ij} + \varepsilon_i \quad (2)$$

where bwj in β_{bwj} represents the bandwidth employed to calibrate the j -th conditional relationship.

4.2. Geographical Detectors

The geographic detector, an innovative spatial statistical framework introduced by Wang, serves as a tool for assessing and pinpointing Spatially Stratified Heterogeneity (SSH) within data. It plays a crucial role in examining the interplay between two variables, Y and X , signifying their tangible relevance. Moreover, the model delves into the broader dynamics among two explanatory variables, X_1 and X_2 , alongside a response variable, Y .

Comprising four distinct sub-models—namely, risk detector, factor detector, ecological detector, and interaction detector—the geographic detector model is designed to unravel the determinants of metro ridership and the intricate interdependencies among varied

factors. The factor detector and interaction detector were specifically employed to scrutinize the pivotal factors influencing rail transit ridership and the degree of interplay among these factors.

4.2.1. Factor Detector

The factor detector assesses the impact of each factor on metro ridership by comparing the ratio of accumulated dispersion variance in each subregion to the total dispersion variance in the entire study area. In this study, the q -value proposed by Wang [10] is employed for measurement, with the calculation formula as follows:

$$q = 1 - \frac{\sum_{h=1}^L N_h \sigma_h^2}{N \sigma^2} = 1 - \frac{SSW}{SST} \quad (3)$$

where N represents the number of units in the study area; σ^2 and σ_h^2 denote the global variance of the dependent variable of the study area and the variance of the dependent variable in the sub-areas, respectively; SSW and SST represent within sum of squares and total sum of squares. A larger q -value indicates a greater contribution of the factor to rail transit ridership.

4.2.2. Interaction Detector

The interaction detector can compare the sum of the impact contributions to rail transit ridership from two individual attributes with the contribution when both attributes are considered together. The model categorizes the interaction between the two factors into the following five types.

- (1) Weaken, nonlinear: $q(X1 \cap X2) < \text{Min}(q(X1), q(X2))$.
- (2) Weaken, uni-: $\text{Min}(q(X1), q(X2)) < q(X1 \cap X2) < \text{Max}(q(X1), q(X2))$.
- (3) Enhance, bi-: $q(X1 \cap X2) > \text{Max}(q(X1), q(X2))$.
- (4) Independent: $q(X1 \cap X2) = q(X1) + q(X2)$.
- (5) Enhance, nonlinear: $q(X1 \cap X2) > q(X1) + q(X2)$.

5. Results and Discussion

5.1. Spatial–Temporal Variability of Metro Ridership

The 12 variables selected in Table 1 were used as independent variables, with the peak and off-peak metro ridership on weekdays and weekends as dependent variables. An OLS model was employed for modeling, and the modeling results are presented in Table 2. The variance inflation factors (VIF) were all below 10, indicating the absence of significant collinearity among the independent variables. Since the p -values for medical service and education were both greater than 0.05, indicating no significant impact on metro ridership, these two variables were excluded from further analysis, leaving the remaining 10 variables for consideration in subsequent modeling.

The Moran's I index is used to conduct a spatial autocorrelation test on the variables; the results are shown in Table 3. All variables passed the test for spatial autocorrelation, indicating the possibility of utilizing GWR and MGWR for spatial heterogeneity analysis. Among them, metro ridership exhibits spatiotemporal heterogeneity, where off-peak hours show stronger heterogeneity compared to peak hours, and weekdays exhibit stronger heterogeneity compared to non-weekdays.

Table 2. Regression Results of OLS Model.

Variables	<i>p</i> _Value						VIF
	Weekday			Weekend			
	Morning	Evening	No Peak	Morning	Evening	No Peak	
(Intercept)	***	***	***	***	***	***	
Transportation Service	0.324 *	0.318 **	0.316 **	0.415 **	0.291 *	0.296 *	9.253
Food & Beverages	0.267 *	0.324 **	0.279 **	0.228	0.336 **	0.337 **	7.845
Sports & Recreation	−0.448 ***	−0.363 **	−0.371 **	−0.494 ***	−0.339 **	−0.353 **	8.800
Population density	0.293 ***	0.275 ***	0.276 ***	0.305 ***	0.265 ***	0.26 ***	2.702
Commercial & Industrial place	0.510 ***	0.452 ***	0.355 ***	0.313 ***	0.252 **	0.226 **	3.408
Medical service	0.111	0.038	0.055	0.042	−0.047	−0.028	2.102
Education	0.059	0.041	0.052	0.03	0.008	0.016	1.502
Government agency	−0.154 *	−0.198 **	−0.136 *	−0.132	−0.198 **	−0.155 *	3.089
Accommodation service	0.205 *	0.232 **	0.35 ***	0.422 ***	0.445 ***	0.421 ***	3.956
Scenic Spot	0.125 *	0.182 **	0.201 ***	0.071	0.208 ***	0.235 ***	1.824
Land use diversity	0.239 **	0.226 **	0.221 **	0.231 **	0.208 **	0.213 **	1.179
Road density	0.129 *	0.232 **	0.209 **	−0.021	0.21 **	0.217 **	1.374

Notes. Coefficients and Standard errors. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3. Moran's I Analysis of Variables.

Variables		Weekday			Weekend		
		Moran's I	<i>p</i>	<i>z</i>	Moran's I	<i>p</i>	<i>z</i>
Metro ridership	Morning	0.26	0.001	7.7125	0.173	0.001	5.0781
	Evening	0.289	0.001	8.3621	0.222	0.001	6.661
	No peak	0.297	0.001	8.7019	0.24	0.001	7.1648
Transportation Service		0.774	0.001	21.5453	0.774	0.001	21.5453
Food & Beverages		0.632	0.001	18.2026	0.632	0.001	18.2026
Sports & Recreation		0.707	0.001	19.4424	0.707	0.001	19.4424
Population density		0.801	0.001	21.9514	0.801	0.001	21.9514
Commercial & Industrial place		0.508	0.001	14.5214	0.508	0.001	14.5214
Government agency		0.65	0.001	19.1416	0.65	0.001	19.1416
Accommodation service		0.606	0.001	17.2693	0.606	0.001	17.2693
Scenic Spot		0.395	0.001	11.6727	0.395	0.001	11.6727
Land use diversity		0.139	0.001	4.1564	0.139	0.001	4.1564
Road density		0.344	0.001	10.1992	0.344	0.001	10.1992

Note. When $p = 0.001$, if $z > 2.58$, Moran's I is significant.

5.2. The Comparison of Different Models

Models of OLS, GWR, and MGWR were established for the morning peak, evening peak, and off-peak periods on both weekdays and non-weekdays, with the modeling results presented in Table 4. Combining the data in the table, for instance, in the morning peak period on weekdays, the Residual Sum of Squares (RSS) for OLS, GWR, and MGWR models are 127.824, 97.682, and 97.087, respectively. It is evident that the residuals of the MGWR model are generally smaller compared to OLS and GWR models. The R-squared values for GWR and MGWR models are 0.641 and 0.643, respectively, with the MGWR model showing lower variance compared to the GWR model. Similar conclusions can be drawn for other time periods. In summary, the MGWR model demonstrates better fitting performance.

Table 4. Comparison of OLS, GWR, MGWR Results.

Model	Index	Weekday			Weekend		
		Morning	Evening	No Peak	Morning	Evening	No Peak
OLS	RSS	127.824	105.432	100.053	156.697	114.379	110.574
	Log-likelihood	−283.251	−257.059	−249.938	−310.949	−268.136	−263.536
	Degree of freedom	259	259	259	259	259	259
	AIC	588.502	536.118	521.875	643.898	558.273	549.072
	AICC	591.706	539.322	525.08	647.103	561.478	552.276
	R ²	0.53	0.612	0.632	0.424	0.579	0.593
	Adj. R ²	0.512	0.598	0.618	0.402	0.563	0.578
GWR	RSS	97.682	88.198	84.639	127.785	111.864	108.099
	Log-likelihood	−246.676	−232.785	−227.184	−283.21	−265.112	−260.456
	Degree of freedom	240.027	245.083	245.485	244.222	257.383	257.362
	RMSE	0.638	0.6	0.587	0.835	0.659	0.949
	AIC	559.298	521.403	509.397	623.976	561.458	552.189
	AICC	568.71	528.045	515.842	631.052	563.49	554.227
	R ²	0.641	0.676	0.689	0.53	0.589	0.603
MGWR	Adj. R ²	0.593	0.64	0.655	0.477	0.565	0.58
	RSS	97.087	87.709	81.771	126.556	101.486	97.724
	Log-likelihood	−245.845	−232.03	−222.496	−281.896	−251.871	−246.734
	Degree of freedom	234.927	243.837	244.222	241.791	250.692	250.692
	RMSE	0.643	0.6	0.579	0.82	0.882	0.882
	AIC	567.835	522.386	502.548	626.209	548.359	538.085
	AICC	580.608	529.661	509.623	634.594	552.541	542.266
	R ²	0.643	0.678	0.699	0.535	0.627	0.641
	Adj. R ²	0.586	0.64	0.665	0.476	0.595	0.61

5.3. Spatial Variation in Coefficients from MGWR Model

In Tables 5 and 6, we compared the bandwidth and regression coefficients of the GWR and MGWR models established for weekdays and non-weekdays. As shown in the tables,

the GWR model sets a fixed bandwidth for each variable, assuming spatial correlations are consistent across the entire study area. In contrast, the MGWR model assigns different bandwidths for each variable. Taking the weekday modeling data as an example, except for the “Food & Beverages” variable, the bandwidth of the GWR model is significantly smaller than that of the MGWR model for the remaining variables. In practical research, there exists spatial heterogeneity in the relationships among different independent variables. The MGWR model can adjust the range of the regression neighborhood based on the characteristics of each variable, capturing local spatial variations and heterogeneity more effectively, enabling a finer modeling approach and thus providing more accurate and reliable estimation results.

Table 5. Summary Statistics of Regression Coefficients for GWR and MGWR on Weekdays.

Time	Morning				Evening				No Peak			
Model	GWR		MGWR		GWR		MGWR		GWR		MGWR	
Index	BW	Mean	BW	Mean	BW	Mean	BW	Mean	BW	Mean	BW	Mean
Intercept	155	0.05	92	0.105	192	0.025	269	0.088	194	0.001	262	0.05
Transportation Service	155	0.325	271	0.329	192	0.267	271	0.277	194	0.21	271	0.202
Food & Beverages	155	0.26	46	0.434	192	0.289	48	0.493	194	0.243	48	0.434
Sports & Recreation	155	−0.381	271	−0.439	192	−0.287	259	−0.414	194	−0.256	244	−0.372
Population density	155	0.297	271	0.243	192	0.278	271	0.271	194	0.25	271	0.231
Commercial & Industrial place	155	0.491	271	0.503	192	0.457	270	0.457	194	0.399	260	0.383
Government agency	155	−0.146	271	−0.157	192	−0.209	271	−0.211	194	−0.138	271	−0.135
Accommodation service	155	0.257	271	0.25	192	0.277	271	0.266	194	0.398	271	0.37
Scenic Spot	155	0.117	271	0.121	192	0.179	271	0.168	194	0.188	271	0.169
Land use diversity	155	0.227	251	0.232	192	0.215	251	0.204	194	0.219	271	0.207
Road density	155	0.137	271	0.127	192	0.239	271	0.237	194	0.206	271	0.22

In Tables 5 and 6, except for Sports & Recreation and Government agency, the remaining eight variables all show positive effects on metro ridership. By comparing the variable coefficients of the MGWR model across different time periods and regions, it is observed that environmental variables exhibit significantly different impacts on metro ridership under various spatiotemporal conditions.

Transportation services include transportation hubs such as airports, railway stations, bus stations and parking lots, all of which have a positive impact on metro ridership. The coefficients of the variables for different time periods are shown in Figure 1, with darker colors indicating a greater degree of their influence. It indicates that the transportation service has the greatest impact on metro ridership at the morning peak hour. This could be attributed to the commuting needs of office workers during the morning rush hour, who may opt for convenient transfers near metro stations at bus stops and parking lots. Airports and railway stations are typically directly connected to the metro, facilitating

intra-city commuting for out-of-town travelers, thereby boosting metro ridership through long-distance passengers. Bus stations complement the metro system, providing transfer opportunities, expanding the reach of the metro's services. Bus stations offer advantages in terms of flexibility and cost-effectiveness, attracting more passengers to choose metro travel. In order to address the “first and last mile” issue, urban rail transit operators have constructed transfer parking lots at most stations. Existing literature indicates that Park and Ride (P + R) facilities play a promotional role in increasing public transportation ridership [23]. In Shanghai, there are a total of 20 Park and Ride facilities across 9 metro lines, providing a combined total of 5759 parking spaces. These facilities primarily cater to commuters from areas outside the city center with inadequate public transportation services. By offering certain parking fee discounts, these facilities encourage individuals in these areas to park their vehicles and transfer to public transportation. The well-developed comprehensive system consisting of a high-density road network and parking facilities enhances travel efficiency while increasing the attractiveness of public transportation. This integration of infrastructure contributes to promoting urban rail ridership by leveraging the spatial heterogeneity of the built environment.

Table 6. Summary Statistics of Regression Coefficients for GWR and MGWR on Weekend.

Time	Morning				Evening				No Peak			
Model	GWR		MGWR		GWR		MGWR		GWR		MGWR	
Index	BW	Mean	BW	Mean	BW	Mean	BW	Mean	BW	Mean	BW	Mean
Intercept	194	−0.009	271	0.094	230	−0.008	262	0.007	230	−0.006	262	0.011
Transportation Service	194	0.292	271	0.342	230	0.167	271	0.228	230	0.173	271	0.236
Food & Beverages	194	0.185	48	0.392	230	0.284	186	0.291	230	0.288	186	0.276
Sports & Recreation	194	−0.393	260	−0.5	230	−0.276	271	−0.31	230	−0.283	271	−0.304
Population density	194	0.271	96	0.336	230	0.253	271	0.255	230	0.246	271	0.247
Commercial & Industrial place	194	0.378	271	0.347	230	0.313	271	0.282	230	0.285	271	0.255
Government agency	194	−0.137	271	−0.114	230	−0.221	271	−0.216	230	−0.171	271	−0.169
Accommodation service	194	0.46	271	0.455	230	0.493	271	0.476	230	0.468	269	0.46
Scenic Spot	194	0.061	271	0.058	230	0.202	271	0.207	230	0.227	271	0.234
Land use diversity	194	0.234	271	0.217	230	0.202	271	0.200	230	0.209	271	0.208
Road density	194	−0.018	268	−0.019	230	0.209	271	0.213	230	0.215	271	0.218

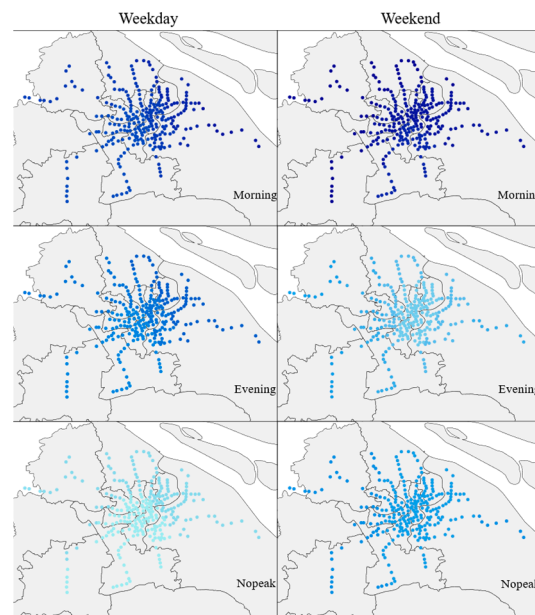


Figure 1. Distribution of the Impact of Transportation service (darker colors indicate a greater degree of their influence).

Food & Beverages includes Chinese food restaurants, foreign food restaurants, fast food restaurants, coffee houses, dessert houses, and similar establishments. The coefficients of the variables for different time periods are shown in Figure 2, with darker colors indicating a greater degree of their influence. The impact on weekdays is significantly higher than that on non-weekdays, possibly because there are usually more dining options near metro stations. People often choose nearby dining establishments to save commuting time, thereby contributing to increased metro ridership.

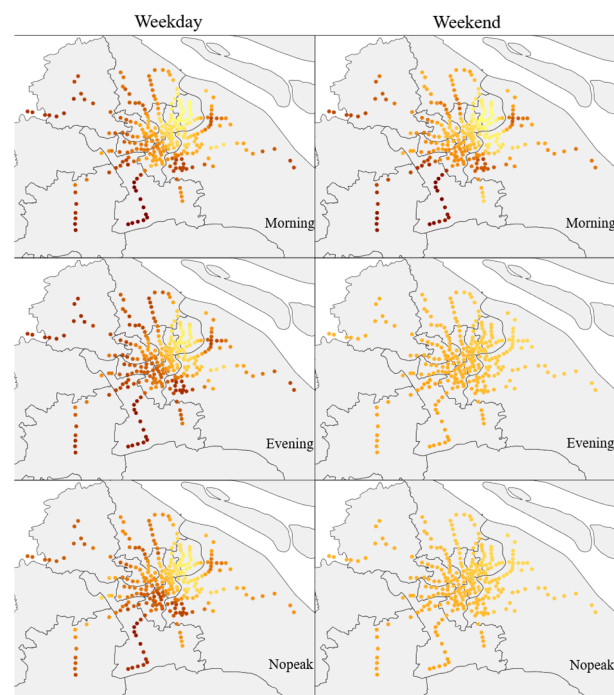


Figure 2. Distribution of the Impact of Food & Beverages (darker colors indicate a greater degree of their influence).

Sports & Recreation have a negative impact on metro ridership. Places such as sports stadiums, recreation centers, theaters, and cinemas are not typically located near metro

stations. People usually choose to drive or walk when going to these venues, which does not contribute to an increase in metro ridership.

Population density has a positive impact on metro ridership. The greater the population density, the higher the demand for residents to travel, thus promoting an increase in metro ridership.

The impact of Commercial & Industrial places is shown in Figure 3, with darker colors indicating a greater degree of their influence. Commercial & Industrial places have a positive impact on metro ridership, with a higher impact on weekdays than on non-weekdays, and a greater impact in the northeast compared to the southwest (Figure 3). Commercial and industrial areas typically concentrate numerous businesses and office spaces, attracting a large number of employees to work in these areas. The metro system, as a fast and efficient commuting option, provides convenient transportation services, helping employees reach their workplaces and return home quickly, thereby increasing metro ridership.

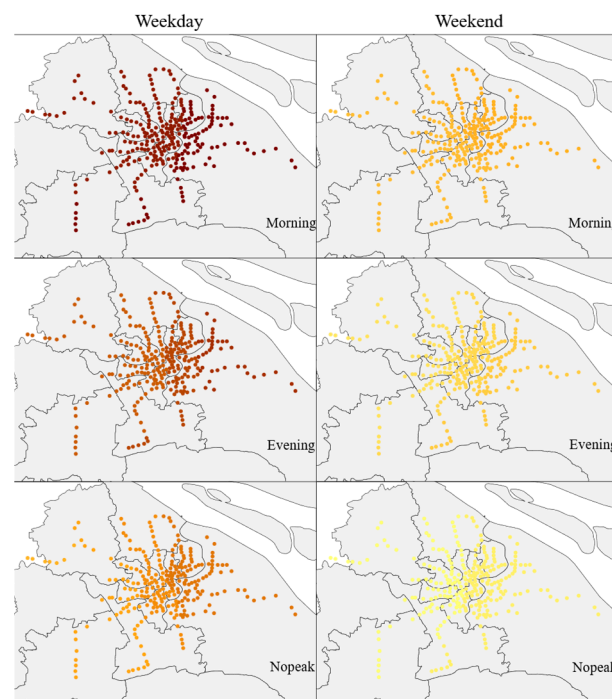


Figure 3. Distribution of the Impact of Commercial & Industrial places (darker colors indicate a greater degree of their influence).

Government agencies mainly include government offices, public security and judicial agencies, industrial and commercial tax authorities, etc., typically serving as workplaces for government personnel, resulting in an overall negative impact on metro ridership.

Accommodation services have an overall positive impact on metro ridership. The more hotels, guesthouses, and similar establishments are distributed, the greater the metro ridership. Since those in need of accommodation services are often travelers from out of town or business professionals, considering the need for public transportation, they tend to choose hotels located near metro stations, thereby increasing metro ridership. In terms of temporal and spatial distribution, the impact on non-weekdays is noticeably higher than on weekdays, with the impact gradually increasing from north to south (Figure 4).

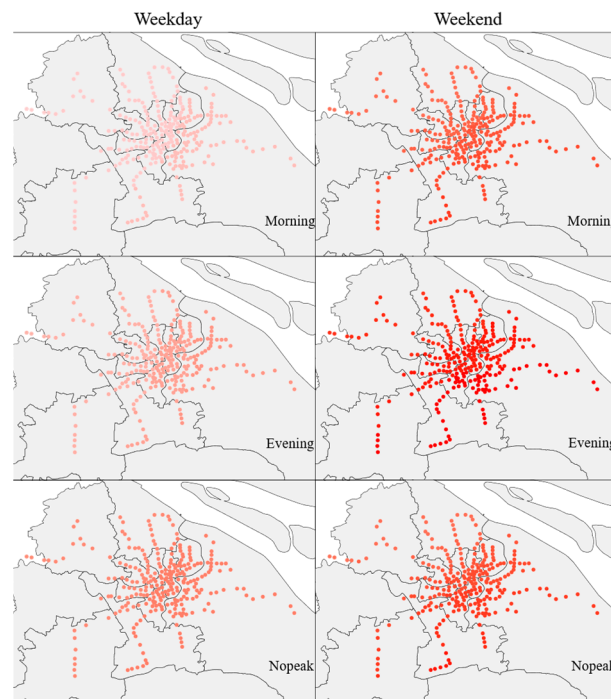


Figure 4. Distribution of the Impact of Accommodation services (darker colors indicate a greater degree of their influence).

Scenic spots have a positive impact on metro ridership. Tourist attractions typically attract a large number of visitors and are often located around metro stations. As a convenient mode of transportation, the metro can efficiently transport tourists directly to their destinations, attracting more people to choose the metro to travel to scenic spots, thereby increasing metro ridership. In terms of time distribution, the impact of non-working days is greater than that of working days, with the least impact during the morning rush hour period. This is because people typically visit tourist attractions during non-working hours, indicating a relatively active leisure lifestyle in Shanghai [11]. In terms of spatial distribution, the impact gradually strengthens from south to north.

Land use diversity has an overall positive impact on metro ridership [5]. The greater the diversity in land use, with multiple functional zones indicating the presence of commercial, office, residential, cultural, tourism, educational, and other various types of areas, the metro, as a convenient and efficient mode of public transportation, can meet the travel needs of different groups, thereby promoting an increase in metro ridership.

Road density has a positive impact on metro ridership, indicating that a well-connected street network with convenient pathways can increase the number of metro passengers. Existing research has also confirmed this relationship [6]. A higher road network density indicates a well-developed road network in the area, connecting multiple functional zones and possibly being positioned as a transportation hub that attracts residents. Additionally, the transportation environment in the area is complex, with a significant volume of traffic, leading to prominent issues of vehicle congestion. Residents tend to prefer the timely and efficient metro as their mode of transportation in such areas.

5.4. The Interaction Influence of Factors

By using factor analysis, an analysis was conducted on the impact of various variables on metro ridership changes during different time periods. Figure 5 compares the q-values of different environmental variables during weekdays and weekends at different time periods. From the graph, it is evident that there are differences in the q-values of different

environmental variables during various time periods. Apart from Road density, most variables have the highest q -values during off-peak hours and the lowest q -values during peak hours.



Figure 5. Distribution of q -values for each variable at different time periods.

Furthermore, the q -values of the single-factor impact levels of road density, population density, and food & beverages all exceed 0.9, making them some of the variables with the greatest impact on changes in metro ridership. To facilitate subsequent analysis of two-factor impact levels, these variables will be excluded.

Interactions detectors are used to check whether two influencing factors work independently and further determine the type of interaction. This method has been applied in detecting influencing factors in traffic accidents research [44]. It was found that all factors mutually reinforce each other to increase their impact on metro ridership, involving two types of interactions: nonlinear enhancement and bi-enhancement. When any two factors work together, their combined explanatory power on metro ridership is greater than that of individual factors.

In terms of explanatory power ranking, the details of the top three interaction effects during each time period are shown in Table 7. It was observed that the factors with influence exceeding 0.7 in univariate analysis are transportation service, commercial & industrial place, and sports & recreation in Table 7. The strongest explanations in bivariate interaction effects come from interactions between three main factors and other factors. Specifically, while the univariate impact of Land use diversity does not exceed 0.3, indicating it is insignificantly influential on metro ridership, its impact level reaches 0.99 when interacting with main factors.

Table 7. The Interactive Detector Results.

Days	Time	Ranks	Factors	Single q	Interactive q	Enhancement
Weekday	Morning	1	Commercial & Industrial place $\cap$ Transportation Service	0.821996	0.99966	21.61%
		2	Land use diversity $\cap$ Transportation Service	0.821996	0.99895	21.53%
		3	Land use diversity $\cap$ Commercial & Industrial place	0.782282	0.996781	27.42%
	Evening	1	Commercial & Industrial place $\cap$ Transportation Service	0.851932	0.999823	17.36%
		2	Land use diversity $\cap$ Transportation Service	0.851932	0.998827	17.24%
		3	Land use diversity $\cap$ Commercial & Industrial place	0.83608	0.99818	19.39%
	No peak	1	Commercial & Industrial place $\cap$ Transportation Service	0.87528	0.999767	14.22%
		2	Land use diversity $\cap$ Transportation Service	0.87528	0.999157	14.15%
		3	Land use diversity $\cap$ Commercial & Industrial place	0.832894	0.998841	19.92%
Weekend	Morning	1	Commercial & Industrial place $\cap$ Transportation Service	0.799317	0.999264	25.01%
		2	Land use diversity $\cap$ Transportation Service	0.799317	0.998591	24.93%
		3	Land use diversity $\cap$ Sports & Recreation	0.698638	0.997424	42.77%
	Evening	1	Commercial & Industrial place $\cap$ Transportation Service	0.883352	0.999737	13.18%
		2	Land use diversity $\cap$ Transportation Service	0.883352	0.999043	13.10%
		3	Land use diversity $\cap$ Sports & Recreation	0.838603	0.999028	19.13%
	No peak	1	Commercial & Industrial place $\cap$ Transportation Service	0.889219	0.999768	12.43%
		2	Land use diversity $\cap$ Sports & Recreation	0.839402	0.999391	19.06%
		3	Land use diversity $\cap$ Transportation Service	0.889219	0.999384	12.39%

Furthermore, in the context of bivariate interaction effects across six distinct time intervals, the majority manifest bi-enhancement proclivities, where the cumulative impact surpasses the maximum individual factor impact. Concurrently, interactions involving Land use diversity and other factors, namely Government agency, Accommodation Service, and Scenic Spot, all adopt nonlinear enhancement characteristics. It significantly escalates the combined explanatory prowess in such scenarios. The interaction effects revealed by GeoDetector analysis provide actionable insights for integrated urban planning. The synergistic enhancement between land use diversity and other factors suggests that mixed-use development policies should be implemented as part of comprehensive packages

rather than isolated interventions. For instance, when developing new metro stations, simultaneously introducing diverse commercial facilities, improving road connectivity, and ensuring adequate public service provisions can generate multiplicative effects on ridership. This finding challenges the conventional single-factor optimization approach and advocates for coordinated multi-sectoral planning strategies. Urban planners should leverage these interaction effects by creating policy bundles that combine transportation infrastructure investments with targeted land use regulations and public facility allocations, thereby maximizing the return on public transit investments.

6. Conclusions

Based on the case study of Shanghai, this research investigates the impact of BE factors on metro ridership. We employed the MGWR model with a more flexible bandwidth setting to analyze spatial heterogeneity of BE on metro ridership. By comparing the modeling results with GWR and OLS models, we validated the potential application value of the MGWR model in analyzing factors influencing rail transit ridership. The analysis of single-factor effects on rail transit ridership indicates that variables such as Transportation Service, Food & Beverages, Population Density, Commercial & Industrial Places, Accommodation Service, and Scenic Spots all have a positive impact. Particularly, Food & Beverages and Accommodation services, respectively, have the greatest impact on metro ridership on weekday and weekend. Considering limited resources and feasibility of construction, it could be beneficial to increase connectivity by strategically locating transportation hubs near metro stations. Placing malls, office buildings, and other commercial establishments near metro stations can also boost rail transit ridership.

Following single-factor analysis, the GeoDetector was utilized to analyze the interactive effects of built environment factors. The findings revealed a significant improvement in explanatory power with the consideration of bivariate interaction effects. The results from the analysis of bivariate interaction effects reveal that in conjunction with Land Use Diversity and other variables, there is a significant enhancement in the impact on rail transit ridership. Thus, it is recommended to diversify land use near metro stations by implementing incentive measures to encourage the development of mixed-use buildings. This approach can create a diverse environment that caters to various needs and contributes to increasing rail transit ridership.

This study holds significant implications for sustainable urban development. The findings indicate that the metro ridership in central urban areas is primarily driven by commercial density, while suburban ridership is more sensitive to accessibility of public services. This necessitates differentiated policy interventions—prioritizing the allocation of hospitals, schools, and other essential facilities near suburban stations to mitigate spatial deprivation of public services. In addition, these research findings demonstrate that coordinated planning of transportation hubs and commercial facilities can increase the share of rail-based travel. By optimizing mixed-use development within an 800 m radius around metro stations (e.g., transit-oriented development (TOD) models), reliance on private vehicles for short-distance trips can be reduced.

Current limitations in data sources may introduce potential biases related to variable types and temporal coverage. While the 2016 data used in this study, the fundamental relationships between built environment characteristics and transit ridership patterns tend to remain stable over medium-term periods. Shanghai's metro network expansion since 2016 has primarily occurred in peripheral areas, while the core network analyzed in this study has remained largely unchanged. Furthermore, the methodological framework we present—combining MGWR with GeoDetector for interaction analysis—remains valid and can be readily applied to more recent datasets as they become available. In future research,

we aim to acquire a more diverse and comprehensive set of data variables to further refine our models. This will allow us to explore the factors influencing rail transit ridership more comprehensively and deeply, providing valuable insights and recommendations for sustainable transportation development.

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