

Article

Interactive Impacts of Built Environment Factors on Metro Ridership Using GeoDetector: From the Perspective of TOD

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Abstract: TOD (transit-oriented development) is a planning concept that uses public transportation stations as the center of development, and it aims to integrate land use efficiency and transportation planning linkages to encourage the use of public transportation. The impact of metro TOD projects on urban transportation is multifaceted and complex, and the promotion of metro TOD ridership is an important topic in academic circles. However, the theoretical analysis framework of the impact mechanism of metro TOD ridership is still not perfect. Most studies ignore the TOD characteristics of the stations and the interaction between the station area's land use and the station area functional linkage. Moreover, a few studies have focused on the mechanisms of the impact of TOD built environment factors on the spatial differentiation of station ridership, and the interactive effects of built environment factors. In this paper, the factors of a metro TOD station built environment were selected based on the node–place–linkage model expanded by the 5D principle of TOD, and a solution is provided for the computable transformation of the 5D principle. The GeoDetector method was used to detect the individual and interactive effects of the TOD built environment factors. The results show that the spatial distribution of the metro TOD station area ridership shows a core–peripheral structure and spatial heterogeneity, both on weekdays and weekends. Moreover, the individual effects of each factor can explain up to 49% and 35% of the traffic distribution on weekdays and weekends, respectively. In addition, the two-factor interactive effect has a stronger influence on metro ridership. The interactive effect can explain up to 72% and 77% of the traffic distribution on weekdays and weekends, respectively. Furthermore, the individual effects of each factor exhibited spatial heterogeneity in the local spaces, showing spatial facilitation and inhibition, respectively. Finally, the main policy recommendations are as follows: One of the important ways to guide the development of cities toward polycentric structure is to promote a TOD model in the peripheral areas of the cities. Building more public open spaces in TOD station areas and improving the collection and distribution capacity of the bus transport systems can effectively stimulate the ridership of metro stations.

Keywords: metro ridership; built environment; GeoDetector; node–place–linkage model; Guangzhou



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1. Introduction

In the context of the smart growth and new urbanism in the United States, effective responses to urban sprawl development and reducing urban traffic congestion and air pollution have become important issues [1]. In response to these theories, transit-oriented development (TOD) has become popular in urban planning practice [2–4]. As it is described as a planning approach that is designed to integrate land use and transportation planning, TOD is conceptually designed to encourage people to walk, cycle, and use public transportation rather than drive cars. It is utilized in the development of neighborhoods around high-density, mixed-use public transportation stations to create a walkable built

environment [1,5,6]. The TOD model is emerging as a sustainable spatial planning strategy to achieve the goal of public transportation mobility [7–9]. Over the past three decades, an increasing number of Chinese cities have constructed new rail transit systems, reshaping the public transportation networks of cities and guiding TOD. As an urban development model, TOD can effectively organize various functional units in cities, guide people to take advantage of more low-carbon and environmentally friendly travel modes, and improve the land construction of metro station areas in terms of compactness and efficiency to alleviate problems such as urban land constraints and sprawl [10,11]. TOD projects effectively integrate public transportation networks with urban land use development, and they are widely considered to be an efficient spatial planning tool [7,12,13]. The completion of new TOD projects and the improvement of the quality of the built environment around the station facilities not only changes the spatial distribution of regional ridership and improves the travel patterns of more residents. According to the theories of environmental psychology [14,15], the completion and quality of a TOD station area as a built environment will affect the travel behavior of local people, and thus, it will have an impact on the station ridership.

For the sustainability of urban metro TOD projects and the feasibility of new projects, it is of great interest to study the connection between the metro facilities and the built environment of metro TOD stations [16]. A TOD station area is a spatial unit within a certain distance from a metro station [17,18], and there are multiple complex influences of a TOD built environment on metro station ridership [19,20]; there are many of them due to the diversity of the influencing factors, and they are complex in the sense that there may be an individual factor or a combination of factors. The studies on the influence of metro TOD on ridership can provide planning references for the development of urban transportation and urban spaces and their renewal [4,21,22]. However, the existing research has not yet fulfilled the terms of the theory and method of TOD built environment evaluation index selection and the heterogeneity of the TOD built environment impact on station ridership.

In terms of research theory, the current studies on TOD station area spaces are mainly based on the 3D or 5D principles of TOD [23–26]. As an analytical framework, a node–place model is often used to evaluate the characteristics of TOD site attributes and opportunities for the differentiated development of TOD station spaces [27]. The model aims to analyze two functions of TOD and their interactions: the locational characteristics of TOD (“node” function) and the development of land for people’s activities (“place” function) [9,28,29], which incorporates the 3D principles of TOD (Density, Diversity, and Design) into the specific expression of the place function. Although this analytical framework promotes the development of station area planning methods for TOD, it ignores the interaction of the TOD site location characteristics with the station area’s land use and the coupled linkage of station area functions [30]. Therefore, we consider the TOD site attribute characteristics and the “5D” principle of TOD (Density, Diversity, Design, Distance to transit, and Destination accessibility) and add the “linkage” dimension to the node–place model for the evaluation of the TOD station characteristics [8,9]. Since TOD is only a planning concept and there is a lack of unified planning standards, scholars have used the node–place–linkage model differently, but the common denominator is that they are research studies which aim to increase metro ridership [8,9,31,32]. However, it is certain that the TOD principles provide a theoretical framework for TOD spatial studies, while each TOD station area study relies on the interpretation of TOD connotations and 3D (or 5D) principles, which are translated into corresponding methods to achieve the factor measurement of principle transformation and the acquisition of built environment data. Although the extended node–place–linkage model is advantageous for summarizing the characteristics of the TOD station areas, studies on the use of the node–place–linkage model to explain metro ridership are still relatively limited [28,32].

In terms of the research methodology, in recent years, due to the application of the direct ridership model (DRM), there has been an increasing number of studies investigating the factors affecting the ridership at TOD stations by estimating ridership as a function

of the characteristics of each TOD built environment [19,20]. These studies introduced ordinary least squares regression, structural equation modeling, Poisson regression, distance decay regression, and other models to explore the influence relationship between the built environment of a TOD station area and station ridership [17,19,33–35]. Urban planning practitioners and policy makers can easily understand the process and results of a model analysis and respond accordingly [36]. Later studies have suggested that the use of geographically weighted regression (GWR) and geographically and temporally weighted regression (GTWR), etc., could overcome the spatial heterogeneity problem that exists in the built environment [20,29,37,38]. In addition, models such as GWR consider spatial instability can reveal the spatial heterogeneity of the whole spatial parameters and quantify the influence coefficients of each factor on the dependent variable in the local space. However, the influence mechanism of metro ridership is multifaceted and complex, and the coupling and interactive effects among the factors cannot be ignored [39], which is crucial for exploring the variation mechanism of subway ridership. The GeoDetector model is an effective tool that is used to explain the spatial heterogeneity of spatial parameters and to detect the individual and interactive effects of potential influencing factors [40]. Compared with the GWR model, the GeoDetector model is characterized by the ability to detect the interactive effects of the factors on the dependent variable. However, the GeoDetector model has only been applied to detect the interactive effects of bike sharing usage or traffic congestion on the built environment factors in transportation studies [39,41], and we have not yet found any application that can be used to explore the influence mechanisms that affect metro ridership.

In this study, we propose two objectives, the first of which is a theoretical objective. We hope that the node–place–linkage model, which is based on the 5D principle of TOD, can explain the influence mechanism of built environment factors on metro ridership. This can improve the research on the expanding “node–place” model to explain the influence mechanism of metro ridership. The second objective is empirical. This study aimed to use the GeoDetector method to explore the influence of the built environment factors on metro ridership, individual and interactive factor effects, and the local spatial differences in the influence of the built environment factors. Guangzhou, the third largest city in China in terms of metro mileage, was selected for this empirical study, and the results of the study will provide reference suggestions for the sustainable development and land use spatial planning of urban TOD model.

This study is divided into five sections. Following the introduction, Section 2 reviews the existing literature, Section 3 describes the study area and research methodology used, Section 4 discusses the implications based on the analysis, Section 5 presents the results of this study, and Section 6 summarizes the findings and proposes relevant policy implications.

2. Review

2.1. Relationship between Metro TOD Station Area and Metro Ridership

A large number of studies have been conducted to analyze the factors affecting the ridership at metro stations, and the types of influencing factors include the metro TOD station characteristics, as well as socioeconomic factors, and the built environment of the metro station area [42–44]. In terms of the metro TOD station characteristics, metro ridership is related to metro station types (interchange and intermediate stations). Interchange stations tend to attract more ridership than intermediate stations do due to the multiple lines passing through them [17,20]. Additionally, the path distance of a metro TOD station from the city center [35,45] and its accessibility in the metro network [46] are correlated because people generally prefer to use public transportation to travel in the city center. As the distance to the city center increases, the time taken to travel by car significantly increases, whereas the increase in this by public transportation is much more larger [47]. In addition, the economic locations of the metro TOD station areas are also correlated with metro ridership, and the station areas with higher economic locations can be spatially represented as generating more economic activity, thus promoting the use of public transportation [48].

In terms of the important factors affecting ridership, the built environment factors of the metro TOD station areas can be categorized into three dimensions: density, diversity, and design [49]. The density of the station area is a key factor stimulating ridership, including the building density and population density of the station area, and it has a positive correlation with metro ridership [13,50–52]. The significance of this is that the large number of commercial and entertainment services available around metro station areas can attract more people to use the metro [53]. Additionally, a higher land use mix is considered to be a key factor that is positively correlated with metro ridership [4]. This is manifested by the diversity of land uses in the planar space and the mix of building uses in the vertical direction of the metro station area, both of which can be effective land use policies that increase transit ridership [38]. In addition, metro station areas are designed to combine a land functional mixture to create more livable neighborhoods, making it easier for people to walk to the stations and increasing ridership [2,19]. The traditional grid-like neighborhood layout pattern improves the ease of access to the metro stations, and the density of the intersections and public open spaces in the neighborhood contribute to people's interaction activities and neighborhood vitality [54,55]. Therefore, at the design level, the number of road intersections and the area of the public open space in the metro station area have a catalytic effect on increasing metro ridership.

However, metro station ridership is not only related to the built environment of the TOD station area, but it is also closely linked to the ease of public transportation interchanges in the surrounding area. The higher the ease of access to public transit services in a metro TOD station area is, the more frequently that people will use the metro and public transport [34,47,52]. Easier Better pedestrian accessibility within the metro TOD station area is also considered to be one of the key factors in increasing metro station ridership [8].

The above studies provide a basis for the selection of the built environment factors of the metro TOD station areas explored in this paper. The difference is that this study considers not only the influence of individual factors on ridership, but also the influence of interactions between the factors.

2.2. Evaluation Methodology

In terms of the methodology, various measurement models have been used to analyze the relationship between the influence of the metro TOD station areas and their ridership. Using the direct ridership model (DRM), the study can investigate the influencing factors of ridership at TOD stations by constructing regression functions of the TOD built environment characteristics factors [19,20]. The most popular method is the use of ordinary least squares regression (OLS) to analyze the influence of external factors on metro station ridership [18,33,34,56]. Subsequent scholars have also used the Poisson regression model [35,57], distance-decay weighted regression [19], and the structural equation model (SEM) [17] in order to study the determinants affecting metro station ridership. However, the above models have shortcomings in their spatial influence analyses as they assume that the influence parameters of the factors are spatially consistent [20]. Therefore, they cannot explain the existence of spatial autocorrelation and spatial unsteadiness of the dependent variable, which is manifested as the spatial heterogeneity of ridership in the metro TOD station area [37,58,59]. Spatial heterogeneity refers to the fact that the metro station areas that are close to each other have similar characteristics, while the metro station areas that are far from each other have different characteristics, thus leading to the existence of spatial heterogeneity in metro station ridership.

As it is a local regression model, geographically weighted regression (GWR) is considered to be a better approach, especially for solving the problems of spatial autocorrelation and spatial non-smoothness in modeling [20,29,60–62]. These studies also confirmed that the GWR model outperforms the global linear models such as OLS regression in terms of predictive performance and realistic conclusions. In recent years, various improved GWR models have been introduced to analyze the impact mechanism of metro ridership, and all

of these models aim to improve the accuracy of the ridership regression analysis [63–66]. The GeoDetector model is also a spatial and statistical method that is used to measure spatial heterogeneity and the driving forces behind it [40,67,68], and this model has different characteristics compared to those of the GWR model. In the GeoDetector model, the linear correlation of geographic variables does not have to be assumed, and it can detect the degree of influence of factor interaction combination effects on the spatial heterogeneity of the dependent variable. With the GeoDetector factor detector and interaction detector modules, it is possible to clarify the statistically significant independent variables and their explanatory power on the dependent variable. GeoDetector is based on a spatially stratified heterogeneity analysis, which compares the intra-stratigraphic spatial variance and the between-strata spatial variance. The main advantage of spatially stratified heterogeneity analysis is that geographic variables do not require any assumptions and it reflects the true spatial association of geographic attributes [40]. However, both OLS regression and GWR regression are modeled by mechanisms based on the assumption of a linear correlation between the independent and dependent variables, and thus, they are linearly correlated impact evaluation models. GeoDetector is a nonlinear correlation model.

However, there are multiple complex influence mechanisms of geographic phenomena, i.e., they may exist as spatial phenomena due to the combined effects of mono- or multi-factors [39]. Therefore, the influence of an individual built environment factor on metro ridership cannot only be focused on the interaction between these influencing factors. The interaction detector module of GeoDetector is used to further determine whether there is an interaction between the independent variables and their strength and type of interaction [69–73]. However, at present, among the effects of the built environment factors in transportation, we found that only the GeoDetector model has been applied to detect the interactive effects between bike sharing usage or road traffic congestion and the built environment factors [39,41], and we have not yet found applications to explore the influence mechanisms affecting metro ridership. Exploring the interaction between the factors is crucial for public transportation planning and it should be a key focus of transportation research. In order to improve the application of the GeoDetector model in the influence effect of metro ridership, this study focuses on using this model (factor detector and interaction detector module) to analyze the influence mechanism between the built environment of the metro TOD station area and metro station ridership, further comparing the influential difference between the individual effect of each factor and the interactive effect between each of the two factors. Ultimately, the findings of this research can be used to provide relevant policy support for the construction of urban metro TOD station areas.

3. Materials and Methods

3.1. Study Domain

Guangzhou (Canton), the capital of Guangdong Province, is the political, economic, educational, and cultural center of South China, covering an area of 7434 km² with a population of 18.81 million inhabitants (2020). Guangzhou is an ideal case study for unravelling the relationship between the built environment factors of metro TOD stations and metro ridership and informing policy responses of urban planners for several reasons. Firstly, Guangzhou has a large number of metro lines in operation with a large coverage in terms of distance. Guangzhou is the third largest city in China in terms of population as well as metro mileage. As of 2020, Guangzhou had 15 metro lines, covering a total distance of 515 km, ranking among the top three largest metro networks in the world. Secondly, Guangzhou's metro ridership is huge, with it remaining stable and rising all year round. In 2020, 2.413 billion trips were made, with an average daily ridership of 6.5916 million, ranking second in China. Thirdly, a vast number of metro stations are planned for the future; therefore, there is great potential to carry out a ridership study on these planned metro stations. According to the 2025 long-term plan for Guangzhou Metro, the city will accommodate 23 metro lines with a total combined distance of 981.8 km. As

shown in Figure 1, this study selected 213 metro stations in Guangzhou that were opened in November 2020 as the research object.

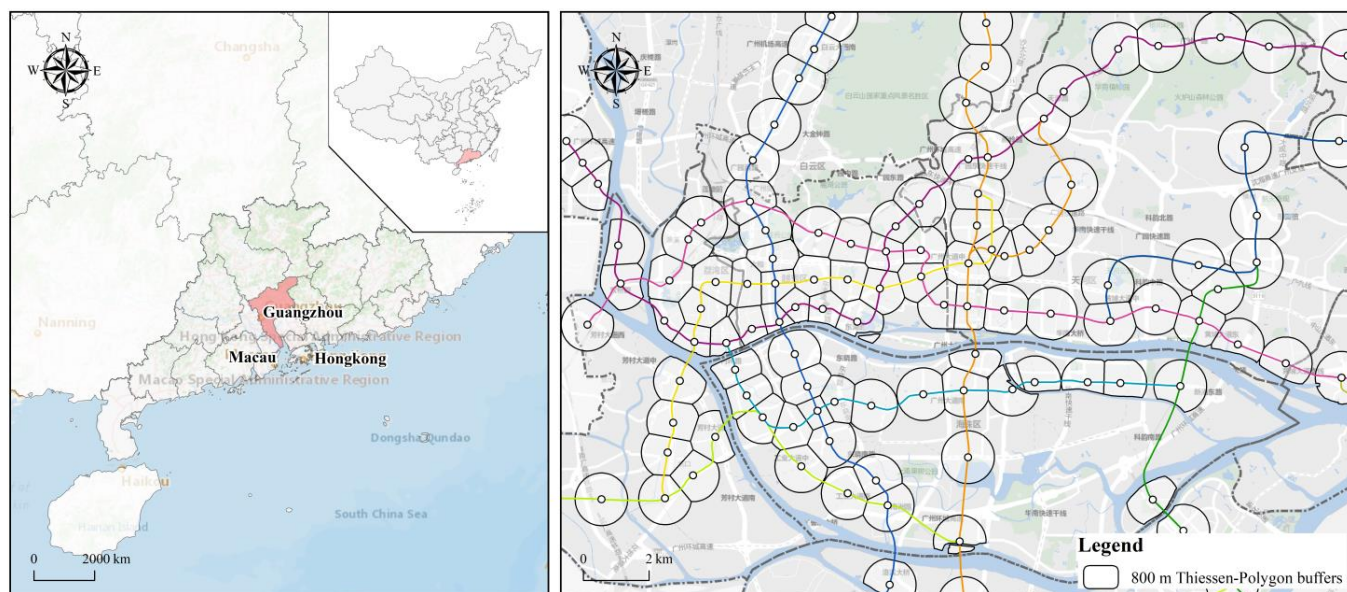


Figure 1. Study domain and 800 m metro station area (Thiessen polygon buffers).

3.2. Determination of Metro TOD Station Area

From the planning and construction process of TOD in Guangzhou, a few TOD station areas have been constructed and developed in Guangzhou. Therefore, the TOD station area defined in this study is oriented to planning and construction, rather than to the current environment of the TOD station area. Under the guidance of the TOD model, a complex space with mixed functions is formed around a certain range of transportation stations (referred to as the TOD station area in this study), and the delineation of the TOD station area is mainly based on the station as the center, with 500~1000 m being the radius or the reachable range of 10~15 min of travel on foot. According to relevant studies, the influence area of the rail station area is a radius of 1500 m around the station area, and the core area is 800 m around the station area [1,18,20,29]. The document entitled *Implementation Rules for the Construction and Comprehensive Development of Land Around the Guangzhou Metro Station Complex* proposes that the comprehensive development of the land around a metro station should be combined with the TOD theory to establish a complex urban functional area within an 800 m (about 15 min walking distance) radius of the station complex, contributing to successful urban development. Therefore, this study selects an 800 m radius around the Guangzhou metro station, instead of the 800 m walking path, as the spatial boundary of the TOD station area.

In our study, it is very important to consider the radius range that the metro TOD station area can realistically influence. Firstly, the role of natural boundaries in the actual sphere of influence of the TOD station area cannot be ignored, especially if this influences its ridership. The area through which the river passes does not encompass the metro TOD station's area of influence. These areas of influence are also partially blocked by the river, so the above mentioned areas need to be erased [74]. Secondly, each statistical area of the metro TOD station area needs to ensure the independence of the study area. The extent of the 800 m radius buffer zone between the metro TOD station areas tends to overlap, especially in central urban areas. To avoid some elements being double-counted by the station areas, a Thiessen polygon analysis was used [29,62,74,75]. The final example of metro TOD station area in this study (Thiessen polygon buffers) is shown in Figure 1.

3.3. Metro Smart Card Data Processing

Smart card data, including those from smart card IDs, metro station IDs, and exit or entry times and dates, were obtained from Guangzhou Metro for Thursday, 17 September 2020 and Sunday, 20 September 2020. According to the 2020 Guangzhou Metro Annual Report, metro ridership returned to high and stable levels during July and August, thus we avoided the impact caused by the city's COVID-19 epidemic prevention policy. During this period, Guangzhou did not host festivals, major exhibition events, or sporting events, nor did it experience fare adjustments or extreme weather such as typhoons, thereby excluding the potential impact of price changes and emergencies. We counted two indicators: the daily ridership on weekdays and at weekends in order to recognize and explain the spatial distribution characteristics of Guangzhou metro ridership and its driving mechanism.

3.4. Selection of Built Environment Impact Factors for Metro TOD Station Area

Based on the 5D principle of TOD (Density, Diversity, Design, Distance to transit, and Destination accessibility) proposed by Cervero, the impact factors of the metro TOD station area were constructed based on the node–place–linkage model as the analysis framework (Figure 2). ① The node dimension reflects the relationship between the metro TOD station area, the metro network, and the city that is expressed by each type of location. The route distance to the city center reflects the urban location of the TOD station area, the average land price within the radius of the station area reflects the economic location of the station area, the average travel time from the station area to each metro station area reflects the transportation location, and the type of metro station area—an interchange or intermediate station—reflects the rail network location of the station area. ② The place dimension reflects the development intensity of the metro TOD station area, which is expressed in terms of station area density, diversity, and design indicators. The density sub-dimension indicates the density and functions of the urban population, the diversity sub-dimension indicates the functional mix of different land use types and the buildings where they are located, and the design sub-dimension indicates the friendliness of the built environment for the residents' daily travel use. ③ The linkage dimension reflects the internal spatial structure of the metro station area, which is expressed in terms of traffic transfer capacity and its walking accessibility. The number of bus lines within the station area reflects the convenience of the interchange; the ratio of the 800 m walkable boundary to the TOD station area reflects the walkability of the station area. The selection of impact factors follows the following principles: (1) matching them with the theoretical construction of the expanded node–place model; (2) consistency with the related literature; (3) the availability of data; (4) reflecting the characteristics of Guangzhou TOD station area construction. Finally, an index system with 14 impact factors was constructed. The indicator system is shown in Tables 1 and 2.

3.5. Modeling the Impact of Ridership Analysis at Metro Stations Using the GeoDetector

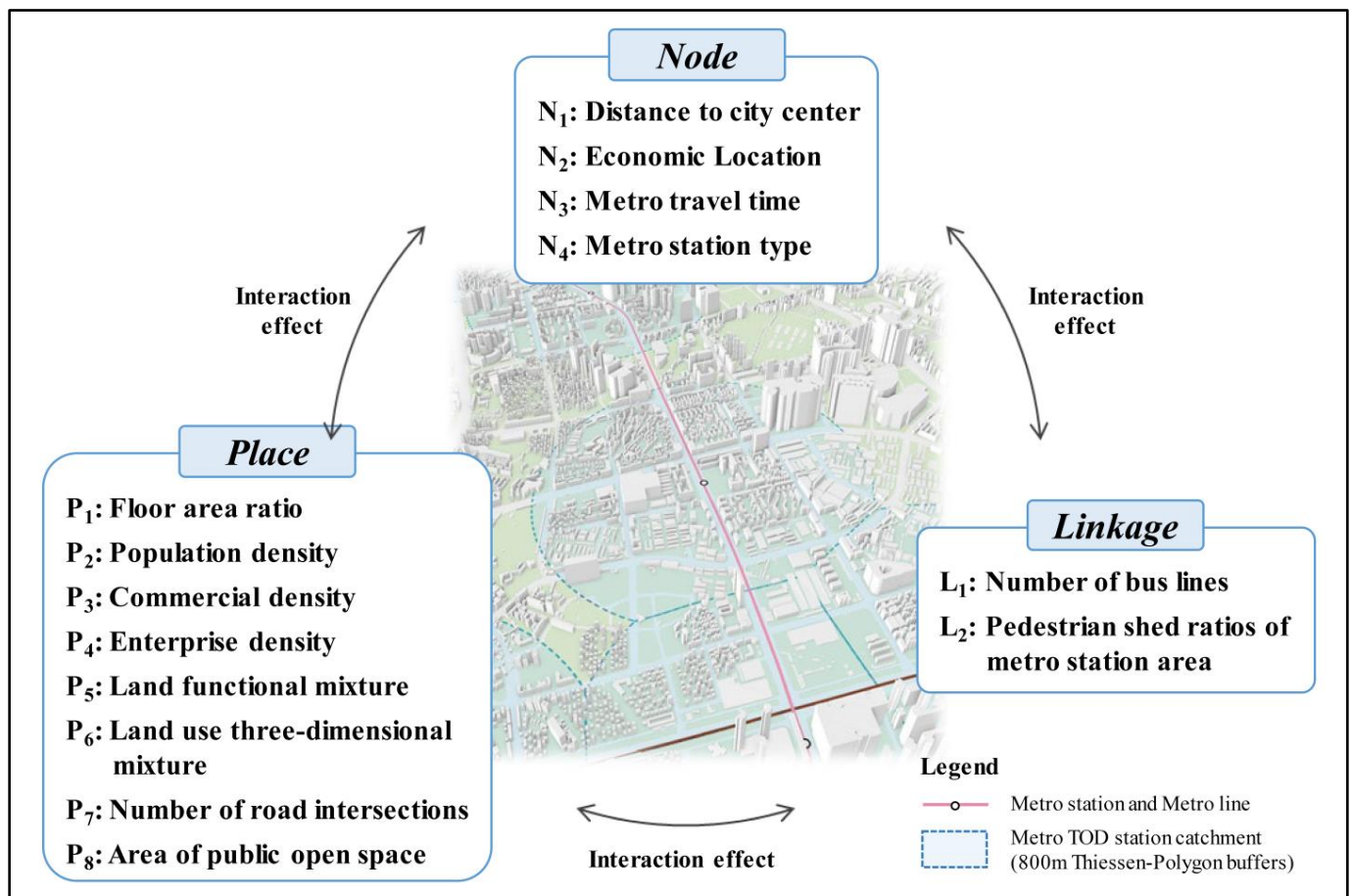
The GeoDetector proposed by Wang et al. is advantageous for detecting spatial heterogeneity and in revealing the driving forces behind it, especially in revealing the individual and interactive effects of influencing factors on the dependent variables [40,69–72]. Among the GeoDetector modules, the two most common modules used in geography are the factor detector and the interaction detector, while the risk detector and the ecological detector are more widely used in the ecological domain [76,77].

Table 1. TOD Indicator system.

Dimension	Sub-Dimension	Factor Name	Calculation Methodology
Node	Station characteristic	N ₁ Distance to city center	Use the “route planning” module of Amap API to measure the distance of public transportation from the station area to the city center (https://lbs.amap.com (accessed on 10 July 2022)).
		N ₂ Economic location	Based on the benchmark land price data of Guangzhou city, the average land price within the station area was measured.
		N ₃ Metro travel time	Use the “route planning” module of Amap API to measure the average travel time of the metro from “station to station”.
		N ₄ Metro station type	Whether it is an interchange station (1 = Yes; 0 = No).
Place	Density	P ₁ Floor area ratio	Use the Amap API to obtain building data and correct it to measure the average volume ratio within the station area.
		P ₂ Population Density	Extract Worldpop 100 m population grid data and correct it with the 2020 Census of China and use ArcGIS Zonal Statistics as Table tool to count the average number of people (person/km ²) falling into the station area.
		P ₃ Business Density	Density of commercial POIs within the station area (pcs/km ²) is calculated by using Amap POI data.
		P ₄ Enterprise density	Density of Enterprise POIs within the station area (pcs/km ²) is calculated by using Amap POI data.
	Diversity	P ₅ Land functional mixture	$F = 1 - \frac{(a - \frac{b}{d}) - (a - \frac{c}{d})}{2}$ Where $a = \text{Max}(D_1, D_2, D_3, D_4, D_5, D_6)$; $b = \text{Min}(D_1, D_2, D_3, D_4, D_5, D_6)$; $c = \text{Average}(D_1, D_2, D_3, D_4, D_5, D_6)$; $d = \text{Sum}(D_1, D_2, D_3, D_4, D_5, D_6)$; D ₁ : commercial service land; D ₂ : business office land; D ₃ : residential land; D ₄ : industrial land; D ₅ : public service facility land; D ₆ : culture, sports and leisure land; D ₁ ~D ₆ indicate the proportion of land area.
		P ₆ Land use three-dimensional mixture	$H_b = - \sum_i^n b_i \log(b_i), \quad b_i = \frac{\sum_j A_{ij} f_{ij}}{\sum_i \sum_j A_{ij} f_{ij}}$ Where A_{ij} is the floor area of building j on land use type i , and f_i is the number of building floors. $i \in [D_1 : D_6]$.
	Design	P ₇ Number of road intersections	Ratio of the number of road intersections to the area of metro stations (pcs/km ²).
		P ₈ Area of public open space	The sum of the public open space areas within the metro station area (including plaza space, open sports venues and arenas, open parks, including the public open space area of mountain parks according to the 10 m buffer zone on both sides of the path).
Linkage	Distance to transit	L ₁ Number of bus lines	Counting the number of bus lines within the metro station area.
	Destination Accessibility	L ₂ Pedestrian shed ratios of metro station area	Use the service area analysis tool in ArcGIS network analysis module to measure the 800 m walkable boundary of the station area and count the shed ratio of the walkable area to the area of the station area.

Table 2. Descriptive statistics of the selected factors.

Factors	Max	Min	Ave.	Std.
N ₁ Distance to city center	66.91	3.81	21.48	16.45
N ₂ Economic location	25,077.69	2495.58	11,514.43	6251.87
N ₃ Metro travel time	80.06	23.87	38.16	14.10
N ₄ Metro station type	1	0	0.1596	0.3671
P ₁ Floor area ratio	4.37	0.01	1.09	0.83
P ₂ Population density	93,100	300	16,153.52	18,478.29
P ₃ Commercial density	3624.45	1.99	658.92	642.19
P ₄ Enterprise density	347	0	83.35	70.84
P ₅ Land functional mixture	0.9445	0.8335	0.9130	0.0194
P ₆ Land use three-dimensional mixture	1.8130	0.0000	0.9525	0.3600
P ₇ Number of road intersections	154.00	5.00	25.29	17.47
P ₈ Area of public open space	1,946,386	0	133,840.86	260,542.56
L ₁ Number of bus lines	134	1	32.93	25.72
L ₂ Pedestrian shed ratios of metro station area	0.9945	0.1929	0.5479	0.1586

**Figure 2.** Built environment factors influencing metro ridership.

(1) Factor detector (reflecting individual effect of factors)

The factor detector is mainly used to detect the spatial heterogeneity of the dependent variable Y and to detect the extent to which an influence factor X can explain the spatial heterogeneity of the dependent variable Y, which is expressed as a q-value. The range of the q-value is [0, 1], and the higher the q-value is, the greater the contribution of this influence factor to the dependent variable is. In an extreme case, a q-value of 1 indicates that factor X

completely controls the spatial distribution of Y , while a q -value of 0 indicates that factor X has no relationship with Y . The formula for calculating the statistic q -value is as follows:

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

$$SSW = \sum_{h=1}^L N_h \sigma_h^2 \quad (2)$$

$$SST = N \sigma^2 \quad (3)$$

In Equations (1)–(3), N refers to a study area that consists of N units, which is stratified into $h = 1, 2, \dots, L$ stratum, i.e., classification or partition; stratum N consists of N_h units; σ_h^2 and σ^2 denote the variance of the sub-areas (stratums) and the whole area, respectively; SSW and SST denote the values within the sum of squares and the total sum of squares, respectively. In this study, the independent variables (built environment factors) include the type of variables and the continuous variables, and it is necessary to discretize the continuous variables into the type of variables and then perform GeoDetector model operations [40]. The discretization method of continuous variables is an important factor that affects the results of the model operations, and different spatial arrangements of independent variables produce different analytical results [78]. Therefore, we compared different discretization methods and selected the best combination of discretization methods and interruption values for each geographically continuous variable as the optimal discretization parameters [39,70,79]. Under these parameters, the best combination generates the maximum q -value, indicating the highest degree of explanation of the variables from the perspective of spatially stratified heterogeneity. The discretization methods include three commonly used methods: the natural break method, the equal interval method [80], and the quantile method [81].

(2) Interaction detector (reflecting the interactive effect of factors)

We identified the interaction between the different risk factors A and B , i.e., we assessed whether the factors A and B together increase or decrease the explanatory power of the dependent variable Y or whether the effects of these factors on Y are independent of each other. The assessment was carried out by first calculating the q -value of the two factors, A and B , for the dependent variable Y separately, $q(A)$ and $q(B)$, respectively, and by calculating the q -value when they interacted (the new polygon distribution formed by the intersection of the two layers of the superimposed variables A and B): $q(A \cap B)$. Then, $q(A)$, $q(B)$, and $q(A \cap B)$ were compared.

The interaction detector was used to determine whether the combined contribution of the two enhances or weakens each other by comparing the two individual influence factors and their independent contributions. Finally, the model classifies the interactions between the two factors into five types, as shown in Equation (4).

$$\begin{aligned} \text{Enhance, nonlinear: } & q(A \cap B) > (q(A) + q(B)) \\ \text{Enhance, bi-: } & \text{Max}(q(A), q(B)) < q(A \cap B) < (q(A) + q(B)) \\ \text{Independent: } & q(A \cap B) = (q(A) + q(B)) \\ \text{Weaken, uni-: } & \text{Min}(q(A), q(B)) < q(A \cap B) < \text{Max}(q(A), q(B)) \\ \text{Weaken, nonlinear: } & q(A \cap B) < \text{Min}(q(A), q(B)) \end{aligned} \quad (4)$$

3.6. The Differentiation Characteristics of the Influence Degree of Metro Ridership in a Local Area

Spatial autocorrelation refers to the interdependence of spatial element attributes on the spatial location. As it is a method that is used to measure spatial agglomeration, spatial autocorrelation analysis can measure whether the attribute values of an area are correlated with the neighboring areas and reveal the spatial agglomeration effect and divergence characteristics between multiple variables. According to the size of the spatial scope, autocorrelation can be divided into global spatial autocorrelation and local spatial

autocorrelation. Global spatial autocorrelation is a description of the spatial characteristics of the attribute values of the whole region, and it is used to measure the degree of spatial correlation of the whole region, while local spatial autocorrelation reveals whether there is spatial similarity or heterogeneity between the attribute feature values of a spatial unit and its neighboring units. Therefore, the possible spatial correlation patterns at different spatial locations can be identified, so that the local unsteadiness of spatial correlation can be discovered, and the aggregation and divergence characteristics of local spatial elements can be more accurately grasped to provide a basis for classification and decision making [82,83].

In order to portray the spatial correlation between multiple variables, bivariate spatial autocorrelation analysis provides a feasible method for revealing the correlation of spatial distribution of different elements [84,85]. Bivariate spatial autocorrelation analysis includes bivariate global spatial autocorrelation (see Equation (5)) and bivariate local spatial autocorrelation, and it is usually measured by Moran's I index. The bivariate local spatial autocorrelation formula is shown in Equation (6).

$$Moran' I_{global} = \frac{n \sum_{i=1}^n \sum_{j \neq i}^n W_{ij} \cdot (X_i - \bar{X}) \cdot (X_j - \bar{X})}{\sum_{i=1}^n (X_i - \bar{X}) \sum_{j \neq i}^n W_{ij}} \quad (5)$$

$$Moran' I_{local(h,k)} = \frac{X_h^i - \bar{X}_h}{\sigma_h} \cdot \sum_{j=1}^n W_{ij} \left(\frac{X_k^j - \bar{X}_k}{\sigma_k} \right) = z_h^i \cdot \sum_{j=1}^n W_{ij} \cdot z_k^j \quad (6)$$

In Equation (6), $Moran's I_{local(h,k)}$ is the bivariate local spatial autocorrelation index, X_h^i and X_k^j are the i -value of attribute h and j -value of attribute k of the geographic unit, respectively, $\bar{X}_h$ and $\bar{X}_k$ are the mean values of attributes h and k , respectively, σ_h and σ_k are the standard deviations of attributes h and k , respectively, z_h^i and z_k^j denote the normalized variables with respect to the mean and standard deviation, respectively, and W_{ij} is the spatial weight matrix. $Moran's I$ range is $[-1, 1]$, and the values of $Moran's I < 0$, $Moran's I > 0$ and $Moran's I = 0$ indicate negative spatial autocorrelation, positive spatial autocorrelation, and no spatial autocorrelation, respectively. The larger the absolute value of $Moran's I$ is, the stronger the degree of spatial autocorrelation is.

The results of bivariate local spatial autocorrelation can be classified into four types of spatial clustering using bivariate LISA clustering diagrams for the spatial association between the independent variables and the dependent variable: the high–high (H–H), high–low (H–L), low–high (L–H) and low–low (L–L) types. Among these, the H–H and L–L types indicate a positive spatial correlation between spatial element i and spatial element j , while the high–Low (H–L) and low–high (L–H) types indicate a negative correlation, and the four types have significant spatial differentiation.

In this study, GeoDetector was used to detect the spatial heterogeneity of the dependent variables and the extent to which a built environment factor could explain the spatial heterogeneity of metro station ridership to determine the influence of a built environment factor on such ridership. The local spatial autocorrelation analysis can provide an explanation for the variation of the spatial variance in the local space. Using the spatial differentiation of spatial correlation between the built environment factors and the metro station ridership in local spaces, we found that the instability of spatial correlation between the built environment factors and metro station ridership generates corresponding mutual promotion or suppression effects, which equally affect the influence of built environment factors on metro station ridership in local spaces, generating instability as a result. This study hopes that the results of this spatial instability can provide references for TOD policy makers to formulate different public policies.

4. Results

4.1. Spatial Distribution of Metro Ridership

The spatial distribution of ridership in the TOD station area shows a core–peripheral structural feature and spatial heterogeneity, both on weekdays and at weekends (Figure 3). The high value of ridership is distributed in the city center, CBD, and external transportation hubs, and value of ridership gradually decreases as the distance between the TOD station area and the city center increases. At the same time, this finding also shows that adjacent stations have a similar ridership value, i.e., spatial autocorrelation may affect station ridership (as shown in Table 3). In other words, metro ridership is determined by interactions with other stations that are within spatial proximity. However, when we were comparing the “core area” of the metro used on weekdays and at weekends, it became clear that the weekday ridership value in the core area is significantly greater than that of weekends, which may be related to the activity radius of people’s weekday commuting and weekend leisure travel. Therefore, we can speculate that the construction of TOD metro stations has led to the multipolar development of Guangzhou, forming several urban businesses and residential clusters, but leisure and entertainment spaces may still have a monocentric cluster distribution phenomenon in the city.

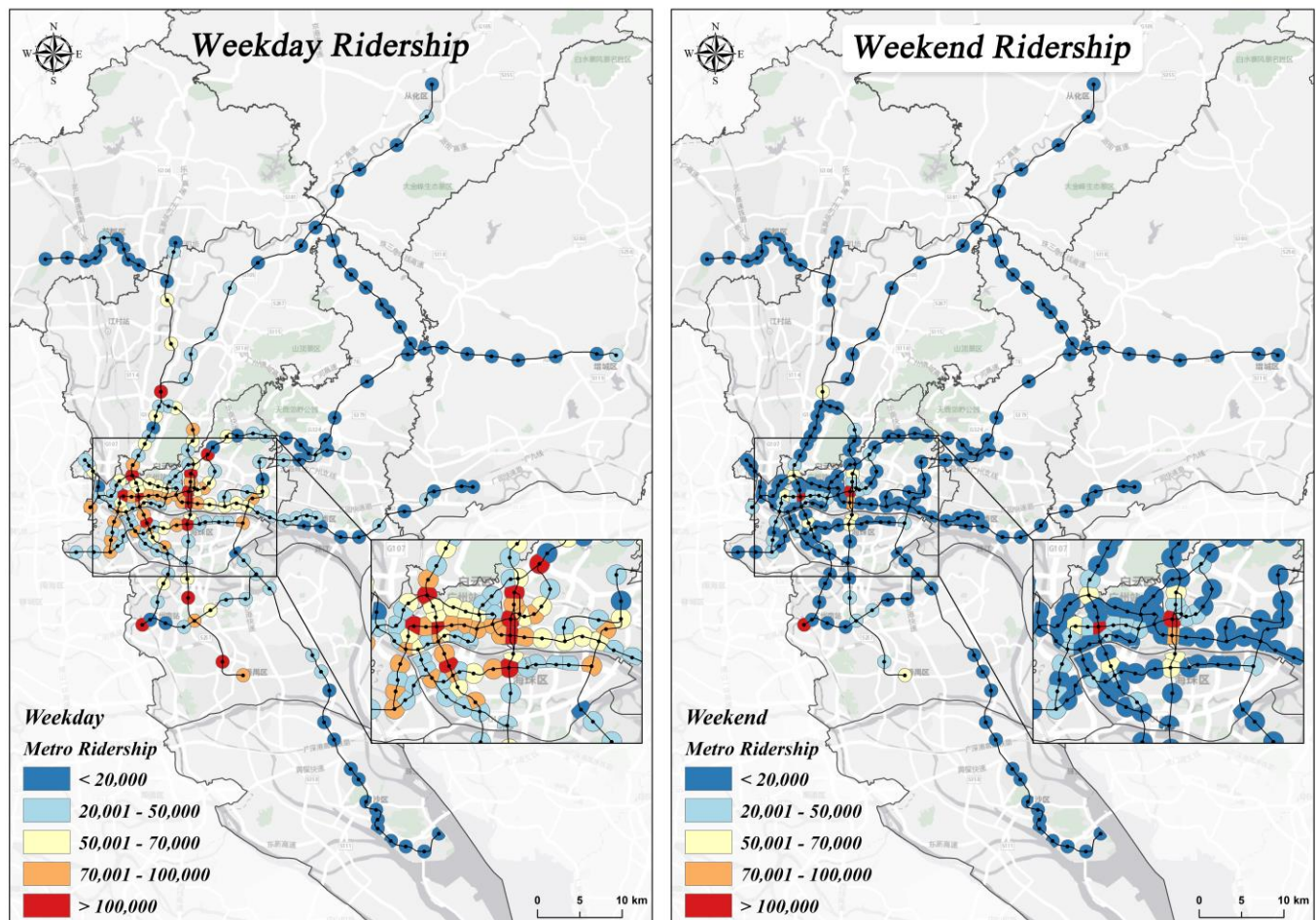


Figure 3. Spatial distribution of ridership at TOD stations on weekdays and at weekends.

Table 3. Results of Spatial Autocorrelation Analysis of Ridership at Metro TOD Stations.

Metro Ridership Type	Global Moran's I	p-Value
Weekday ridership	0.4658	0.0000
Weekend ridership	0.1779	0.0005

4.2. Individual Effects of Built Environment on Ridership at Metro Stations

4.2.1. Individual Effects on Weekday Ridership

The individual effects of 14 selected built environment factors for the TOD station areas on metro station ridership were analyzed using the GeoDetector factor detector, and we found similar results in relation to those of other TOD ridership studies [29,61]. There was a significant contribution of all the built environment factors to the total weekday ridership at p -values that were less than 0.00 (Table 4). We found that P_2 (population density; q -value = 0.4940) was the most influential factor. In addition, N_1 (distance to city center), N_2 (economic location), N_3 (metro travel time), P_1 (floor area ratio), P_3 (commercial density), and L_1 (number of bus lines) had an above average influence (q -value = 0.3590). This indicates that the main influencing factors on weekday metro ridership are land use density and the distance-related factors.

Table 4. Individual effects of built environment factors (weekday ridership).

Dimension	Sub-Dimension	Code	Factor Name	Weekday Ridership			
				q-Value	p-Value	Rank	Discretization Quantity
Node	Station Characteristic	N_1	Distance to city center	0.4022	0.0000	7	3
		N_2	Economic location	0.4665	0.0000	2	3
		N_3	Metro travel time	0.4095	0.0000	6	3
		N_4	Metro station type	0.2174	0.0000	12	2
Place	Density	P_1	Floor area ratio	0.4628	0.0000	3	6
		P_2	Population density	0.4940	0.0000	1	13
		P_3	Commercial density	0.4563	0.0000	4	3
		P_4	Enterprise density	0.3447	0.0000	9	4
	Diversity	P_5	Land functional mixture	0.1715	0.0000	13	2
		P_6	Land use three-dimensional mixture	0.1589	0.0000	14	3
		P_7	Number of road intersections	0.3401	0.0000	10	4
	Design	P_8	Area of public open space	0.2927	0.0000	11	7
Linkage	Distance to transit	L_1	Number of bus lines	0.4516	0.0000	5	5
	Destination accessibility	L_2	Pedestrian shed ratios of metro station area	0.3576	0.0000	8	6

As shown in Table 4, from the 5D principle of TOD and site characteristics, the factors with significant effects are mainly the station characteristic, and the density and distance to transit sub-dimensions, which also help us to further explain the influence mechanism of the individual effects.

The density sub-dimension of the place dimension is the most influential category of factors, including population density, the floor area ratio, and the commercial density factors. According to the theory of the GeoDetector model, the population density factor explains about 49% of the weekday metro ridership distribution. For the areas of the city with a higher population density distribution, more people will use the metro for daily commuting on weekdays. In addition, a higher floor area ratio, commercial density, or enterprise density will each have a stronger influence on weekday metro ridership. Therefore, a higher density TOD station area can provide more offices and residential spaces and accommodate more jobs, which is conducive to more people using the metro for commuting instead of driving cars.

The station characteristic sub-dimension of the node dimension has a significant impact on weekday metro ridership. The economic location area (N_2) of the metro TOD station reflects the comprehensive land prices and local socio-economic development of the region, where the metro ridership explanation level for this factor is at around 47%. In addition, the distance from the metro TOD station area to the city center and the average travel time using the metro network are also important explanatory factors. Therefore,

improving the comprehensive location level of the TOD station area is crucial to attract weekday ridership.

The distance from the transit sub-dimension to the linkage dimension is also an important factor affecting weekday metro ridership. It is mainly expressed as the number of bus routes (L_1) that can be interchanged within an 800 m radius of the metro TOD station area, reflecting the ease of interchange between the metro and the buses. For the commuters, if the convenience of metro–bus interchange is high, it can improve their travel accessibility, shorten the commuting time, and reduce the travel costs. Therefore, improving the metro–bus interchange is important to enhance metro commuter ridership.

4.2.2. Individual Effects on Weekend Ridership

From the results of the factor detector, we found that there is a significant difference in the mechanism of influence of weekend metro ridership compared to weekday metro ridership. At p -values of less than 0.01, all the built environment factors significantly contribute to the total weekday ridership (Table 5). We found that N_2 (economic location; q -value = 0.3535) and P_8 (public open space area; q -value = 0.3518) were the two factors with the strongest influence, indicating that weekend trip ridership was directed to two types of geographic areas: the downtown area and the recreation area, respectively. The factors with a higher than average level of influence (q -value = 0.2420) are N_1 (distance to city center), P_2 (population density), P_3 (commercial density), L_1 (number of bus lines), and L_2 (pedestrian shed ratios of metro station area). This indicates that the land use density, the transit system's ability to collect and disperse, and the pedestrian environment factors have important impacts on weekend metro ridership.

Table 5. Individual impact effects of built environment factors (weekend ridership).

Dimension	Sub-Dimension	Code	Factor Name	Weekend Ridership			
				q-Value	p-Value	Rank	Discretization Quantity
Node	Station Characteristic	N_1	Distance to city center	0.2993	0.0000	5	8
		N_2	Economic location	0.3535	0.0000	1	5
		N_3	Metro travel time	0.1659	0.0000	12	2
		N_4	Metro station type	0.1962	0.0000	10	2
Place	Density	P_1	Floor area ratio	0.2116	0.0000	8	3
		P_2	Population density	0.2811	0.0000	6	6
		P_3	Commercial density	0.3422	0.0000	3	4
		P_4	Enterprise density	0.1378	0.0002	13	2
	Diversity	P_5	Land functional mixture	0.2042	0.0000	9	4
		P_6	Land use three-dimensional mixture	0.0588	0.0017	14	2
	Design	P_7	Number of road intersections	0.1842	0.0000	11	2
		P_8	Area of public open space	0.3518	0.0000	2	9
Linkage	Distance to transit	L_1	Number of bus lines	0.3360	0.0000	4	8
	Destination accessibility	L_2	Pedestrian shed ratios of metro station area	0.2651	0.0000	7	5

As shown in Table 5, from the 5D principle of TOD and the station characteristics, the factors with significant effects are mainly the station characteristics, density, design, distance to transit, and destination accessibility sub-dimensions, which also help us to further explain the influence mechanism of individual effects.

The station characteristics of the node dimension reflect the locational advantage of the metro TOD station area, and they are the most influential category of factors, including the metro travel time and distance to the city center factors. The economic location (N_2) factor explains about 35% of the weekend metro ridership distribution. This indicates that people tend to visit the urban highland area, which is the main urban area, for leisure

travel on the weekends. The main urban area attracts more people because it comprises many shops and entertainment venues and has a good public service distribution. This also validates our analysis that the distance to the city center (N_1) can explain about 30% of the weekend metro ridership. Therefore, for people's weekend leisure travel activities, the agglomeration of urban commercial activities and public services and the cost of traveling to the city center are both important influencing factors.

The density and the design sub-dimension of the place dimension reflects the place where people prefer to travel for weekend activities. The area of public open space (P_8) also accounts for about 35% of the weekend metro ridership distribution, while commercial density (P_3) and population density (P_2) account for 34% and 28% of it, respectively. These results reflect that people tend to go to areas with more urban squares, green parks, stadiums, and commercial entertainment spaces, while they travel to more densely populated areas for leisure and recreational activities during the weekends. Guangzhou is a city that relies on commercial activities, such as the Beijing Road and Tianhe City business districts. The pedestrianized Beijing Road is home to many commercial businesses and historical and cultural attractions, thus attracting many people to shop and carry out recreational activities here at weekends, while the Tianhe City business district has more than five large commercial complexes, connecting the Tianhe Sports Center in the north and Huacheng Square in the south through a three-dimensional space. Therefore, it is important to build public open spaces and commercial entertainment spaces in densely populated areas to enhance the weekend metro ridership.

The distance to transit and destination accessibility in the sub-dimension of the linkage dimension reflect the convenience of pedestrian connections in the TOD station area, and both the number of bus lines (L_1) and the pedestrian shed ratios of the metro station area (L_2) are the main factors affecting weekend metro ridership. Both the ease of transferring between the metro and buses and the pedestrian connectivity of the TOD stations reflect the same influencing factor, i.e., improving the pedestrian friendliness of metro TOD stations so that people can access more urban facilities is important for encouraging people to travel for leisure on weekends. Therefore, improving weekend metro ridership requires not only focusing on the creation of spaces, but also improving the connectivity of the pedestrian environment in the TOD station areas.

Regarding the dependent variable's influence mechanism, a large number of studies currently focus only on the individual influence of each factor with various linear regression models, which is not conducive to studying the joint driving effect of multiple factors. However, the influence mechanisms on the spatial distribution of geographic phenomena are complex, especially those with spatial heterogeneity in space. In this section, we discuss the results of the individual effects of the built environment factors on metro ridership, and the interactive effects of multiple factors are presented in the next section.

4.3. Interactive Effects of Factor Combinations on Metro Ridership

4.3.1. Interactive Effects on Weekday Ridership

The two-factor interactive effect has a strong influence on metro ridership. As shown in Figure 4 and Table 6, 91 pairs of independent interaction combinations can be interactively formed by 14 factors, and we found that the q-values of this interactive effect are all higher than the maximum value of original individual effects is, and they pass the significance test with p-values that are less than 0.01. The interactive effect of population density (P_2) and the area of public open space (P_8) factors have the strongest influence on weekday metro ridership, with an interactive effect q-value of 0.7243, which is followed by population density (P_2) and the number of bus lines (P_8) (q-value = 0.7233), the floor area ratio (P_1) and population density (P_2) (q-value = 0.7123). In addition, there are 21 pairs with interactive effects that are above 0.60, indicating that more than 60% of the weekday metro ridership can be explained by the above combinations. From the results of the interactive effects, the top 10 interaction combinations are all two-factor enhancement effects (as shown in Table 5), i.e., by simultaneously improving a set of built environment factors, the effect of

improving weekday ridership is greater than the effect of improving any other factor. The factor interactive effect results are more helpful to policy makers in improving weekday metro ridership than the effect of an individual factor would be, with a maximum impact of 49%.

$q(A \cap B)$	N ₁	N ₂	N ₃	N ₄	P ₁	P ₂	P ₃	P ₄	P ₅	P ₆	P ₇	P ₈	L ₁	L ₂
N ₁														
N ₂	0.5038													
N ₃	0.4541	0.5056												
N ₄	0.5225	0.5790	0.5189											
P ₁	0.5342	0.5544	0.5270	0.6247										
P ₂	0.6516	0.6797	0.6220	0.6693	0.7123									
P ₃	0.5284	0.5791	0.5695	0.5723	0.5737	0.6794								
P ₄	0.4860	0.5302	0.5050	0.5430	0.5380	0.6620	0.4932							
P ₅	0.4239	0.4783	0.4366	0.3593	0.4913	0.5209	0.4598	0.3778						
P ₆	0.4312	0.5196	0.4459	0.3341	0.5590	0.6423	0.5159	0.4257	0.2600					
P ₇	0.4974	0.5697	0.5278	0.4818	0.5683	0.7085	0.5161	0.5229	0.3967	0.4456				
P ₈	0.6013	0.5938	0.5723	0.4426	0.6401	0.7243	0.6555	0.5473	0.4654	0.4243	0.5583			
L ₁	0.5405	0.5886	0.5787	0.5812	0.6264	0.7233	0.5519	0.5640	0.4599	0.4733	0.6161	0.6478		
L ₂	0.4627	0.5243	0.4850	0.5141	0.5316	0.6937	0.5256	0.4853	0.3897	0.4438	0.4864	0.6039	0.6086	

Figure 4. The interactive effect of built environment factors on weekday metro ridership.

Table 6. Interactive effects of built environment factors (weekday ridership).

Interaction	$q(A \cap B)$	$q(A) + q(B)$	Description	Interaction Result	Rank
$P_2 \cap P_8$	0.7243	0.7867	$\text{Max}(q(A), q(B)) < q(A \cap B) < q(A) + q(B)$	Enhance_bi-	1
$P_2 \cap L_1$	0.7233	0.9456	$\text{Max}(q(A), q(B)) < q(A \cap B) < q(A) + q(B)$	Enhance_bi-	2
$P_1 \cap P_2$	0.7123	0.9569	$\text{Max}(q(A), q(B)) < q(A \cap B) < q(A) + q(B)$	Enhance_bi-	3
$P_2 \cap P_7$	0.7085	0.8341	$\text{Max}(q(A), q(B)) < q(A \cap B) < q(A) + q(B)$	Enhance_bi-	4
$P_2 \cap L_2$	0.6937	0.8516	$\text{Max}(q(A), q(B)) < q(A \cap B) < q(A) + q(B)$	Enhance_bi-	5
$N_2 \cap P_2$	0.6797	0.9605	$\text{Max}(q(A), q(B)) < q(A \cap B) < q(A) + q(B)$	Enhance_bi-	6
$P_2 \cap P_3$	0.6794	0.9503	$\text{Max}(q(A), q(B)) < q(A \cap B) < q(A) + q(B)$	Enhance_bi-	7
$N_4 \cap P_2$	0.6693	0.7115	$\text{Max}(q(A), q(B)) < q(A \cap B) < q(A) + q(B)$	Enhance_bi-	8
$P_2 \cap P_4$	0.6620	0.8387	$\text{Max}(q(A), q(B)) < q(A \cap B) < q(A) + q(B)$	Enhance_bi-	9
$P_3 \cap P_8$	0.6555	0.7489	$\text{Max}(q(A), q(B)) < q(A \cap B) < q(A) + q(B)$	Enhance_bi-	10

Combining the individual and interactive effects reveals that population density is the core factor influencing the spatial distribution of weekday metro ridership, with nine of the top ten combinations of individual effects containing the population density factor. Among them, the interactive effect of population density (P_2) and the number of bus lines (P_8) indicates that the metro TOD station areas with a high population density and areas with more public open spaces within the station area tend to attract more work commuters during weekdays.

In addition, we also noted that the combination of the two factors with the highest individual effects (economic location and population density) does not have the highest

interactive effect ($q(N_2 \cap P_2) = 0.6797$; it ranked sixth). In contrast, the combination of individual effects that ranked 1st and 11th produced a highest interactive effect ($q(P_2 \cap P_8) = 0.7243$). This suggests that the interaction between the two factors is complex, and the interactive combination does not directly produce the total individual effects of both of them ($q(N_2) + q(P_2) = 0.9605$) due to the different mechanisms of mutual reinforcement of the factor combinations. Therefore, policy makers can develop reasonable measures for increasing weekday metro commuter ridership based on the results of the two effects.

4.3.2. Interactive Effects on Weekend Ridership

The results of the interactive effects of the constructed environment factors are shown in Figure 5 and Table 7. Through the interactive effects of the determinants, we found that the q -values of the interactive effects are all higher than the maximum value of the original individual effects is, and they pass the significance test with p -values that are less than 0.01. Among these q -values, the interactive effect of population density (P_2) and the number of bus lines (L_1) has the strongest influence on weekend metro ridership with an interactive q -value of 0.7662, which is followed by the distance to the city center (N_1), and an area of public open space (P_8) (q -value = 0.7568), population density (P_2), and an area of public open space (P_8) (q -value = 0.7487). Regarding the top 20 combinations of interactive effects, their influence is above 0.60, indicating that more than 60% of the weekend metro ridership can be explained by the above interaction combinations. Regarding the results of the interactive effects, the top 10 interaction combinations are all dominated by non-linear enhancement effects (e.g., Table 7), suggesting that by simultaneously improving a set of built environment factors, the improvement in weekend ridership is greater than the total individual effects of improving any other single factor. The results are very helpful for policy makers who are aiming to improve metro ridership.

Table 7. Interactive effects of built environment factors (weekend ridership).

Interaction	$q(A \cap B)$	$q(A) + q(B)$	Description	Interaction Result	Rank
$P_2 \cap L_1$	0.7662	0.6171	$q(A \cap B) > q(A) + q(B)$	Enhance_nonlinear	1
$N_1 \cap P_8$	0.7568	0.6511	$q(A \cap B) > q(A) + q(B)$	Enhance_nonlinear	2
$P_2 \cap P_8$	0.7487	0.6329	$q(A \cap B) > q(A) + q(B)$	Enhance_nonlinear	3
$N_2 \cap P_2$	0.7475	0.6345	$q(A \cap B) > q(A) + q(B)$	Enhance_nonlinear	4
$N_2 \cap P_8$	0.7314	0.7052	$q(A \cap B) > q(A) + q(B)$	Enhance_nonlinear	5
$N_4 \cap N_2$	0.7071	0.5497	$q(A \cap B) > q(A) + q(B)$	Enhance_nonlinear	6
$L_1 \cap P_8$	0.6980	0.6878	$q(A \cap B) > q(A) + q(B)$	Enhance_nonlinear	7
$N_1 \cap P_2$	0.6919	0.5804	$q(A \cap B) > q(A) + q(B)$	Enhance_nonlinear	8
$N_1 \cap L_1$	0.6811	0.6353	$q(A \cap B) > q(A) + q(B)$	Enhance_nonlinear	9
$P_8 \cap L_2$	0.6742	0.6169	$q(A \cap B) > q(A) + q(B)$	Enhance_nonlinear	10

In terms of the individual and interactive effects, population density, public open space areas, economic location, the number of bus lines, and the distance to the city center are the main factors affecting the spatial distribution of weekend metro ridership. Among these factors, the interactive effect of population density (P_2) and number of bus lines (L_1) indicate that a high population density in the metro TOD station area and the availability of more bus transfers within the station area tend to attract more leisure travelers on weekends.

In addition, we also note that the multiplier effect of the factor interactive effect has a higher degree of metro ridership on weekends compared to weekdays. On the other hand, the multiplier effect of the factor interaction is not generated in the combination of the two factors with the strongest individual effects, which have the same characteristics as the interaction results for weekday ridership. The combination of the two factors with the highest individual effects (economic location and public open space) did not have the highest interactive effect ($q(N_2 \cap P_8) = 0.7314$; it ranked fifth). In contrast, the combination of individual effects that were ranked fourth and sixth produced the highest interactive

effect ($q(P_2 \cap L_1) = 0.7662$; it ranked first). This suggests that there are interactions between the factors with different forces of action, resulting in different synergistic effects. This important for policy makers, and practitioners can also make urban planning decisions based on the different effect results and synergistic effects.

4.4. Local Spatial Differentiation Characteristics Analysis of the Influence Degree of Metro Station Ridership

4.4.1. Local Spatial Differentiation Characteristics on Weekday Ridership

The local spatial autocorrelation results can visually present the specific spatial location and the extent of the clustering area of the spatial variables, which explains the spatial divergence characteristics of the local area. The three factors with the strongest individual effects of q -values in the GeoDetector were used as independent variables, metro ridership was used as the dependent variable, and the bivariate local Moran's index values between these variables and their significance were separately calculated using the Geoda software to explore the spatial correlation characteristics of the two elements in order to reveal the local spatial differentiation characteristics of the influence of metro ridership.

Based on passing the z -score test (p -value ≤ 0.05), we plotted the bivariate local spatial autocorrelation cluster areas of the built environment factors, such as population density (P_2), economic location (N_2), and volume ratio (P_1), respectively, with weekday metro ridership (Y_1) (as in Figure 6). The results show that the H–H cluster areas are mainly located in the city center and urbanized areas, such as Tianhe District, Yuexiu District, and Haizhu District. The L–L cluster areas are concentrated in the urban fringe, such as Huadu District, Conghua District, Zengcheng District, and Nansha District, while the H–L and L–H cluster areas are less distributed. The non-significant areas are mainly located in the urbanized area and urban fringe area, i.e., the circle layer between the H–H and L–L cluster areas. From the results, the above built environment factors strongly promote metro ridership in the H–H and L–L cluster areas, while they have a strongly inhibit ridership in H–L and L–H cluster areas, and there is a random distribution of promoting and inhibiting effects in the non-significant areas.

$q(A \cap B)$	N_1	N_2	N_3	N_4	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	L_1	L_2
N_1														
N_2	0.6009													
N_3	0.3456	0.4180												
N_4	0.6271	0.7071	0.3194											
P_1	0.5111	0.4344	0.2881	0.3545										
P_2	0.6919	0.7475	0.3943	0.5522	0.5053									
P_3	0.5427	0.5487	0.4167	0.5947	0.3616	0.6381								
P_4	0.5709	0.4651	0.2675	0.4621	0.3149	0.5539	0.3893							
P_5	0.4414	0.5284	0.3643	0.3515	0.3480	0.4625	0.3883	0.2925						
P_6	0.4611	0.5416	0.2310	0.2423	0.2484	0.4558	0.3892	0.2418	0.2573					
P_7	0.4308	0.4283	0.2722	0.3727	0.2699	0.5094	0.3884	0.3038	0.3542	0.2264				
P_8	0.7568	0.7314	0.4315	0.6066	0.5826	0.7487	0.6706	0.5435	0.6189	0.4408	0.4822			
L_1	0.6811	0.6735	0.4592	0.6491	0.4676	0.7662	0.5795	0.4073	0.5105	0.3535	0.4114	0.6980		
L_2	0.5723	0.6226	0.3581	0.5106	0.3552	0.5916	0.5246	0.4939	0.4639	0.3350	0.3268	0.6742	0.6620	

Figure 5. Interactive effects of built environment factors on weekend metro ridership.

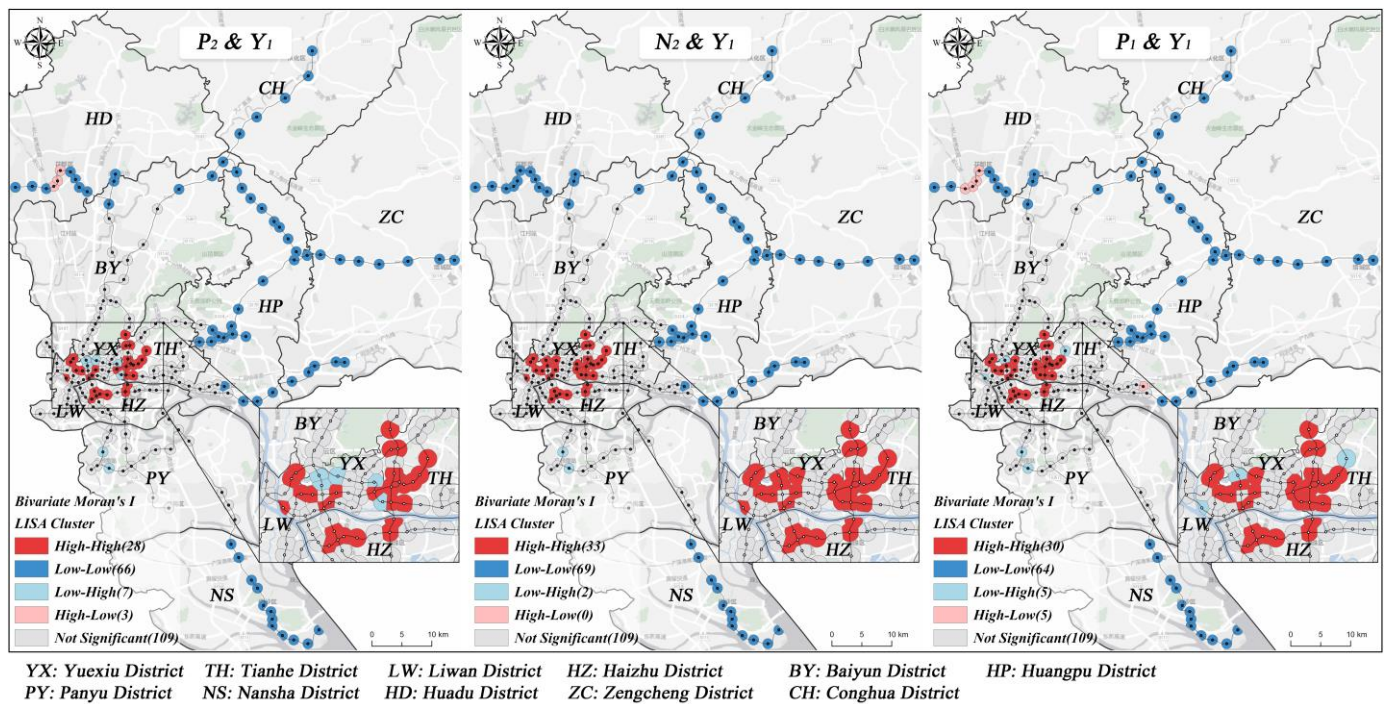


Figure 6. LISA clustering distribution of bivariate local spatial autocorrelation (on weekdays).

4.4.2. Local Spatial Differentiation Characteristics on Weekend Ridership

By comparing the weekday and weekend cases, the local spatial autocorrelation results have similar spatial heterogeneity characteristics, which are useful for summarizing the spatial differentiation characteristics in the local spaces. Based on passing the z-score test ($p\text{-value} \leq 0.05$), we plotted the bivariate local spatial autocorrelation clusters of the economic location (N_2), the area of public open spaces (P_8), and the commercial density (P_3), which are the top three factors of weekend metro ridership (Y_2) (as shown in Figure 7) in terms of their q-value influence on the factor detector results, respectively. Among these factors, the H–H cluster areas are mainly located in the city center areas such as Tianhe District and Yuexiu District; the L–L cluster areas are concentrated in the urban fringe areas, such as Huadu District, Conghua District, Zengcheng District, and Nansha District; the H–L and L–H cluster areas are less distributed; the L–H areas are sporadically distributed in the middle of Yuexiu District, Tianhe District, and Panyu District. The L–H cluster areas are sporadically distributed in urbanized areas, such as Yuexiu District, Tianhe District, and Panyu District, while the H–L cluster areas are mainly distributed in the rural fringe areas, such as Huangpu District, Huadu District, and Nansha District. From the results, the above built environment factors strongly promote metro ridership in the H–H and L–L cluster areas, while they strongly inhibit ridership in the sporadically distributed H–L and L–H cluster areas, and there is a random distribution of promoting and inhibiting effects in the non-significant areas. Compared with the facilitation and inhibition effects on weekday ridership, the cluster areas with a strong facilitation effect are more concentratedly distributed at the weekends.

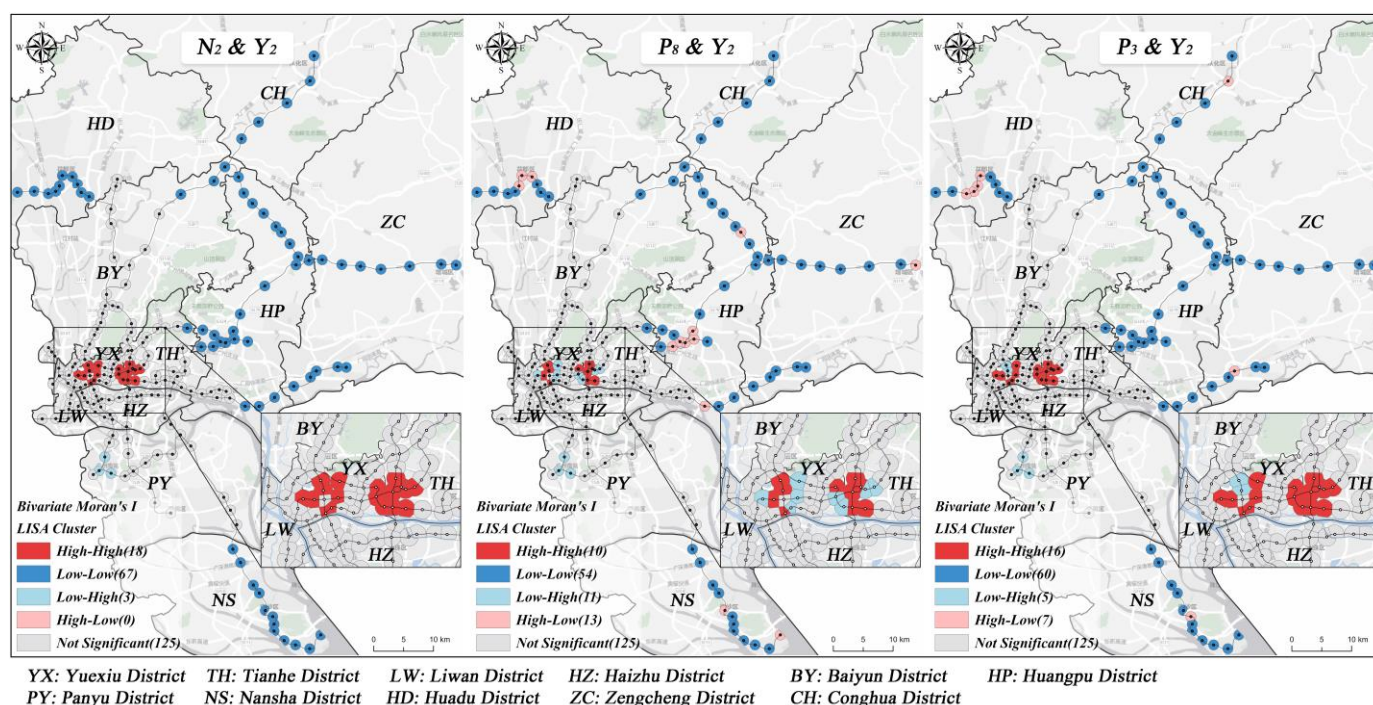


Figure 7. LISA clustering distribution of bivariate local spatial autocorrelation (at weekends).

5. Discussion

In terms of the individual effects, the factor detector results of the GeoDetector model show that built environment factors such as density and the location of the metro station area are key influencing factors on weekday metro TOD ridership, while location, design, and density are key influencing factors on weekend ridership, reflecting the difference in people's travel demands between weekdays and weekends. This result is roughly the same as previous studies, such as Pan and Li's study [29,56], except this study also agrees with the idea that improving the convenience of metro–bus interchanges can improve metro ridership to a greater extent [18,33,57]. However, the results of the study also show some differences. Firstly, whether a metro TOD station is an interchange station or intermediate station is a weak factor influencing this study, and it not a key influence factor in metro ridership [17,20,29]. Secondly, the number of road intersections, which is usually considered a key influencing factor for metro ridership [37,61], is not a significant contributor in our study for weekdays or weekends. Lastly, the land functional mixture and the land use three-dimensional mixture are supposedly beneficial in promoting people to use the metro [7,12], but the factor influence level of both of them is relatively weak in our study, which may be related to the common mixed use of land use in East Asian cities.

The contributions of this study can be summarized as follows. Overall, in this study, we used the node–place–linkage model to construct a factor analysis framework, and we selected 14 built environment factors from the “5D” principle of TOD and its site attribute characteristics to analyze the spatial distribution of weekday and weekend ridership. From the structural system of TOD, we explained the influence mechanism from the perspective of each built environment factor and structural factor of TOD. Furthermore, we analyzed the individual and interactive effects of the built environment factors using the GeoDetector model and the mechanism of the factor combination effects on metro ridership. The results show that the two-factor interactive effect has a stronger influence on metro ridership, which has a further explanatory effect on revealing the influence mechanism of metro ridership. A few articles have been published that study the impact of the interaction effect of influence factors on metro ridership. Finally, we used a bivariate local spatial autocorrelation analysis to explore the spatial differentiation of the influence degree of the individual effects on metro ridership and the results show that the influence degree of

individual effects on metro ridership is spatially differentiated in the local space, showing mutual promotion and suppression effects, which has significant implications for policy making in TOD.

Despite the strengths of this study, it also has some shortcomings that we hope will be addressed in future research. Spatial and temporal variations and demographic attributes are important factors influencing whether people use public transportation to travel, and this study used rail swipe card data to analyze this driving mechanism. However, daily swipe card data cannot directly affect spatio-temporal ridership, nor can they reflect relevant information such as the demographic attributes. Future research and validation can be conducted by further applying spatio-temporal travel pattern mining methods [86] and combining social media location data [87] and cell phone signal data [88]. In addition, the measurement of the spatial heterogeneity of the built environment factors on the influence of metro station ridership can be quantitatively analyzed in the future, and local spatial regression models such as GWR [89] and GTWR [38] can be used to further quantify the strength of the influence mechanism of metro station ridership, as well as the measure of spatial heterogeneity and spatio-temporal heterogeneity of the influence mechanism.

6. Conclusions and Policy Implications

Based on the node–place–linkage model, this study constructed a framework for analyzing the ridership of metro TOD stations, identified 14 built environment factors, and used multi-source data to measure the factor indicators of each metro TOD station area. The GeoDetector model was used to analyze the driving mechanism of the spatial distribution of ridership on weekdays and weekends in Guangzhou Metro from the perspective of the individual and interactive effects of the built environment factors. The main findings are as follows:

1. The spatial distribution of ridership in the TOD station area of the metro shows a core–peripheral structure and spatial heterogeneity in the spatial distribution of ridership on both weekdays and weekends. For Guangzhou, a city with a monocentric spatial structure, the TOD construction of the metro has changed the population from being centralized to having a more spatially balanced distribution, which can be verified by the spatial distribution of ridership on the weekdays. Therefore, guiding the development of the cities into a polycentric structure through metro TOD construction in order to avoid the disadvantages caused by the over-concentration of urban elements is an important research topic in urban planning.
2. According to the results of the GeoDetector (factor detector) model, the individual effect of each factor can explain up to 49% and 35% of the ridership distribution on the weekdays and weekends, respectively. The individual effects show different influence characteristics in the two cases. The main drivers of the weekday metro ridership are the population density, economic location, volume ratio, commercial density, and the number of bus lines, while the main drivers of weekend ridership are the economic location, public open space area, commercial density, the number of bus lines, and the distance to the city center.
3. Additionally, the GeoDetector (interaction detector) model results show that the two-factor interactive effect has a strong influence on metro ridership. The interactive effect explains up to 72% and 77% of ridership distribution on the weekdays and weekends, respectively. For weekday ridership, the interactive effect is significant when population density interacts with public open spaces or when population density interacts with the number of bus routes, and there is a two-factor-enhanced incremental effect. For the weekend case, when population density interacts with the number of bus lines or the distance to the city center interacts with the area of public open space, the interactive effect is significant, and the multiplier effect is non-linearly enhanced. The synergistic effect of the two-factor combination is more significant for weekend ridership.

4. The local spatial heterogeneity of the influence degree of the built environment factors on metro station ridership was measured using a bivariate local spatial autocorrelation method. From the results, the influence factors form H–H cluster areas in the city center areas, L–L cluster areas in the urban fringe areas, and the H–L and L–H cluster areas are sporadically distributed in the urbanized areas and urban fringe areas. Among them, the built environment factors have a strong promoting effect on the metro ridership in the H–H and L–L cluster areas, while they have a strong inhibiting effect in the sporadically distributed H–L and L–H cluster areas. In terms of the heterogeneity of spatial interactions, this finding could provide a good indication of how to increase metro ridership in urbanized areas and urban fringe areas and how to avoid overstressing metro ridership in the central city areas. This will mitigate the loss of metro ridership, establishing differentiated TOD policies.

It is worth noting that the results of this study could guide urban planners and policy makers. One of the most significant ways to guide cities toward a polycentric structure is the compact development of TOD station areas in the peripheral areas of the cities. We conclude that the factorial interactive effects obtained using the GeoDetector model are more conducive to increasing metro ridership, and such findings can be applied for urban renewal and the development of new districts. This can be achieved by increasing the population density of new urban areas, while improving the allocation of bus routes within the TOD station area, or increasing the population density, while building more public open space within the TOD station area. These methods may be very effective in promoting the development of a polycentric urban structure. Secondly, it is very important for the city managers to improve metro ridership in built-up areas and encourage people to use rail transit and other public transport in the city. Therefore, the GeoDetector model results can be combined to explore the metro TOD station areas with a higher potential for improvement by different impact factors and to develop corresponding urban renewal policies. From the results of the spatial correlation between the variables in the local spaces, the metro station areas that are subject to the spatial promotion effect are important for improving metro station ridership. For the metro station areas with an inhibiting effect, the loss of metro ridership should be avoided. Finally, for future metro lines, urban planning departments must take into account which built environment characteristics are more suitable for laying out metro lines to improve their efficiency as much as possible, in addition to considering the equity and justice for traveling throughout the city. The findings of this study can provide the necessary references for the this planning.

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References

1. Calthorpe, P. *The next American Metropolis: Ecology, Community, and the American Dream*; Princeton Architectural Press: New York, NY, USA, 1993; ISBN 1-878271-68-7.
2. Cervero, R.; Duncan, M. *Residential Self Selection and Rail Commuting: A Nested Logit Analysis*; University of California Transportation Center: Los Angeles, CA, USA, 2002.
3. Cervero, R. *Transit Oriented Development in America: Contemporary Practices, Impacts, and Policy Directions*; National Center for Smart Growth Research and Education: College Park, MD, USA, 2004.
4. Cervero, R. *Transit-Oriented Development in the United States: Experiences, Challenges, and Prospects*; Transportation Research Board: Washington, DC, USA, 2004.
5. Schlossberg, M.; Brown, N. Comparing Transit-Oriented Development Sites by Walkability Indicators. *Transp. Res. Rec.* **2004**, *1887*, 34–42. [\[CrossRef\]](#)
6. Dittmar, H.; Ohland, G. *The New Transit Town: Best Practices in Transit-Oriented Development*; Island Press: Washington, DC, USA, 2012; ISBN 978-1-59726-894-3.
7. Nasri, A.; Zhang, L. The Analysis of Transit-Oriented Development (TOD) in Washington, D.C. and Baltimore Metropolitan Areas. *Transp. Policy* **2014**, *32*, 172–179. [\[CrossRef\]](#)
8. Vale, D.S. Transit-Oriented Development, Integration of Land Use and Transport, and Pedestrian Accessibility: Combining Node-Place Model with Pedestrian Shed Ratio to Evaluate and Classify Station Areas in Lisbon. *J. Transp. Geogr.* **2015**, *45*, 70–80. [\[CrossRef\]](#)
9. Lyu, G.; Bertolini, L.; Pfeffer, K. Developing a TOD Typology for Beijing Metro Station Areas. *J. Transp. Geogr.* **2016**, *55*, 40–50. [\[CrossRef\]](#)
10. Crane, R.; Schweitzer, L.A. Transport and Sustainability: The Role of the Built Environment. *Built Environ.* **2003**, *29*, 238–252. [\[CrossRef\]](#)
11. Cervero, R.; Sullivan, C. Green TODs: Marrying Transit-Oriented Development and Green Urbanism. *Int. J. Sustain. Dev. World Ecol.* **2011**, *18*, 210–218. [\[CrossRef\]](#)
12. Chakour, V.; Eluru, N. Examining the Influence of Stop Level Infrastructure and Built Environment on Bus Ridership in Montreal. *J. Transp. Geogr.* **2016**, *51*, 205–217. [\[CrossRef\]](#)
13. Lin, J.-J.; Zhao, P.; Takada, K.; Li, S.; Yai, T.; Chen, C.-H. Built Environment and Public Bike Usage for Metro Access: A Comparison of Neighborhoods in Beijing, Taipei, and Tokyo. *Transp. Res. Part Transp. Environ.* **2018**, *63*, 209–221. [\[CrossRef\]](#)
14. Stokols, D. Environmental Psychology. *Annu. Rev. Psychol.* **1978**, *29*, 253–295. [\[CrossRef\]](#)
15. Russell, J.A.; Ward, L.M. Environmental Psychology. *Annu. Rev. Psychol.* **1982**, *33*, 651–689. [\[CrossRef\]](#)
16. Cervero, R.B. Linking Urban Transport and Land Use in Developing Countries. *J. Transp. Land Use* **2013**, *6*, 7–24. [\[CrossRef\]](#)
17. Sohn, K.; Shim, H. Factors Generating Boardings at Metro Stations in the Seoul Metropolitan Area. *Cities* **2010**, *27*, 358–368. [\[CrossRef\]](#)
18. Zhao, J.; Deng, W.; Song, Y.; Zhu, Y. What Influences Metro Station Ridership in China? Insights from Nanjing. *Cities* **2013**, *35*, 114–124. [\[CrossRef\]](#)
19. Gutiérrez, J.; Cardozo, O.D.; García-Palomares, J.C. Transit Ridership Forecasting at Station Level: An Approach Based on Distance-Decay Weighted Regression. *J. Transp. Geogr.* **2011**, *19*, 1081–1092. [\[CrossRef\]](#)
20. Cardozo, O.D.; García-Palomares, J.C.; Gutiérrez, J. Application of Geographically Weighted Regression to the Direct Forecasting of Transit Ridership at Station-Level. *Appl. Geogr.* **2012**, *34*, 548–558. [\[CrossRef\]](#)
21. Cervero, R.; Day, J. Suburbanization and Transit-Oriented Development in China. *Transp. Policy* **2008**, *15*, 315–323. [\[CrossRef\]](#)
22. Reusser, D.E.; Loukopoulos, P.; Stauffacher, M.; Scholz, R.W. Classifying Railway Stations for Sustainable Transitions—Balancing Node and Place Functions. *J. Transp. Geogr.* **2008**, *16*, 191–202. [\[CrossRef\]](#)
23. Cervero, R.; Kockelman, K. Travel Demand and the 3Ds: Density, Diversity, and Design. *Transp. Res. Part Transp. Environ.* **1997**, *2*, 199–219. [\[CrossRef\]](#)
24. Ewing, R.; Cervero, R. Travel and the Built Environment: A Synthesis. *Transp. Res. Rec.* **2001**, *1780*, 87–114. [\[CrossRef\]](#)
25. Ewing, R.; Cervero, R. Travel and the Built Environment. *J. Am. Plann. Assoc.* **2010**, *76*, 265–294. [\[CrossRef\]](#)
26. Wang, D.; Zhou, M. The Built Environment and Travel Behavior in Urban China: A Literature Review. *Transp. Res. Part Transp. Environ.* **2017**, *52*, 574–585. [\[CrossRef\]](#)
27. Bertolini, L. Spatial Development Patterns and Public Transport: The Application of an Analytical Model in the Netherlands. *Plan. Pract. Res.* **1999**, *14*, 199–210. [\[CrossRef\]](#)
28. Caset, F.; Blainey, S.; Derudder, B.; Boussauw, K.; Witlox, F. Integrating Node-Place and Trip End Models to Explore Drivers of Rail Ridership in Flanders, Belgium. *J. Transp. Geogr.* **2020**, *87*, 102796. [\[CrossRef\]](#)
29. Li, S.; Lyu, D.; Huang, G.; Zhang, X.; Gao, F.; Chen, Y.; Liu, X. Spatially Varying Impacts of Built Environment Factors on Rail Transit Ridership at Station Level: A Case Study in Guangzhou, China. *J. Transp. Geogr.* **2020**, *82*, 102631. [\[CrossRef\]](#)
30. Cummings, C.; Mahmassani, H. Does Intercity Rail Station Placement Matter? Expansion of the Node-Place Model to Identify Station Location Impacts on Amtrak Ridership. *J. Transp. Geogr.* **2022**, *99*, 103278. [\[CrossRef\]](#)
31. Vale, D.S.; Viana, C.M.; Pereira, M. The Extended Node-Place Model at the Local Scale: Evaluating the Integration of Land Use and Transport for Lisbon's Subway Network. *J. Transp. Geogr.* **2018**, *69*, 282–293. [\[CrossRef\]](#)

32. Su, S.; Zhang, H.; Wang, M.; Weng, M.; Kang, M. Transit-Oriented Development (TOD) Typologies around Metro Station Areas in Urban China: A Comparative Analysis of Five Typical Megacities for Planning Implications. *J. Transp. Geogr.* **2021**, *90*, 102939. [\[CrossRef\]](#)
33. Loo, B.P.Y.; Chen, C.; Chan, E.T.H. Rail-Based Transit-Oriented Development: Lessons from New York City and Hong Kong. *Landsc. Urban Plan.* **2010**, *97*, 202–212. [\[CrossRef\]](#)
34. Sung, H.; Oh, J.-T. Transit-Oriented Development in a High-Density City: Identifying Its Association with Transit Ridership in Seoul, Korea. *Cities* **2011**, *28*, 70–82. [\[CrossRef\]](#)
35. Zhao, J.; Deng, W.; Song, Y.; Zhu, Y. Analysis of Metro Ridership at Station Level and Station-to-Station Level in Nanjing: An Approach Based on Direct Demand Models. *Transportation* **2014**, *41*, 133–155. [\[CrossRef\]](#)
36. Cervero, R. Alternative Approaches to Modeling the Travel-Demand Impacts of Smart Growth. *J. Am. Plann. Assoc.* **2006**, *72*, 285–295. [\[CrossRef\]](#)
37. Chen, E.; Ye, Z.; Wang, C.; Zhang, W. Discovering the Spatio-Temporal Impacts of Built Environment on Metro Ridership Using Smart Card Data. *Cities* **2019**, *95*, 102359. [\[CrossRef\]](#)
38. Su, S.; Zhao, C.; Zhou, H.; Li, B.; Kang, M. Unraveling the Relative Contribution of TOD Structural Factors to Metro Ridership: A Novel Localized Modeling Approach with Implications on Spatial Planning. *J. Transp. Geogr.* **2022**, *100*, 103308. [\[CrossRef\]](#)
39. Gao, F.; Li, S.; Tan, Z.; Wu, Z.; Zhang, X.; Huang, G.; Huang, Z. Understanding the Modifiable Areal Unit Problem in Dockless Bike Sharing Usage and Exploring the Interactive Effects of Built Environment Factors. *Int. J. Geogr. Inf. Sci.* **2021**, *35*, 1905–1925. [\[CrossRef\]](#)
40. Wang, J.; Li, X.; Christakos, G.; Liao, Y.; Zhang, T.; Gu, X.; Zheng, X. Geographical Detectors-Based Health Risk Assessment and Its Application in the Neural Tube Defects Study of the Heshun Region, China. *Int. J. Geogr. Inf. Sci.* **2010**, *24*, 107–127. [\[CrossRef\]](#)
41. Song, J.; Zhao, C.; Zhong, S.; Nielsen, T.A.S.; Prishchepov, A.V. Mapping Spatio-Temporal Patterns and Detecting the Factors of Traffic Congestion with Multi-Source Data Fusion and Mining Techniques. *Comput. Environ. Urban Syst.* **2019**, *77*, 101364. [\[CrossRef\]](#)
42. Chow, A.S.Y. Urban Design, Transport Sustainability and Residents’ Perceived Sustainability: A Case Study of Transit-Oriented Development in Hong Kong. *J. Comp. Asian Dev.* **2014**, *13*, 73–104. [\[CrossRef\]](#)
43. Higgins, C.D.; Kanaroglou, P.S. A Latent Class Method for Classifying and Evaluating the Performance of Station Area Transit-Oriented Development in the Toronto Region. *J. Transp. Geogr.* **2016**, *52*, 61–72. [\[CrossRef\]](#)
44. Li, C.-N.; Lin, C.; Hsieh, T.-K. TOD District Planning Based on Residents’ Perspectives. *ISPRS Int. J. Geo-Inf.* **2016**, *5*, 52. [\[CrossRef\]](#)
45. Ding, C.; Cao, X.; Liu, C. How Does the Station-Area Built Environment Influence Metrorail Ridership? Using Gradient Boosting Decision Trees to Identify Non-Linear Thresholds. *J. Transp. Geogr.* **2019**, *77*, 70–78. [\[CrossRef\]](#)
46. Kuby, M.; Barranda, A.; Upchurch, C. Factors Influencing Light-Rail Station Boardings in the United States. *Transp. Res. Part Policy Pract.* **2004**, *38*, 223–247. [\[CrossRef\]](#)
47. Liu, C.; Erdogan, S.; Ma, T.; Ducca, F.W. How to Increase Rail Ridership in Maryland: Direct Ridership Models for Policy Guidance. *J. Urban Plan. Dev.* **2016**, *142*, 04016017. [\[CrossRef\]](#)
48. Teng, L.; Zhong, C.; Cai, D. Study on the Spatial Type Differentiation of Guangzhou Metro TOD Zones: Based on “Node-Place-Linkage” Coupling Model. *Econ. Geogr.* **2022**, *42*, 103–111. [\[CrossRef\]](#)
49. Bernick, M.; Cervero, R. *Transit Villages in the 21st Century*; H-Urban: Chicago, IL, USA, 1997; ISBN 978-0-07-005475-2.
50. Blainey, S. Trip End Models of Local Rail Demand in England and Wales. *J. Transp. Geogr.* **2010**, *18*, 153–165. [\[CrossRef\]](#)
51. Zhang, D.; Wang, X. (Cara) Transit Ridership Estimation with Network Kriging: A Case Study of Second Avenue Subway, NYC. *J. Transp. Geogr.* **2014**, *41*, 107–115. [\[CrossRef\]](#)
52. Sun, G.; Zacharias, J.; Ma, B.; Oreskovic, N.M. How Do Metro Stations Integrate with Walking Environments? Results from Walking Access within Three Types of Built Environment in Beijing. *Cities* **2016**, *56*, 91–98. [\[CrossRef\]](#)
53. Wang, Y.; de Correia, G.H.A.; de Romph, E.; Timmermans, H.J.P. Using Metro Smart Card Data to Model Location Choice of After-Work Activities: An Application to Shanghai. *J. Transp. Geogr.* **2017**, *63*, 40–47. [\[CrossRef\]](#)
54. Cervero, R.; Sarmiento, O.L.; Jacoby, E.; Gomez, L.F.; Neiman, A. Influences of Built Environments on Walking and Cycling: Lessons from Bogotá. *Int. J. Sustain. Transp.* **2009**, *3*, 203–226. [\[CrossRef\]](#)
55. Durning, M.; Townsend, C. Direct Ridership Model of Rail Rapid Transit Systems in Canada. *Transp. Res. Rec.* **2015**, *2537*, 96–102. [\[CrossRef\]](#)
56. Pan, H.; Li, J.; Shen, Q.; Shi, C. What Determines Rail Transit Passenger Volume? Implications for Transit Oriented Development Planning. *Transp. Res. Part Transp. Environ.* **2017**, *57*, 52–63. [\[CrossRef\]](#)
57. Choi, J.; Lee, Y.J.; Kim, T.; Sohn, K. An Analysis of Metro Ridership at the Station-to-Station Level in Seoul. *Transportation* **2012**, *39*, 705–722. [\[CrossRef\]](#)
58. Hong, J.; Shen, Q.; Zhang, L. How Do Built-Environment Factors Affect Travel Behavior? A Spatial Analysis at Different Geographic Scales. *Transportation* **2014**, *41*, 419–440. [\[CrossRef\]](#)
59. Liu, X.; Wu, J.; Huang, J.; Zhang, J.; Chen, B.Y.; Chen, A. Spatial-Interaction Network Analysis of Built Environmental Influence on Daily Public Transport Demand. *J. Transp. Geogr.* **2021**, *92*, 102991. [\[CrossRef\]](#)
60. Liu, Y.; Ji, Y.; Shi, Z.; Gao, L. The Influence of the Built Environment on School Children’s Metro Ridership: An Exploration Using Geographically Weighted Poisson Regression Models. *Sustainability* **2018**, *10*, 4684. [\[CrossRef\]](#)

61. An, D.; Tong, X.; Liu, K.; Chan, E.H.W. Understanding the Impact of Built Environment on Metro Ridership Using Open Source in Shanghai. *Cities* **2019**, *93*, 177–187. [\[CrossRef\]](#)
62. Li, S.; Lyu, D.; Liu, X.; Tan, Z.; Gao, F.; Huang, G.; Wu, Z. The Varying Patterns of Rail Transit Ridership and Their Relationships with Fine-Scale Built Environment Factors: Big Data Analytics from Guangzhou. *Cities* **2020**, *99*, 102580. [\[CrossRef\]](#)
63. Chiou, Y.-C.; Jou, R.-C.; Yang, C.-H. Factors Affecting Public Transportation Usage Rate: Geographically Weighted Regression. *Transp. Res. Part Policy Pract.* **2015**, *78*, 161–177. [\[CrossRef\]](#)
64. Ma, X.; Zhang, J.; Ding, C.; Wang, Y. A Geographically and Temporally Weighted Regression Model to Explore the Spatiotemporal Influence of Built Environment on Transit Ridership. *Comput. Environ. Urban Syst.* **2018**, *70*, 113–124. [\[CrossRef\]](#)
65. Tang, J.; Gao, F.; Liu, F.; Han, C.; Lee, J. Spatial Heterogeneity Analysis of Macro-Level Crashes Using Geographically Weighted Poisson Quantile Regression. *Accid. Anal. Prev.* **2020**, *148*, 105833. [\[CrossRef\]](#)
66. Gao, F.; Yang, L.; Han, C.; Tang, J.; Li, Z. A Network-Distance-Based Geographically Weighted Regression Model to Examine Spatiotemporal Effects of Station-Level Built Environments on Metro Ridership. *J. Transp. Geogr.* **2022**, *105*, 103472. [\[CrossRef\]](#)
67. Wang, J.-F.; Hu, Y. Environmental Health Risk Detection with GeoDetector. *Environ. Model. Softw.* **2012**, *33*, 114–115. [\[CrossRef\]](#)
68. Wang, J.-F.; Zhang, T.-L.; Fu, B.-J. A Measure of Spatial Stratified Heterogeneity. *Ecol. Indic.* **2016**, *67*, 250–256. [\[CrossRef\]](#)
69. Du, Z.; Xu, X.; Zhang, H.; Wu, Z.; Liu, Y. Geographical Detector-Based Identification of the Impact of Major Determinants on Aeolian Desertification Risk. *PLoS ONE* **2016**, *11*, e0151331. [\[CrossRef\]](#) [\[PubMed\]](#)
70. Ju, H.; Zhang, Z.; Zuo, L.; Wang, J.; Zhang, S.; Wang, X.; Zhao, X. Driving Forces and Their Interactions of Built-up Land Expansion Based on the Geographical Detector—A Case Study of Beijing, China. *Int. J. Geogr. Inf. Sci.* **2016**, *30*, 2188–2207. [\[CrossRef\]](#)
71. Wu, R.; Zhang, J.; Bao, Y.; Zhang, F. Geographical Detector Model for Influencing Factors of Industrial Sector Carbon Dioxide Emissions in Inner Mongolia, China. *Sustainability* **2016**, *8*, 149. [\[CrossRef\]](#)
72. Guo, X.; Chen, H.; Yang, X. An Evaluation of Street Dynamic Vitality and Its Influential Factors Based on Multi-Source Big Data. *ISPRS Int. J. Geo-Inf.* **2021**, *10*, 143. [\[CrossRef\]](#)
73. Deng, X.; Liu, Y.; Gao, F.; Liao, S.; Zhou, F.; Cai, G. Spatial Distribution and Mechanism of Urban Occupation Mixture in Guangzhou: An Optimized GeoDetector-Based Index to Compare Individual and Interactive Effects. *ISPRS Int. J. Geo-Inf.* **2021**, *10*, 659. [\[CrossRef\]](#)
74. Wang, R.; Lu, Y.; Wu, X.; Liu, Y.; Yao, Y. Relationship between Eye-Level Greenness and Cycling Frequency around Metro Stations in Shenzhen, China: A Big Data Approach. *Sustain. Cities Soc.* **2020**, *59*, 102201. [\[CrossRef\]](#)
75. Alani, H.; Jones, C.B.; Tudhope, D. Voronoi-Based Region Approximation for Geographical Information Retrieval with Gazetteers. *Int. J. Geogr. Inf. Sci.* **2001**, *15*, 287–306. [\[CrossRef\]](#)
76. Zhou, Y.; Li, X.; Liu, Y. Land Use Change and Driving Factors in Rural China during the Period 1995–2015. *Land Use Policy* **2020**, *99*, 105048. [\[CrossRef\]](#)
77. Zhu, L.; Meng, J.; Zhu, L. Applying Geodetector to Disentangle the Contributions of Natural and Anthropogenic Factors to NDVI Variations in the Middle Reaches of the Heihe River Basin. *Ecol. Indic.* **2020**, *117*, 106545. [\[CrossRef\]](#)
78. Jelinski, D.E.; Wu, J. The Modifiable Areal Unit Problem and Implications for Landscape Ecology. *Landsc. Ecol.* **1996**, *11*, 129–140. [\[CrossRef\]](#)
79. Song, Y.; Wang, J.; Ge, Y.; Xu, C. An Optimal Parameters-Based Geographical Detector Model Enhances Geographic Characteristics of Explanatory Variables for Spatial Heterogeneity Analysis: Cases with Different Types of Spatial Data. *GISci. Remote Sens.* **2020**, *57*, 593–610. [\[CrossRef\]](#)
80. Brewer, C.A.; Pickle, L. Evaluation of Methods for Classifying Epidemiological Data on Choropleth Maps in Series. *Ann. Assoc. Am. Geogr.* **2002**, *92*, 662–681. [\[CrossRef\]](#)
81. Cao, F.; Ge, Y.; Wang, J.-F. Optimal Discretization for Geographical Detectors-Based Risk Assessment. *GISci. Remote Sens.* **2013**, *50*, 78–92. [\[CrossRef\]](#)
82. Anselin, L. Local Indicators of Spatial Association—LISA. *Geogr. Anal.* **1995**, *27*, 93–115. [\[CrossRef\]](#)
83. Anselin, L.; Syabri, I.; Kho, Y. GeoDa: An Introduction to Spatial Data Analysis. *Geogr. Anal.* **2006**, *38*, 5–22. [\[CrossRef\]](#)
84. Wartenberg, D. Multivariate Spatial Correlation: A Method for Exploratory Geographical Analysis. *Geogr. Anal.* **1985**, *17*, 263–283. [\[CrossRef\]](#)
85. Anselin, L.; Syabri, I.; Smirnov, O. Visualizing Multivariate Spatial Correlation with Dynamically Linked Windows. In Proceedings of the CSISS Workshop on New Tools for Spatial Data Analysis, Santa Barbara, CA, USA, 10–11 May 2002.
86. Gao, F.; Li, S.; Tan, Z.; Liao, S. Visualizing the Spatiotemporal Characteristics of Dockless Bike Sharing Usage in Shenzhen, China. *J. Geovisualization Spat. Anal.* **2022**, *6*, 12. [\[CrossRef\]](#)
87. Gao, F.; Huang, G.; Li, S.; Huang, Z.; Chai, L. Integrating the Eigendecomposition Approach and K-Means Clustering for Inferring Building Functions with Location-Based Social Media Data. *ISPRS Int. J. Geo-Inf.* **2021**, *10*, 834. [\[CrossRef\]](#)
88. Zhang, X.; Gao, F.; Liao, S.; Zhou, F.; Cai, G.; Li, S. Portraying Citizens' Occupations and Assessing Urban Occupation Mixture with Mobile Phone Data: A Novel Spatiotemporal Analytical Framework. *ISPRS Int. J. Geo-Inf.* **2021**, *10*, 392. [\[CrossRef\]](#)
89. Gao, F.; Li, S.; Tan, Z.; Zhang, X.; Lai, Z.; Tan, Z. How Is Urban Greenness Spatially Associated with Dockless Bike Sharing Usage on Weekdays, Weekends, and Holidays? *ISPRS Int. J. Geo-Inf.* **2021**, *10*, 238. [\[CrossRef\]](#)