

Article

Unraveling the Impact Mechanisms of Built Environment on Urban Vitality: Integrating Scale, Heterogeneity, and Interaction Effects

Xiji Jiang ^{1,†} , Jialin Tian ^{2,†}, Jiaqi Li ¹, Dan Ye ^{3,4} , Wenlong Lan ¹, Dandan Wu ^{5,*}, Naiji Tian ^{1,*} and Jie Yin ^{3,6,7,*} 

¹ College of Architecture, Xi'an University of Architecture and Technology, Xi'an 710055, China; jiangxiji@xauat.edu.cn (X.J.); samoye@xauat.edu.cn (J.L.); lanwenlong@xauat.edu.cn (W.L.)

² School of Architecture and Urban Planning, Nanjing University, Nanjing 210093, China; tianjialin@smail.nju.edu.cn

³ College of Architecture and Urban Planning, Tongji University, Shanghai 200092, China; danye@tongji.edu.cn

⁴ Department of Architecture and Civil Engineering, City University of Hong Kong, Hong Kong 999077, China

⁵ Department of Non-Communicable Disease Prevention, Xi'an Center for Disease Control and Prevention, Xi'an 710054, China

⁶ Shanghai Key Laboratory of Urban Renewal and Spatial Optimization Technology, Shanghai 200092, China

⁷ Shanghai Tongji Urban Planning and Design Institute Co., Ltd., Shanghai 200092, China

* Correspondence: wudandan8686@163.com (D.W.); naijitian@xauat.edu.cn (N.T.); jieyin@tongji.edu.cn (J.Y.)

† These authors are co-first authors of the article.

Abstract

The impact of the built environment on urban vitality is multifaceted, yet a holistic understanding that simultaneously considers its scale dependence, spatial heterogeneity, and interactive mechanisms remains limited. To unravel these multi-scalar mechanisms, this study develops an integrated analytical framework. Taking Xi'an, China, as a case study, we first construct a multidimensional built environment indicator system grounded in Jane Jacobs' theory of vitality. Empirically, we employ the Optimal Parameters-based GeoDetector (OPGD) to objectively identify the optimal spatial scale and detect non-linear and interaction effects. Meanwhile, the Multiscale Geographically Weighted Regression (MGWR) model is used to delineate spatial heterogeneity. Our findings systematically unravel the complex mechanisms: (1) The optimal analysis scale is identified as a 2 km grid; (2) All elements significantly influence vitality, but through distinct linear or non-linear pathways; (3) The effects of attraction density, road network structure, and bus stop density exhibit significant spatial heterogeneity; and (4) Third place density and population density act as key catalysts, non-linearly enhancing the effects of other elements. This research presents a synthesized perspective and nuanced evidence for precision urban regeneration, demonstrating the necessity of integrating scale, heterogeneity, and interaction to understand the drivers of urban vitality.

Keywords: built environment; urban vitality; impact characteristics; planning improvement; Xi'an city



Academic Editor: Nikos A. Salingaros

Received: 18 November 2025

Revised: 18 December 2025

Accepted: 19 December 2025

Published: 21 December 2025

Copyright: © 2025 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

Globally, as urban development shifts from large-scale incremental expansion to stock optimization, the central urban areas of many cities are confronting severe challenges, including the decline of downtown districts, urban shrinkage, and spatial hollowing

out [1–3]. These characteristics often manifest as a significant loss of urban vitality, with a rapid decline in street life, social interactions, and economic activities. This phenomenon is contrary to the United Nations Sustainable Development Goal (SDG 11), making it difficult to support the construction of sustainable cities and human settlements. In the face of global urban decline trends, urban regeneration has become the core strategy for cities to reshape their competitiveness, activate endogenous development momentum, and respond to the SDGs. Within this context, reinvigorating urban vitality is not only a pursuit of physical space transformation but also an important criterion for measuring the success of urban regeneration.

Jacobs described urban vitality in her classic work as the diversity and safety of street flows, which is the essence of urban life [4]. In the contemporary context, urban vitality has taken on a richer connotation. It not only refers to the intensity and diversity of human activities (such as social interaction, economic transactions, and cultural leisure) within urban space, but also reflects the dynamic projection of these activities across temporal and spatial dimensions [5,6]. Thus, we consider that urban vitality can primarily be manifested as the specific spatiotemporal distribution of population density, which is a comprehensive result of diverse behavioral motivations and logics. A vibrant urban space not only stimulates diverse economic activities but also plays a crucial role in shaping an inclusive social environment and fostering community cohesion [7]. Thus, urban vitality can be regarded as the “vital signs” for evaluating the quality of urban space, the health of socio-economic conditions, and the attractiveness of places.

People’s various activities are the fundamental source of vitality within cities, and urban space is the necessary material carrier for people to conduct a rich array of activities. The built environment, as a material entity, forms and defines the morphological boundaries of urban space; it serves as a container for human activities and is widely regarded as a decisive factor in shaping vitality [8,9]. The built environment is an artificial space where people live, work, and recreate [10], comprising urban design, land use, and transportation systems, and encompassing human activities within the physical environment [11]. Ewing R et al. [12] proposed the 5Ds theory for measuring the built environment (i.e., density, diversity, design, destination accessibility, and distance to transit), providing a methodological foundation for quantifying the built environment. Meanwhile, Jacobs argued that concentration, mixed use, short blocks, and aged buildings are necessary conditions for generating vitality, while accessibility and boundary vacuum are secondary conditions [4]. As Mehaffy’s “Network Urbanism” points out, urban vitality stems from complex multiscale network connections, with physical elements serving as nodes that facilitate the exchange of information and social interactions [13]. Similarly, Moreno’s ‘15-min city’ paradigm introduced ‘temporal urbanism’, emphasizing that the quality of urban life depends on the high proximity and accessibility of basic functions within a short time radius [14]. It can be seen that the built environment is not merely static material elements, but rather profoundly regulates the behavioral patterns of micro-individuals through the construction of specific structural features (such as road network morphology and functional mixing), thereby determining the generation and evolution of vitality. Based on this understanding, clarifying the complex interaction mechanism between the built environment and urban vitality has significant practical significance for guiding stock regeneration, optimizing spatial resource allocation, and achieving the sustainable development goal of “people-oriented” development.

How to scientifically recognize, create, and enhance urban vitality in urban planning and design has become a topic of common concern in the academic field. In recent years, with the emergence of multisource big data and rapid development of analytical methods, urban vitality research has shifted from quantitative description to quantitative analysis,

undergoing a profound transformation in terms of both dimensions and depth of analysis. By reviewing recent literature, we have identified three distinct characteristics of related research:

- (1) For vitality measurement, relevant studies have moved beyond traditional indicators such as population density or POIs (Points of Interest), turning instead to data such as mobile phone signaling [15], heat maps [16], social media check-ins [17], and online merchant reviews [18] to construct a comprehensive vitality evaluation system that reflects multidimensional attributes including social, economic, and cultural aspects [19]. Correspondingly, the characterization of the built environment has become increasingly refined, expanding from the classic 5D framework [20] to three-dimensional building morphology [21] and micro-level street quality based on street view image analysis [22], greatly enriching the dimensions and depth of research.
- (2) In terms of the influencing mechanism, traditional research based on Jacobs' theory often assumes that density, mixture, and other factors have a linear correlation with vitality. However, the latest empirical studies on high-density Asian cities are challenging this assumption. Liu et al. [22] utilized research conducted in Shanghai to find that the built environment has a non-linear threshold effect on vitality (for example, the promoting effect only becomes significant when building coverage exceeds 18%). Zhan et al. [23] confirmed the phenomenon of diminishing marginal effects on social vitality after the population density exceeds 10,000 people/km² in their study in Hangzhou. These findings suggest that in the real world, the impact of the built environment on vitality is complex and multifaceted, and is often not a simple linear relationship.
- (3) In terms of analytical methods, research progress is mainly reflected in the revelation of spatial heterogeneity in the impact of the built environment on urban vitality. Researchers have gradually recognized that the impact of the built environment on vitality is not homogeneous in space, and the limitations of traditional global regression models, such as OLS, have become increasingly apparent. Thus, geographically weighted regression (GWR) and its improved models, especially multiscale geographically weighted regression (MGWR), have been widely applied [16,19]. Meanwhile, as research has deepened, scholars have found that there is not a simple linear relationship between built environment factors (especially density and mixity) and vitality. Various machine learning models have been introduced to explore and identify threshold effects in the impact of the built environment [21,22].

Although existing research has made significant progress in data, methodology, and mechanism exploration, there are still some shortcomings:

Firstly, most studies have neglected the scale effect of analysis units. Previous research has employed a variety of spatial analysis units, including standard grids [19,22,23], traffic analysis zones (TAZs) [24], street units [18], and towns [21]. However, to what extent the research conclusions depend on the scale and morphology of the selected units is rarely discussed. Although models, such as MGWR, take into account the "effect scale" of variables, they do not address the potential impact of the scale size of the analysis units themselves on analytical reliability.

Secondly, existing research lacks an integrated analytical framework for multiple complex effects. The impact of the built environment on vitality is complicated, characterized by spatial heterogeneity, non-linearity, interactivity, and scale dependence. However, current research approaches are methodologically fragmented: spatial econometric models excel at handling spatial heterogeneity [16,19], while machine learning models offer greater advantages in mining non-linear relationships [21,22,25]. Currently, few studies have constructed a unified analytical framework that simultaneously incorporates scale effects,

spatial heterogeneity, non-linear components of impacts, and complex interactions among built environment elements, leading to a fragmented understanding of the systematic influence of the built environment on vitality.

Furthermore, the current research context is relatively simplistic, with a lack of attention paid to specific urban types. A review of existing literature reveals that case studies have primarily focused on modern metropolises, such as Oslo [7], Seoul [26], Shenzhen [21,24], Shanghai [15,22], and Hangzhou [23], but the urban forms and development logic of these research subjects are relatively homogeneous. For international historical ancient capitals with high density and coexisting modern and historical landscapes (such as Rome, Athens, and Xi'an), the interactive mechanism between their built environment and vitality may exhibit more complex characteristics: the historical streets and alleys vary in scale, and the urban fabric reflects the differences of different eras. The significant overlap of population, tourism, and commercial functions results in the generation and spread of urban vitality exhibiting patterns that differ from those of typical modern cities.

Based on existing research and classical theories, we propose two hypotheses for our study: (1) Some built environment factors have a significant impact on urban vitality, with the impact manner being mostly non-linear; (2) The impact of the built environment on vitality exhibits apparent spatial heterogeneity. To verify our conjecture, this research focuses on the central urban district of Xi'an, a case area characterized by a complex built environment, aiming to address the gaps in the aforementioned research systematically. We aim to construct an integrated analytical framework to (1) identify the optimal analytical scale for the built environment's impacts on urban vitality; (2) analyze the overall correlation characteristics (significance, linearity/non-linearity); (3) reveal spatial heterogeneity in influences; (4) detect interactive effects among built environment factors. Overall, this study aims to provide solid theoretical foundations and evidence-based support for the revitalization and enhancement of the regeneration and vitality of internationally renowned historical cities.

2. Methods

2.1. Research Framework

Figure 1 illustrates the framework of this study. First, after collecting and cleaning multisource data, we constructed a comprehensive measurement indicator system encompassing six dimensions based on Jacobs' theory of urban vitality. Subsequently, we employed the factor detector in the GeoDetector (GD) method to compare the q-values of variables under six different grid analysis unit sizes. By integrating population spatial behavior characteristics, we comprehensively judged and determined the optimal spatial scale for this study. Then, based on the optimal scale, a comprehensive analysis is conducted, aiming to explore the complex impact of the built environment on urban vitality. This step primarily involves three stages. First, the results from the factor detector in OPGD and the MGWR model are compared to investigate overall correlations. Specifically, the factor detector is used to explore from a global perspective whether relationships exist between built environment variables and the dependent variable, while MGWR is applied to uncover the spatial heterogeneity of these correlations at a local level. Subsequently, for variables exhibiting spatial heterogeneity, we further analyze their spatial patterns using the MGWR results and employ the risk detector within OPGD to examine stratified heterogeneity—that is, the differential impacts of varying levels of environmental variables on vitality. Thirdly, the interaction detector is utilized to clarify the interactive effects among different environmental variables. Finally, this study summarizes the main findings and proposes strategies for optimizing and improving the built environment to promote vitality.

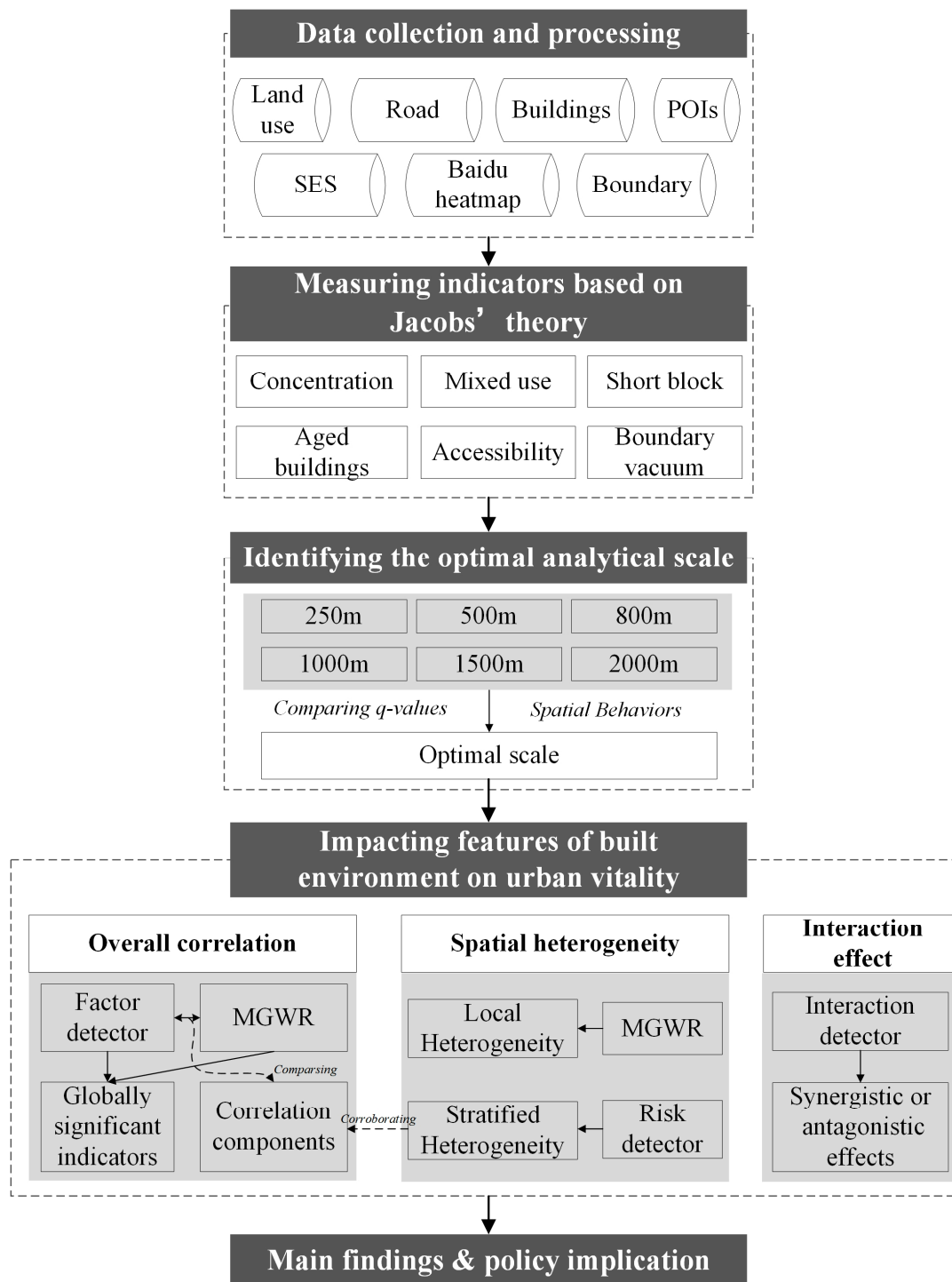


Figure 1. Overall Research Framework.

2.2. Analytic Methods

2.2.1. Optimal Parameters-Based GeoDetector (OPGD)

The GeoDetector (GD) is a method used to detect spatially stratified heterogeneity and reveal its underlying driving forces [27]. Its core principle is that if a specific independent variable has a significant impact on the dependent variable, their spatial distribution characteristics should be similar [27,28]. We employed the factor detector and interaction detector from the geographical detector to explore the significant built environment factors influencing urban vitality, the interactive associations among these factors, and the potential non-linear relationships in their influence. The q value is used to measure the spatial

differentiation of the dependent variable Y , or the influence of the independent variable X on the spatial differentiation characteristics of the dependent variable Y :

$$q = 1 - \frac{SSW}{SST} = 1 - \frac{\sum_{h=1}^L \sum_{i=1}^{N_h} (Y_{hi} - \bar{Y}_h)^2}{\sum_{i=1}^N (Y_i - \bar{Y})^2} = 1 - \frac{\sum_{h=1}^L N_h \sigma_h^2}{N \sigma^2} \quad (1)$$

where $h = 1, 2, \dots, L$ represents the strata of the independent variable Y or the dependent variable X ; N_h denotes the number of analytical units in stratum h , and N is the total number of analytical units in the study area; σ_h^2 indicates the variance of Y values in stratum h , while σ^2 is the overall variance of Y values in the study area; SSW and SST are the sum of within-stratum variances and the total variance of the study area, respectively. The range of q values is from 0 to 1, with larger values indicating more pronounced spatial heterogeneity characteristics of Y . When the strata are consistent with the statistical units of a specific independent variable X , the q value reflects the explanatory power of X on Y (i.e., X explains $100 \times q\%$ of Y); a larger value indicates a stronger ability to explain this spatial distribution pattern.

The GeoDetector has an advantage in exploring interactions between variables, as it is capable of detecting various forms of interactions between two variables (not limited to multiplication) [27]. As the complexity urbanism theory posits, urban elements do not function in isolation but form “patterns” that interact to produce emergent vitality [29]. GeoDetector is helpful in uncovering complex interaction relationship patterns in the real world.

The specific analytical principle involves calculating the q -value of Y by X_1 and X_2 , respectively, then calculating the q -value of the interaction term of the two independent variables ($X_1 \cap X_2$), and finally comparing the relationship and changes among $q(X_1)$, $q(X_2)$, and $q(X_1 \cap X_2)$. The final comparison results can be categorized into 5 different types, including nonlinear-weaken, uni-weaken, bi-enhance, independent and nonlinear-enhance.

The risk detector can determine whether the differences in variables represented by means across layers are significant, using a t -statistic to test the difference between statistics η and K [27]:

$$t_{\bar{Y}_\eta - \bar{Y}_K} = (\bar{Y}_\eta - \bar{Y}_K) / \sqrt{\frac{s_\eta^2}{N_\eta} + \frac{s_K^2}{N_K}} \quad (2)$$

where $\bar{Y}_\eta$ and $\bar{Y}_K$ are, respectively, the mean values of variables of the η and K statistical regions; s_η^2 and s_K^2 are, respectively, the variances of variables of the η and K statistical regions; N_η and N_K are, respectively, the sample sizes of the η and K statistical regions.

However, when using the GeoDetector model, particularly when dealing with continuous independent variables, the method for performing data discretization (i.e., determining the classification method and the number of categories) significantly affects the magnitude of the q statistic. To address this, the Optimal Parameters-based GeoDetector (OPGD) was proposed; it is essentially a parameter optimization tool that automatically identifies the optimal data discretization scheme to maximize the explanatory power of factors [30], and to some extent alleviates the problem of zoning effects in areas with variable unit sizes [31].

In R software (version 4.4), we used the GD package to perform OPGD calculations. Five discretization methods were selected, namely equal interval, natural breaks, quantile, geometric interval, and standard deviation. The number of segments was set between 3 and 7.

2.2.2. Multiscale Geographically Weighted Regression (MGWR)

The MGWR model allows the correlation between the dependent variable and independent variables (or control variables) to vary geographically and across different

influence ranges [32]. It further permits variation in the optimal bandwidth based on the geographically weighted regression (GWR) model to achieve a better fitting effect. The specific calculation formula is:

$$y_i = \sum_{j=1}^k \beta_{bwj}(u_i, v_i) x_{ij} + \varepsilon_i \quad (3)$$

where β is the regression parameter of the i -th sampling point under the bandwidth of the j -th variable, (u_i, v_i) represents the spatial coordinates of the i -th sampling point, and ε_i denotes the random error of the i -th unit.

A spatial heterogeneity analysis of the built environment's influence on urban vitality was conducted via the MGWR toolkit in ArcGIS Pro 3.4, aiming to examine the spatial variation of the vitality effects exerted by various built environment variables.

2.3. Identify the Optimal Analysis Scale

To mitigate the impact of spatial scale differences on the reliability of research results, square grids were adopted as the analytical unit. First, we referenced the scales commonly used in existing empirical studies related to vitality [33–35]. Second, considering the behavioral characteristics of residents and tourists, a 1 km radius centered on them tends to form a meaningful “vitality scene unit”—consistent with the concept of community life circles [36] and the advocacy of slow tourism [37]. As illustrated in Figure 2, converting the 1 km radius into a square results in a side length of 2 km, so the largest square grid was set to 2 km × 2 km. Ultimately, six scales (250 m, 500 m, 800 m, 1000 m, 1500 m, and 2000 m) were selected for our analysis.

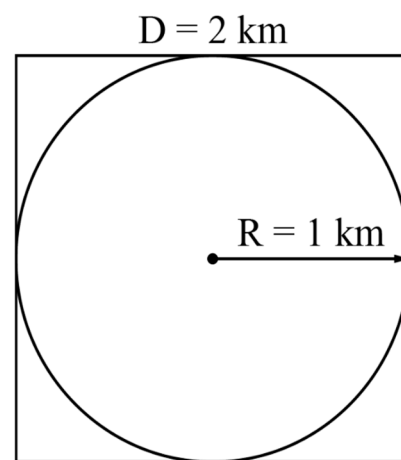


Figure 2. Scale relationship between the 1 km-radius living circle (15-min) and 2 km grid.

We utilized the OPGD method to acquire the q-values of diverse built environment variables at multiple scales. By synthesizing the variation trends of q-values across different scales and their growth rate characteristics, the optimal model was identified, following the criterion that a higher q-value and more stable variation signify a more appropriate analytical scale [30,38].

3. Study Area and Data

3.1. Study Area and Analysis Unit

Our study selected Xi'an, the provincial capital city of Shaanxi Province in China, as the analysis object, with its central urban area as the specific analysis scope, covering a total area of approximately 765.870 km² (Figure 3). The built environment of Xi'an's central urban area is characterized by diversity and significant spatial heterogeneity. On

the one hand, the old urban area—centered on the Ming and Qing Dynasty city walls—has preserved numerous historical relics and is subject to strict development controls, forming the characteristics of high building density and low building height. The relatively high residential population density and cultural tourism flow have made this area a vital hotspot of Xi'an. On the other hand, the city's outward expansion and development have spawned multiple new urban centers, which also exhibit prominent vitality agglomeration effects, supported by well-developed public transportation networks and an abundance of public service facilities.

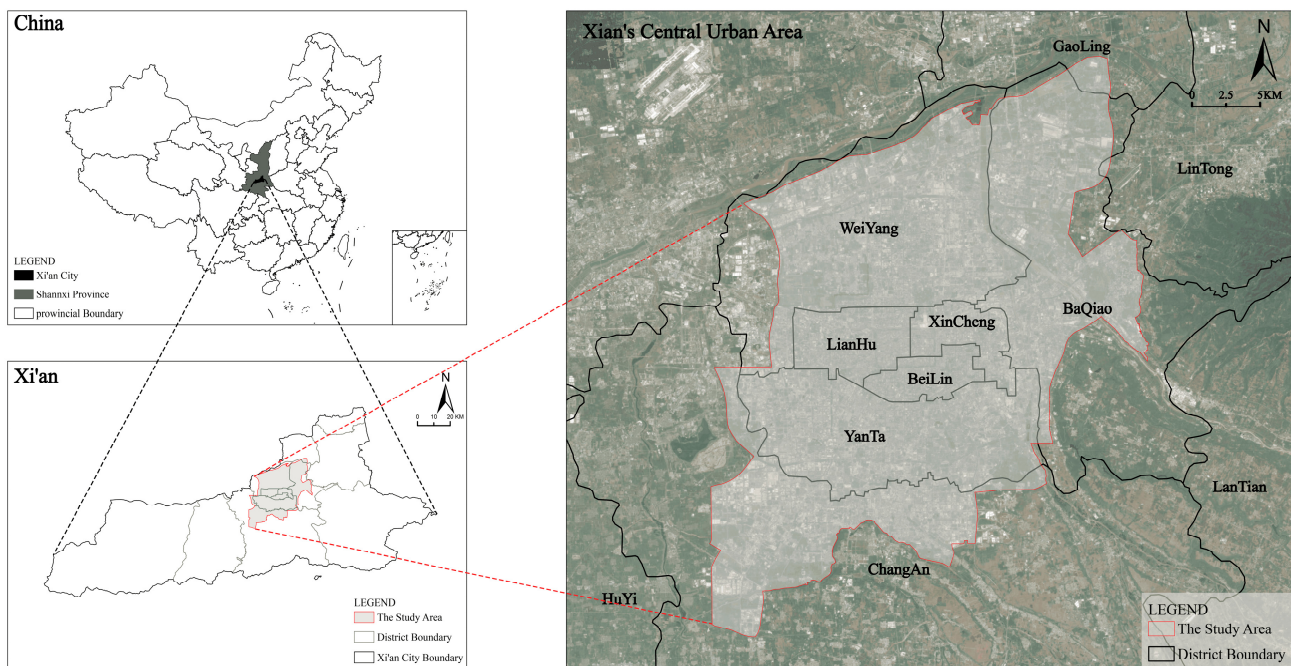


Figure 3. The location of the study area.

This study adopted square grids as the basic unit and conducted comparative analysis on six square scales with side lengths of 250 m, 500 m, 800 m, 1 km, 1.5 km, and 2 km, selecting the optimal scale grid for further exploration. In addition to the factors mentioned in Section 2.3 regarding the formation of “vibrant scene unit” grid units, which facilitate flexible spatial distribution pattern analysis while maintaining consistency and high resolution [39], the aforementioned analytical unit demarcation method was employed. Based on the above six spatial scales, our analytical units have 12,648, 3258, 1316, 858, 400, and 228 units, respectively.

3.2. Indicator System and Data Sources

Based on observations of American cities, Jacobs established a classic framework identifying mixed uses, density, short blocks, and aged buildings—alongside accessibility and the absence of border vacuums—as the core determinants of urban vitality [4]. Similarly, we can also find important clues influencing the generation of vitality from Mehaffy's concept of ‘Pattern Language’, namely that specific geometric characteristics of street networks, such as intersection density and network connectivity, are crucial for generating “contact potential” [13].

Drawing on Jacobs' and Mehaffy's theories and existing empirical evidence, we selected variables that can effectively represent these characteristics. (1) Typically, the concentration of the built environment is reflected in population density, facility density, and construction intensity. (2) Regarding land use mix, functional mix is measured by POI data. It is worth noting that the third place is defined as the physical carrier used for informal in-

teractions outside of the home (first place) and work/school (second place) [40]; it includes various spatial types such as consumption spaces, public spaces, and outdoor spaces [41], and is regarded as an important catalyst for stimulating urban vitality and promoting social interaction [42]. Third places are often combined with other urban functions in their setup, so we calculate their density to a certain extent to reflect mixed characteristics. (3) The structure and scale of the street network are direct representations of small block sizes, and the structure of the road network has been found to correlate with block scale. (4) Building age and housing prices are effective measures for identifying older structures. (5) Accessibility can be indirectly demonstrated through the distribution of public transportation facilities. (6) The border vacuum is measured according to Sung, H. [33]. Ultimately, this study developed and constructed a quantitative measurement system for the built environment, encompassing six dimensions and 21 secondary indicators (Table 1).

This study utilized datasets from multiple sources. The first dataset is the 2022 land use data, which is derived from the China Urban Land Use Map Dataset published by Gong P et al. [43]. The second important dataset, from Baidu Maps in 2023, includes points of interest (POIs), road networks, and building outlines. From this, we selected relevant elements, including commercial facilities, public services, scenic spots, third places, and transportation infrastructure. We also calculated the combined structural features of all POIs, as well as cleaned and computed road network characteristics and building age-related indicators. Another significant dataset relates to social demographics, including high-resolution population-scale data and second-hand housing price data. The former is obtained from the dataset calculated by Chen Y et al. [44] based on the 2020 Seventh National Population Census of China using stacked ensemble learning and geospatial big data algorithms. The latter is sourced from Anjuke (<https://xa.anjuke.com/>, accessed on 10 April 2024), a housing rental and sales platform, which includes building age data as of December 2022 and second-hand housing price data as of November 2023. Additionally, we obtained data from Baidu Heatmap for a total of 28 days during spring (10–16 April), summer (17–23 July), autumn (23–29 October), and winter (9–15 January) in 2024, which consist of coordinate points with heat values. To measure the urban vitality, these raw data were processed to generate daily heat value raster data covering the entire study area using Inverse Distance Weighting (IDW) method with a search distance of 50 m in ArcGIS Pro 3.4. Subsequently, the Raster Calculator was employed to produce an average heat value raster for the entire study period, which could then be aggregated to each grid cell, enabling the measurement of vitality levels for every unit.

To reduce multicollinearity among variables and avoid its impact on model robustness [45–47], we conducted the Variance Inflation Factor (VIF) test on all variables using R version 4.4, iteratively removing the variable with the highest VIF exceeding 10 in each round until all remaining variables had VIF values below 10 in the final test. Ultimately, three variables were eliminated, including Floor Area Ratio (FAR), Density of Commercial Facilities (Den_B), and Density of Public Service Facilities (Den_A). The remaining 18 independent variables were incorporated into subsequent analyses.

Table 1. Built Environment Feature Measurement Indicator System.

Dimension	Indicator		Description	Refs.
	Primary	Secondary		
Concentration	Population	Population Density (PD, persons/km ²)	Persons per kilometer square	[48–50]
	Facilities	Density of Commercial Facilities (Den_B, units/km ²)	Number of commercial facilities per square kilometer	[51]
		Density of Public Service Facilities (Den_A, units/km ²)	Number of public service facilities per kilometer square	[52]
		Density of Attractions (Den_P, units/km ²)	Number of attractions per kilometer square	[53,54]
		Ratio of Green Land (RGL, %)	Ratio of green land to land area	[55]
	Buildings	Floor-area Ratio (FAR, NA)	The ratio of total building area to land area	[55]
		Building Density (BD, %)	Building footprint density	[56]
Mixed use	Function	Mixture of POIs (MP, NA)	The Shannon–Weaver diversity of all POI types	[57]
		Equilibrium Degree of POIs (EDP, NA)	The Shannon–Weaver evenness of all POI types	
	The Third Place	Density of the Third Place (Den_T, units /km ²)	The ratio of the number of third place facilities to land area	[58]
Short block	Scale	Intersection Density (ID, units/km ²)	Number of road intersections per kilometer square	[33,35,57]
		Road Density (RD, km/km ²)	Total road length per kilometer square	
	Network structure	Road Centerline Connectivity (Lconn, NA)	The average ease of reaching a destination for each link	
		Betweenness Euclidean (BTBEn, NA)	The potential of the road to act as a through-movement corridor	

Table 1. Cont.

Dimension	Indicator		Description	Refs.
	Primary	Secondary		
Aged buildings	Age	Building Age Diversity (BAD, NA)	Mixing degree of building age	[59,60]
		Average of Building Age (ABA, year)	The average age of all the buildings	
		Equilibrium Degree of Building Age (EDBA, NA)	The balanced distribution of buildings of different ages	
	Housing Price	Average Price of Second-hand Housing (APSH, RMB/m ²)	The average price per unit area of all traded second-hand housing	[59,61]
Accessibility	Transportation	Number of Bus Stops (NBS, units)	Number of bus stops within each grid	[62]
		Number of Subway Stations (NS, units)	Number of subway stations within each grid	[63,64]
Boundary Vacuum	Isolation	Distance to Boundary Vacuum (DBV, m)	Distance from each grid to the nearest boundary vacuum Element	[33,65]

Note: (1) NA stands for “Not Applicable,” meaning there is no unit. (2) According to Jefre et al. [41], third places include: (i) places for eating, drinking, and socializing (stores, bars, pubs, restaurants, and cafes); (ii) places that organize activities for social capital (worship venues, clubs, organizations, community centers, and senior centers); (iii) outdoor places (squares and parks); and (iv) commercial places (shops, shopping centers, malls, markets, beauty salons, and barbershops). (3) Elements forming boundary vacuums include large-area, single-purpose spaces (e.g., railways, campuses, highways, and large parks), which hinder urban residents’ walking activities [59].

4. Results

4.1. The Optimal Analysis Scale

The explanatory power of built environment variables exhibits significant variation with increasing spatial scale (Figure 4). It can be observed that, over the scale increase from 250 m to 1500 m, the q-values of most variables exhibit a significant growth. Although on the scale from 1500 m to 2000 m, some variables still show an increase in their q-values (8 out of 18; such as Den_T, NBS, RGL; with a growth rate greater than 0.15), many variables’ q-values tend to saturate in growth (6 out of 18; such as ABA, BD, NS; with a growth rate between 0 and 0.15), and even some show a declining trend (including BAD, APSH, EDP, and EDBA). Considering the spatiotemporal behavior characteristics of the vitality-generating population (as mentioned in Section 3.1), we ultimately determine the 2 km grid as the spatial unit for this analysis.

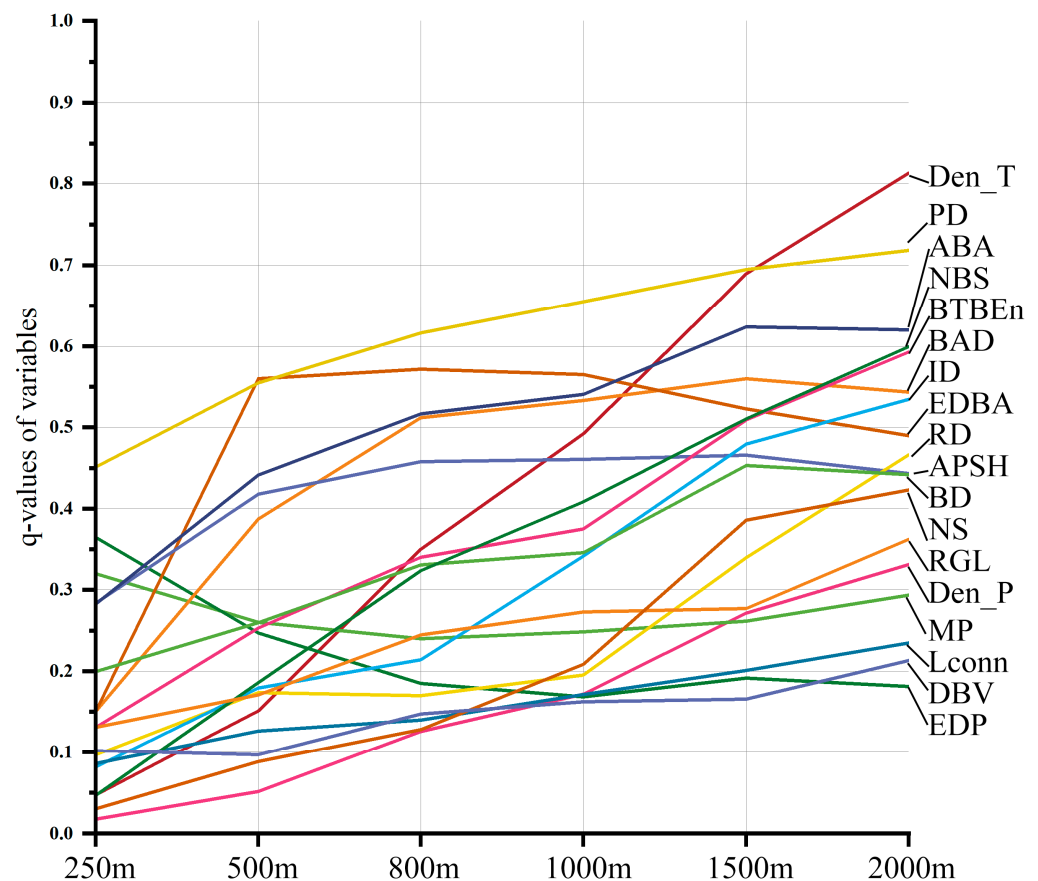


Figure 4. Variation of the q-value of the independent variable at different grid scales.

4.2. Overall Correlation

4.2.1. Single-Model Analysis Results

Tables 2 and 3 present the results obtained from the MGWR model and factor detector analysis. The MGWR model is essentially a linear regression model that takes into account spatial local autocorrelation [32], thereby uncovering linear correlation relationships between the independent variables and the dependent variable. We calculated the regression parameters for all indicators in the MGWR using the mean of all sample units. From the MGWR model results in Table 2, the built environment variables with significant performance include third place density (Den_T), number of bus stops (NBS), population density (PD), intersection density (ID), number of subway stations (NS), road betweenness centrality (BTBEn), and attractions density (Den_P). Their explanatory power for the formation of vitality decreases sequentially, with values of 0.3397, 0.306, 0.258, 0.116, 0.056, 0.053, and -0.044 , respectively. Among these, third place density (Den_T), number of bus stops (NBS), population density (PD), intersection density (ID), number of subway stations (NS), and road betweenness centrality (BTBEn) have significant positive correlations with urban vitality, indicating that as these indicators increase, the urban vitality intensity will also significantly improve. In contrast, the attractions density (Den_P) has a significant negative impact on urban vitality, suggesting that these built environment elements may exert an inhibitory effect on the formation of urban vitality.

Table 2. Overall correlation between the built environment and vitality, and their component (228 samples, grid size = 2 km).

Variables	MGWR Model		Factor Detector		Correlation Type
	β	p	q-Value	p	
Den_P	−0.044 *	0.386	0.331 ***	0.000	Linear and Non-Linear
Den_T	0.340 *	1.000	0.813 ***	0.000	Linear and Non-Linear
MP	0.014	0.000	0.294 ***	0.000	Non-Linear
EDP	0.004	0.000	0.181 ***	0.000	Non-Linear
BAD	0.047	0.000	0.543 ***	0.000	Non-Linear
EDBA	0.006	0.000	0.490 ***	0.000	Non-Linear
APSH	−0.009	0.000	0.443 ***	0.000	Non-Linear
ABA	0.052	0.000	0.624 ***	0.000	Non-Linear
RD	−0.081 *	0.000	0.481 ***	0.000	Non-Linear
PD	0.258 *	1.000	0.718 ***	0.000	Linear and Non-Linear
ID	0.116 *	1.000	0.534 ***	0.000	Linear and Non-Linear
Lconn	0.032	0.000	0.235 ***	0.000	Non-Linear
BTBEn	0.053 *	0.482	0.593 ***	0.000	Linear and Non-Linear
BD	−0.014	0.000	0.448 ***	0.000	Non-Linear
NBS	0.306 *	0.965	0.599 ***	0.000	Linear and Non-Linear
RGL	−0.047	0.000	0.362 ***	0.000	Non-Linear
NS	0.056 *	1.000	0.423 ***	0.000	Linear and Non-Linear
DBV	−0.017	0.000	0.213 ***	0.000	Non-Linear
Overall parameters	$R^2 = 0.944$ Adjust $R^2 = 0.934$ AICc = 74.409 $\sigma^2 = 0.066$		NA		NA

Note: * <0.05, ** <0.01, *** <0.00; NA is the abbreviation of Not Applicable.

Table 3. Summary statistics for MGWR coefficient estimates of variables.

Variables	Coefficients					Significance (% of Features)
	Mean	Standard Error	Minimum	Median	Maxium	
intersect	−0.0016	0.0956	−0.2375	−0.0078	0.1821	78 (34.21)
Den_P	−0.0436	0.0003	−0.0442	−0.0437	−0.0426	88 (38.60)
Den_T	0.3397	0.0003	0.3389	0.3397	0.3405	228 (100.00)
MP	0.0139	0.0039	0.0059	0.0138	0.0239	0 (0.00)
EDP	0.004	0.0009	0.0027	0.0038	0.0066	0 (0.00)
BAD	0.0472	0.0015	0.0433	0.0474	0.0505	0 (0.00)
EDBA	0.006	0.004	−0.0015	0.0059	0.0161	0 (0.00)
APSH	−0.0089	0.0021	−0.0139	−0.0088	−0.0046	0 (0.00)
ABA	0.052	0.0019	0.0479	0.0521	0.0559	0 (0.00)
PD	0.2584	0.0003	0.2575	0.2585	0.259	228 (100.00)
RD	−0.0805	0.0002	−0.0809	−0.0806	−0.0798	0 (0.00)
ID	0.1158	0.0038	0.1068	0.1157	0.1245	228 (100.00)
Lconn	0.0315	0.0012	0.0294	0.0315	0.0343	0 (0.00)
BTBEn	0.0527	0.0669	−0.1141	0.068	0.2052	110 (48.25)
BD	−0.0139	0.0008	−0.0158	−0.0138	−0.0125	0 (0.00)
NS	0.0555	0.002	0.0515	0.0554	0.0596	228 (100.00)
NBS	0.3064	0.0821	0.126	0.3124	0.4336	220 (96.49)
RGL	−0.0473	0.0016	−0.0496	−0.0474	−0.0421	0 (0.00)
DBV	−0.0175	0.0013	−0.0213	−0.0174	−0.0149	0 (0.00)

The factor detector captures spatial heterogeneity, but its results are not influenced by whether the relationships between independent variables and the dependent variable are linear or non-linear [66]. As presented in Table 2, all independent variables exert a significant impact on the dependent variable ($p < 0.001$). Among these, ten built environment factors exhibit explanatory power exceeding 0.5: third place density (Den_T), population density (PD), average building age (ABA), number of bus stops (NBS), road betweenness centrality (BTBEn), building age diversity (BAD), and intersection density (ID) (ranked from highest to lowest q value, with values ranging from 0.887 to 0.534). The remaining factors have relatively weak influences on shaping urban vitality.

4.2.2. Model Results Comparison

We further compared the analytical results of the two to determine the compositional characteristics of the correlation between built environment factors and urban vitality. The variables significant in OPGD must have a significant correlation with the dependent variable; however, whether this correlation is linear or non-linear cannot be determined from OPGD alone. In contrast, the MGWR model relies on a locally linear model for fitting at each location. Thus, it is believed that variables can exhibit a linear relationship in those locations where the MGWR model shows significant partial correlations and a non-linear relationship in areas where the results are not significant, combining the results of both OPGD and MGWR. From Table 2, it can be inferred that POIs mixture (MP), POIs equilibrium (EDP), building age diversity (BAD), building age equilibrium (EDBA), average price of second-hand housing (APSH), average building age (ABA), road density (RD), road central connectivity (Lconn), building density (BD), green space ratio (RGL), and boundary vacuum distance (DBV) are associated with vitality. In contrast, the association between attraction density (Den_P), third place density (Den_T), number of bus stops (NBS), population density (PD), intersection density (ID), number of subway stations (NS), and road betweenness centrality (BTBEn) with vitality may simultaneously contain linear and non-linear components. The absence of indicators with only linear correlation suggests that non-linear components are universally present in the impact of the built environment on urban vitality, reflecting the complexity of real-world influences.

4.3. Spatial Heterogeneity

4.3.1. Local Heterogeneity

This study calculated the global autocorrelation coefficient (Moran's $I = 0.801$, $p < 0.01$), indicating the presence of obvious spatial autocorrelation. Furthermore, we examined the impact of built environment factors on vitality as it varies spatially, exploring local heterogeneity using the analysis parameters of the MGWR model. Figure 5 shows the distribution of regression coefficients of built environment variables that have a significant influence on grid units.

All grid cells exhibit significant correlations with four key variables: population density (PD), third place density (Den_T), intersection density (ID), and number of subway stations (NS). Population density (PD) exerts a positive impact on urban vitality, characterized by higher values in the northwest and relatively lower values in the southeast (Figure 5a). Third place density (Den_T) exhibits a consistent positive correlation with urban vitality across the entire study area, with a slightly stronger influence in the southeast than in the northwest (Figure 5b). Intersection density (ID) has a positive effect on urban vitality throughout the study region, and the influence intensity generally increases from the city's northeast to southwest (Figure 5c). The number of subway stations (NS) demonstrates a significant positive correlation with urban vitality across the study area, with minimal spatial variation in the correlation strength ($\beta = 0.051$ – 0.059) (Figure 5d).

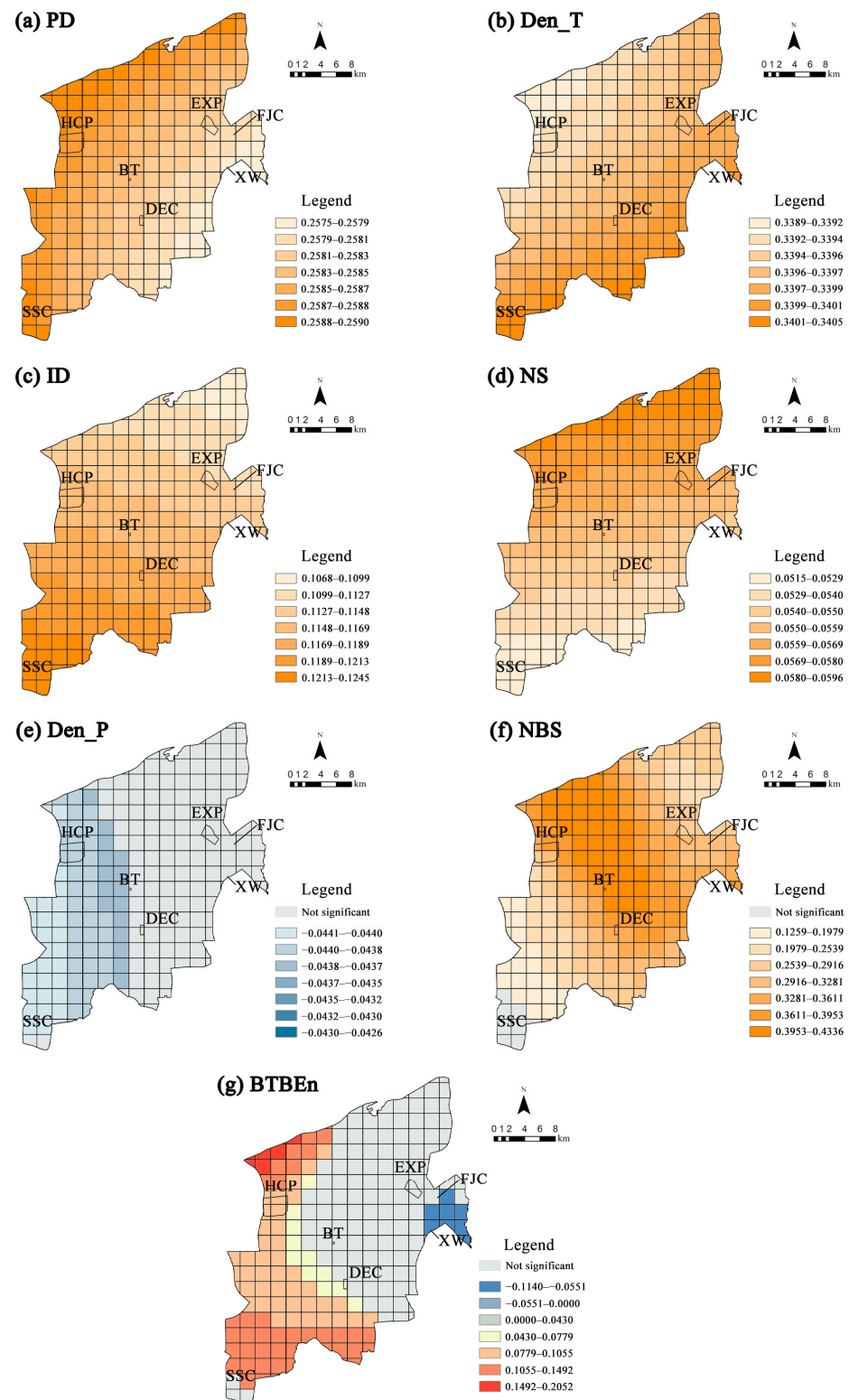


Figure 5. Spatial distribution of local regression coefficients (MGWR). (a) Local regression coefficients of PD (population density); (b) Local regression coefficients of Den_T (density of the third place); (c) Local regression coefficients of ID (intersection density); (d) Local regression coefficients of NS (number of subway stations); (e) Local regression coefficients of Den_P (density of attractions); (f) Local regression coefficients of NBS (number of bus stops); (g) Local regression coefficients of BTBEn (population betweenness euclidean). Note: Only units with significant impact are displayed in color ($p < 0.05$).

The significant variables at the 2 km grid scale include attraction density (Den_P) and the number of bus stops (NBS). Attraction density (Den_P) exerts a negative impact on urban vitality only in the western part of Xi'an's central urban area, with no significant effects in other regions. Within the regions where the impact is significant, the influence intensity increases slightly from west to east (Figure 5e). The number of bus stops (NBS) exhibits a significant positive correlation in most areas, except for the southwest edge of the central urban area, where the correlation is insignificant. In the regions with significant correlations, the influence intensity generally follows a northwest-southeast distribution pattern, decreasing slightly toward the northeast and southwest (Figure 5f).

Notably, road betweenness centrality (BTBEn) exerts both positive and negative impacts on urban vitality simultaneously. The regions with significant influences are concentrated in the westernmost part of the central urban area and a small eastern area: the former exhibits a positive impact, while the latter demonstrates a negative impact. Within the western region, which has a significant influence, the impact intensity is characterized by lower values in the central part and relatively higher values in the peripheral areas (Figure 5g).

4.3.2. Stratified Heterogeneity

The risk detector can compute the average impact of specific influencing factors on urban vitality at a certain stratum, which facilitates the characterization of variations in impact intensity through comparisons across different strata.

As illustrated in Figure 6, ten factors—including building average age (ABA), second-hand housing average price (APSH), building age diversity (BAD), building density (BD), road betweenness centrality (BTBEn), road centerline connectivity (Lconn), building age evenness (EDBA), POIs equilibrium (EDP), POIs mixture (MP), and road density (RD)—exert an “inverted U-shaped” impact on urban vitality. Specifically, as the values of these variables increase, vitality intensity first rises and then declines, exhibiting a distinct “threshold effect.” For instance, BAD reaches its peak in the fifth interval, indicating that the threshold of building age diversity's impact on vitality falls between 1.04 and 1.1 (Figure 6e); building density achieves the maximum effect on vitality shaping when ranging from 24.5% to 30.7%, with further increases in density leading to negative effects (Figure 6n); road density exerts the most substantial positive impact on urban vitality within the interval of 9.18 km/km² to 11.5 km/km² (Figure 6i).

Meanwhile, the line graphs of several indicators—including number of bus stops (NBS), green space ratio (RGL), and boundary vacuum distance (DBV)—exhibit certain volatility or abrupt changes, with no distinct overall pattern. Additionally, variables such as attraction density (Den_P), third place density (Den_T), intersection density (ID), population density (PD), and number of subway stations (NS) generally show a sustained upward or downward trend, reflecting obvious non-linear correlation characteristics.

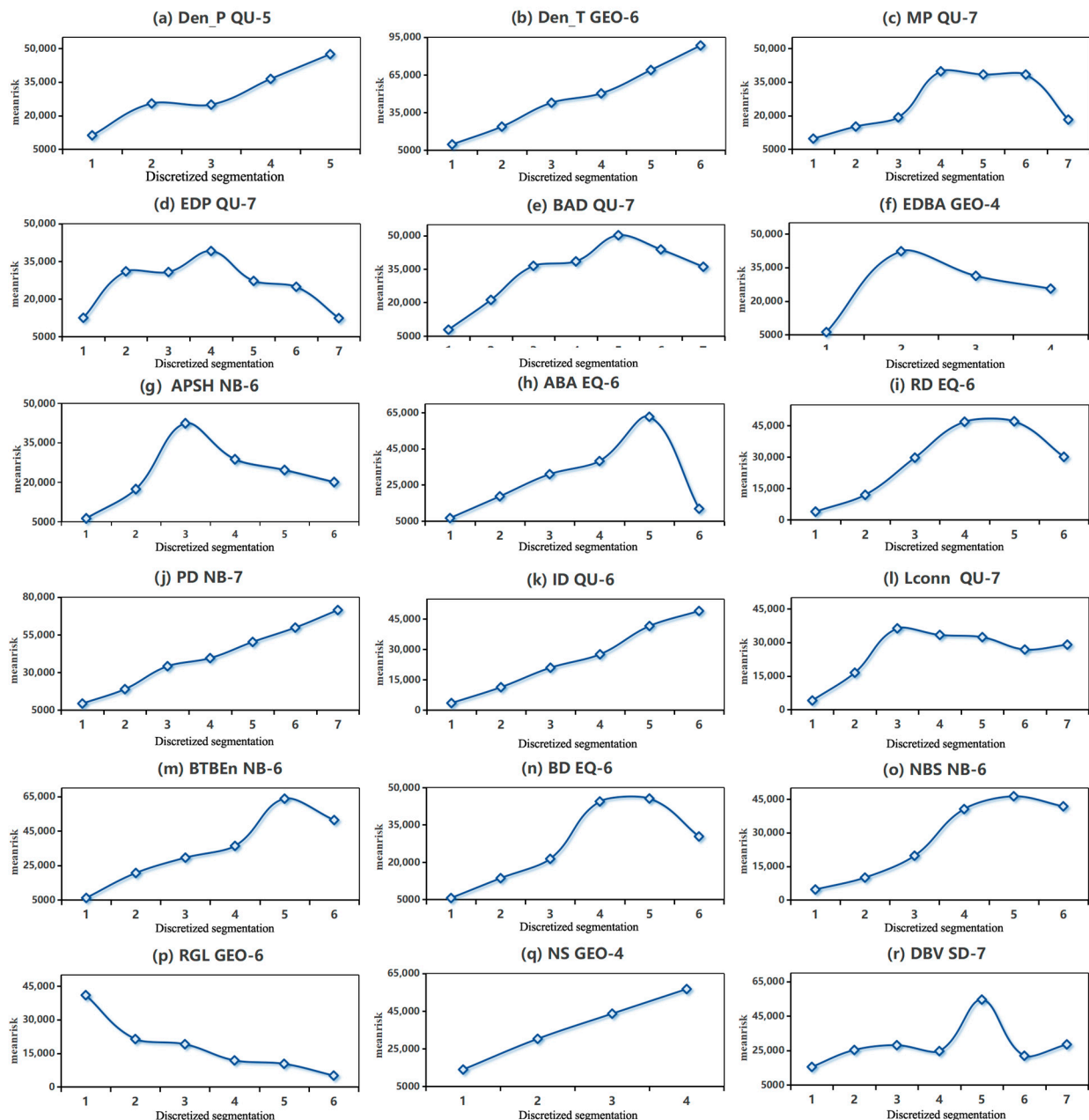


Figure 6. Line charts of risk detector analysis results. (a) Density of Attractions (Den_P) discretized using the quantile method with five segments; (b) Density of the Third Place (Den_T) discretized using the geometric interval method with six segments; (c) Mixture of POIs (MP) discretized using the quantile method with seven segments; (d) Equilibrium Degree of POIs (EDP) discretized using the quantile method with seven segments; (e) Building Age Diversity (BAD) discretized using the quantile method with seven segments; (f) Equilibrium Degree of Building Age (EDBA) discretized using the geometric interval method with four segments; (g) Average Price of Second-hand Housing (APSH) discretized using the natural breaks method with six segments; (h) Average Building Age (ABA) discretized using the equal interval method with six segments; (i) Road Density (RD) discretized using the equal interval method with six segments; (j) Population Density (PD) discretized using the natural breaks method with seven segments; (k) Intersection Density (ID) discretized using the quantile method with six segments; (l) Road Centerline Connectivity (Lconn) discretized using the quantile method with seven segments; (m) Betweenness Euclidean (BTBen) discretized using the natural breaks method with six segments; (n) Building Density (BD) discretized using the equal interval method with six segments; (o) Number of Bus Stops (NBS) discretized using the natural breaks method with six segments; (p) Ratio of Green Land (RGL) discretized using the geometric

interval method with six segments; **(q)** Number of Subway Stations (NS) discretized using the geometric interval method with four segments; **(r)** Distance to Boundary Vacuum (DBV) discretized using the standard deviation method with seven segments. Note: The title of each line graph follows the format “Indicator Code-Discretization Method-Number of Segments”. Discretization methods include natural breaks (NB), quantile (QU), geometric interval (GEO), equal interval (EQ), and standard deviation (SD).

4.4. Results of the Interaction Effect

The interaction detector can examine the combined effect of two independent variables on the explanatory power of the dependent variable. Variable interactions are not limited to multiplicative forms but can also manifest as non-linear enhancement, bivariate factor enhancement, and other types [27]. This method is thus applicable to further clarify the complex impacts of the built environment on urban vitality.

Figure 7 presents the results of the interaction analysis. Pairwise interactions among all built environment variables enhance the explanatory power for urban vitality. Except for six groups of non-linear enhancement combinations—Den_P $\cap$ EDP, Den_P $\cap$ DBV, MP $\cap$ DBV, EDP $\cap$ DBV, EDP $\cap$ Lconn, and Lconn $\cap$ DBV—all other interactions belong to bivariate factor enhancement. The top five combinations with the strongest enhancement effects are Den_T $\cap$ NBS, Den_T $\cap$ ID, Den_T $\cap$ RD, Den_T $\cap$ BAD, and Den_T $\cap$ EDBA, with corresponding interaction q-values of 0.908, 0.888, 0.882, 0.877, and 0.876. These results indicate that third place density (Den_T) exerts a broad-based enhancing effect on the influence of numerous other built environment factors on urban vitality.

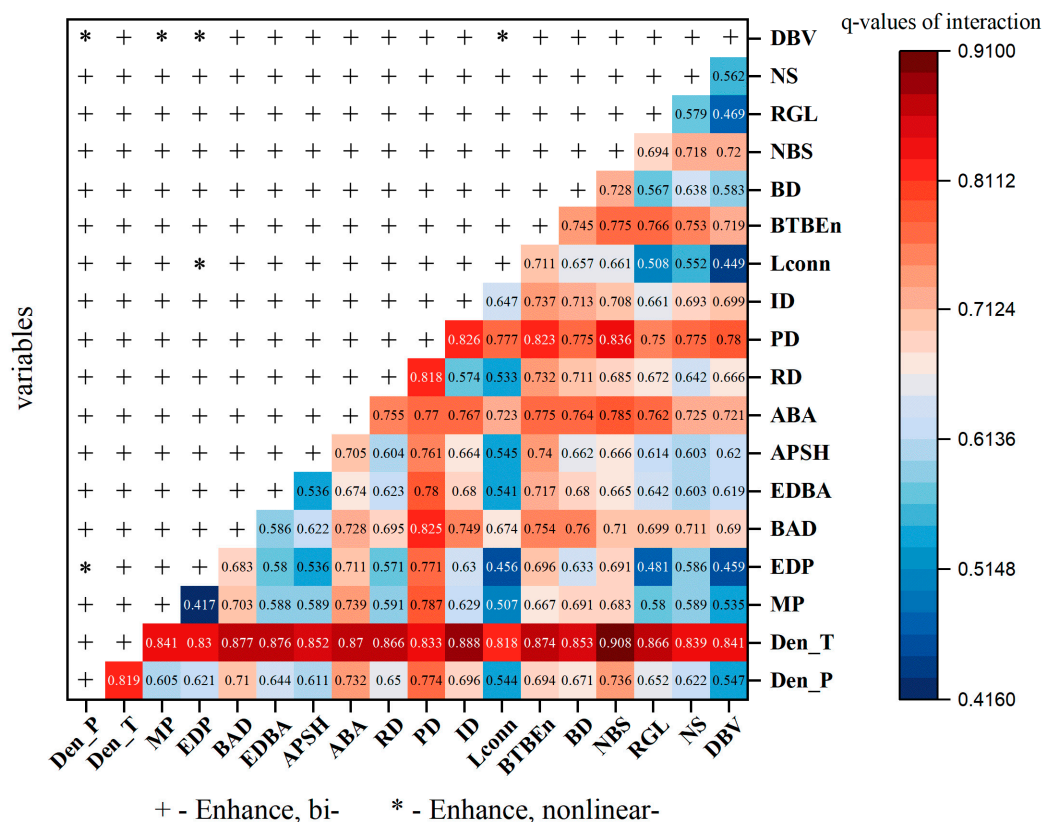


Figure 7. Heatmap of analysis results from the interactive detector.

5. Discussion

5.1. Optimal Scale for Vitality Research

This study integrated the multiscale analysis results of the OPGD method with the spatial behavior characteristics of the population to determine 2 km as the optimal analysis scale. First, comparisons across multiple grid scales revealed that the q-values of numerous built environment variables essentially reached saturation when the grid size increased to 2 km. This indicates that their explanatory power for urban vitality formation had attained a maximum, being statistically optimal.

Second, the 2 km grid scale aligns with the theoretical framework of the “15-Minute City” paradigm [14]. This concept emphasizes “chrono-urbanism”, positing that urban vitality relies on the “hyper-proximity” of essential functions (living, working, supplying, caring, learning, and enjoying) within a short time radius. Within this 2 km living circle, community infrastructure and public spaces provide accessible services that support local residents’ daily lives and social interactions, thereby facilitating the generation and shaping of community vitality [51,67,68].

Meanwhile, external tourists constitute a significant source of urban vitality in Xi’an. Empirical studies have shown that tourist destinations within a 2 km radius are more likely to encourage tourists to adopt slow travel modes or public transportation [69], thereby enhancing their travel experiences and perceptions. Favorable walking conditions can attract greater tourist flows, which in turn increase the vitality of spaces surrounding streets and key scenic spots. These findings indicate that the 2 km spatial analysis scale aligns with the spatial behavior characteristics of the actual activity population (including residents and external tourists) and exhibits strong real-world adaptability.

In addition, scholars have noted that smaller analysis scales struggle to capture complex influencing relationships amid fine-grained local variations [70,71]. Our study identified spatial heterogeneity in the impact of the built environment on urban vitality, and adopting a 2 km grid scale can mitigate the adverse effects of small-scale analysis on modeling reliability and analytical accuracy.

5.2. Overall Characteristics of Vitality-Influencing Factors

Regarding the overall results of the MGWR model, seven variables exhibit a significant positive correlation with urban vitality: attraction density (Den_P), third place density (Den_T), population density (PD), intersection density (ID), road betweenness centrality (BTBEn), number of bus stops (NBS), and number of subway stations (NS). This indicates that these variables have a linear influence on urban vitality. Third place density (Den_T) is primarily composed of catering services, organized social activity venues, outdoor sports facilities, and shopping malls, serving as the core urban spaces for residents and tourists to engage in public interactions [41]. Among these, catering services and venues for organized social activities are the most representative, as they can accommodate high-frequency, long-duration social interactions and attract diverse groups of people. Outdoor sports facilities and shopping malls further complement these functions, providing opportunities for activities beyond daily consumption and social interaction, thus creating richer experiential scenarios. Population constitutes a fundamental prerequisite for vitality formation: areas with high population density typically host a richer diversity of urban activities, thereby fostering vitality [72]. For intersection density (ID), higher values generally imply smaller land parcels and a denser road network, which can provide pedestrians with diverse walking routes, increase street pedestrian flow, and boost commercial vitality [52]. Areas with a higher concentration of subway stations tend to have higher land development intensity and mixed land use [73,74]. For the number of bus stops (NBS), as nodes frequently accessed by various user groups, helps expand the coverage of nearby ‘third places’ and

promotes frequent, short-term visitation activities, thereby maintaining a lively street atmosphere [75]. Road betweenness centrality (BTBEn) reflects the potential of a road to serve as a through traffic corridor, which enhances the visibility and pedestrian flow of adjacent third places. Roads with higher BTBEn can guide people to a broader urban area [76], which is crucial for aggregating vitality in surrounding areas.

Notably, several variables were identified as significant solely in the factor detector results, indicating that these built environment elements may primarily exert non-linear influences on urban vitality. Combined with the risk detector analysis, this study further explored the characteristics of the non-linear relationship between the built environment and urban vitality, revealing a relatively distinct “threshold effect” (i.e., an inverted U-shape):

- (1) Structural characteristics of POIs (MP and EDP). Moderate functional mixing enhances vitality, whereas excessive singularity or a lack of functional dominance leads to insufficiency. Appropriately balanced POI mixing and evenness are known to promote pedestrian and leisure activities, thus attracting more foot traffic [77]. However, hyperdiversification without prominent features can blur an area’s functional positioning, resulting in an adverse impact on the development of local vitality.
- (2) Road network and its structural characteristics (RD, BTBEn, and Lconn). Ample road density and high accessibility are widely recognized as beneficial [78,79], primarily by enhancing public transportation, improving walkability, and ensuring access to destinations. However, this positive relationship is not absolute. Beyond a certain threshold, excessive road density—often correlated with high connectivity and betweenness centrality—can become counterproductive. In line with Downs’ Law [80], a denser road network may induce a proportional increase in motor vehicle traffic (elasticity coefficient ≈ 1).
- (3) Aged buildings and their composite features (ABA, BAD and EDDBA). Historic buildings often possess a unique charm, serving as crucial material embodiments of local character [81]. The integration of new and old buildings, a core prerequisite for organic urban regeneration, has also been shown to significantly enhance urban vitality [82,83]. However, when the average building age of an area becomes excessively high, it often signifies widespread issues, such as functional obsolescence, deteriorated facilities, and an inability to accommodate contemporary business models [84].
- (4) Building density (BD). Moderate building density ensures compact development [85], providing the physical spatial framework for urban activities and serving as a prerequisite for accommodating diverse activities and attracting pedestrian traffic [86]. However, once building density exceeds a certain threshold, its marginal effect on vitality turns negative. This is primarily because excessive density encroaches upon urban public spaces, leading to a reduction in spatial comfort and environmental quality [87,88].

5.3. Spatial Heterogeneity of Vitality-Influencing Factors

The study found that the impact of attraction density (Den_P) (-), number of bus stops (NBS) (+), and road betweenness centrality (BTBEn) ($\pm$) on Xi’an’s urban vitality varies with geographical location.

In terms of Den_P, grids exhibiting a significantly negative impact are concentrated in the western part of Xi’an’s central urban area, whereas the impact in the central and eastern areas is not as pronounced. This may be related to the type of attractions. The central and eastern parts of the study area are concentrated with Xi’an’s famous attractions (e.g., City Wall, Bell Tower (BT), Giant Wild Goose Pagoda, Datang Everbright City (DEC)) and important urban man-made scenic areas (e.g., Expo Park (EXP), Xingfu Lindai), which hold great appeal for tourists and local residents’ leisure [89]. Therefore, an increase in the

number of attraction POIs in these areas does not yield a significant additional increase in popularity. In contrast, the eastern region is dominated by large-scale heritage parks (e.g., Han Chang'an Archaeological Site Park (HCP)), ecological parks, and theme parks. These attractions have limited appeal to tourists and residents and are prone to becoming 'border vacuum' areas [57], which is detrimental to the formation of vitality.

Regarding NBS, most areas exhibit a significant positive correlation with urban vitality, a finding consistent with numerous studies [20,24]. However, a small area in the southwest showed no significant impact. A potential explanation is that this area is a large-scale industrial park (SSC), where internal transportation shuttle services already provide convenient transit access for occupants. This internal provision may render the contribution of municipal public bus stops to enhancing the area's vitality less critical.

The BTBEn exhibits a significant positive impact in the western part of the study area, whereas it plays a markedly negative role in a small area in the easternmost region. The urban road network density in the western area is relatively low, and the degree of network integration is not high. Enhancing the betweenness centrality in this area helps improve the network's connectivity and structure, thereby bringing convenient accessibility and attracting more human activity. Conversely, the eastern area, which exhibits a significant negative correlation, features multiple large-scale highway interchanges that restrict surrounding land development (XW, FJC), resulting in a certain degree of spatial isolation [90]. Increasing the road betweenness centrality in an area with these network characteristics would cause the road's function to be more oriented towards facilitating rapid vehicular pass-through, resulting in a greater through-traffic flow. This is detrimental to the pedestrian-friendliness and commercial agglomeration of the plots along the route [91], further leading to a decline in regional vitality. It is evident that the impact of road network structural characteristics on vitality is complex, requiring targeted strategies adopted in light of the actual situation.

5.4. Interactive Impact of Built Environment Factors on Vitality

Analysis of the interaction effects reveals that third place density (Den_T) exerts a crucial catalytic influence. It can synergistically promote urban vitality when combined with most built-environment factors, especially accessibility, the street network, and old buildings. According to Ray Oldenburg's third place theory [88], these locations are typically open, free, and informal public spaces with high accessibility, which facilitate social interaction and recreational activities. To a great extent, areas with a higher density of third places are more likely to attract pedestrian flow and spatially overlap with other built-environment factors, thus jointly generating a composite impact on vitality. Specifically:

Firstly, the strong interaction between Den_T and the number of bus stops (NBS) suggests that the generation of vitality depends on convenient accessibility, while third places can enhance vitality in areas with readily available public transportation. Convenient public transportation is a prerequisite for breaking down social isolation [92] and promoting cross-district mobility within cities [93]. A well-developed public transportation system brings an adequate flow of visitors to third places, thereby amplifying the role of commercial, recreational, and social functions in enhancing urban vitality.

Secondly, Den_T exhibits strong interactions with intersection density (ID) and road density (RD), indicating the importance of "small blocks and dense road networks" in shaping urban vitality. This empirical finding resonates with the principles of "Network Urbanism" [29], which posits that vitality is an emergent property arising from the "structural coupling" of physical form and social function. As noted in previous studies [76,79], a walkable environment reduces speed and encourages 'lingering'. From a complexity science perspective, this interaction verifies that morphological connectivity (dense streets)

and functional intensity (third places) function as a synergistic system. It is this coupling that transforms a street from a mere channel of movement into a “place” of exchange, maximizing the “contact potential” described in pattern language.

Furthermore, a significant synergistic effect on urban vitality was observed when the Den_T is coupled with the building stock’s average age (BAD) and age equilibrium (EDBA). This suggests that when third places are embedded within neighborhoods possessing a rich historical texture and a blend of building vintages, their ability to embody local cultural characteristics is amplified, thereby generating stronger attractiveness [42]. This finding corroborates previous research, which indicates that a diversity of interaction spaces within historical contexts can foster multidimensional social, economic, and cultural activities [94,95], while simultaneously enhancing place identity and overall appeal [96–98].

While the interaction effect analysis reveals the mechanism by which factors such as third place density, public transport accessibility, street networks, and historical buildings jointly shape urban vitality in Xi’an, the applicability of these findings remains influenced by differences in city type. Xi’an’s central urban area boasts a rich historical foundation, high population density, and a strong coupling between commerce and tourism; its vitality structure relies more heavily on cultural venues, historical districts, and pedestrian networks. Therefore, the interaction reinforcement mechanism identified in this study has substantial reference value for similar international historical cities.

6. Conclusions

The built environment is a fundamental determinant in shaping urban vitality. Our research empirically investigates the central urban area of Xi’an, employing an analytical framework constructed to deconstruct these complex influencing mechanisms. The study first addresses the critical issue of spatial scale by identifying the most appropriate analytical unit for the Xi’an context. Following this, the framework differentiates between the overall (global) and local-level (spatially heterogeneous) effects of the built environment. The analysis then moves beyond simplistic linear assumptions to investigate both the non-linear characteristics of these influences and the synergistic, interactive impacts among key elements of the built environment. These innovative findings and detailed insights provide novel, evidence-based perspectives for urban regeneration strategies that aim to promote vitality.

Based on research findings, we propose that urban decision-makers and planners should abandon uniform approaches and adopt place-based urban regeneration strategies tailored to local characteristics to enhance vitality more precisely (Table 4). For heritage protection areas (such as old towns), built environment improvements should focus on organic regeneration, integrating the “new and old” by preserving heritage buildings while enhancing the cultural atmosphere-shaping effect of third places to maximize their attractiveness. In peripheral areas (such as new towns), policy should focus on optimizing road network density, constructing a “small blocks and dense road networks” pedestrian network, and actively introducing third places to catalyze pedestrian flow and create a pleasant living and leisure environment. Furthermore, for areas impacted by large transportation facilities or spatial isolation, mitigating the “boundary vacuum” effect is key to revitalization; this necessitates avoiding further through-traffic-oriented road construction and instead establishing convenient slow-traffic systems to foster a walkable, vibrant neighborhood environment. Overall, there are two primary strategies applicable to almost all regions: the careful regulation of moderate development intensity and density, and a strategic prioritization of the wide-ranging, catalytic role that third places provide.

Table 4. Targeted planning suggestions for urban regeneration.

Areas	Measures
Heritage protection areas	· Adopt organic renewal and emphasize the integration of old and new fabric · Introduce third places to enhance cultural appeal · Optimize the ground public transportation system
Peripheral areas	· Implement appropriate block scales · Strategically distribute public spaces
Areas impacted by large transportation facilities or spatial isolation	Adjust regional road density and development intensity

It is worth noting that this study is based on the urban spatial type of Xi'an's central urban area, which features high density, historical continuity, and strong tourism characteristics. Therefore, its conclusions should be applied cautiously when considering other cities. For cities with similar rich historical and cultural heritage, diverse streetscapes, and a high degree of overlap between population and tourism functions, the analytical framework and findings proposed in this study are highly applicable. However, for cities with significant differences in morphological structure, their built environment structure and traffic behavior patterns differ fundamentally from those of the subjects of this study, and the results may not be directly applicable. Therefore, when extending this study across different morphological types, it is necessary to re-verify it in conjunction with the local spatial structure, transportation system, and governance model.

Of course, our research has several limitations that warrant acknowledgment. First, although we strive to maintain temporal consistency by using 2023 as the base year and updating indicators as closely as possible to reflect the most recent period, there are update lags due to the fixed release cycles of some datasets (such as the census). Given that the study area did not experience significant environmental or structural changes between 2020 and 2024, we expect the resulting bias to be relatively limited, but it should still be considered a potential source of uncertainty. Second, in addition to the limitations of the data, it is necessary to acknowledge some additional sources of uncertainty. Urban vitality is affected by short-term temporal dynamics—such as policy adjustments, population changes, or event-driven fluctuations—which are not captured in our cross-sectional design. Moreover, non-built environment factors, including governance practices and socio-economic conditions, may interact with the built environment in ways not fully represented in our model. Third, the empirical analysis is predicated on cross-sectional data. This static approach, while effective for revealing spatial patterns, cannot capture the longitudinal dynamics of vitality or the underlying driving mechanisms, nor can it definitively establish causality between the built environment and vitality. Finally, while our framework confirmed the pervasive non-linear relationships between built environment factors and urban vitality, the discretization of indicators required by the OPGD methodology makes it difficult to identify precise impact thresholds. Future research could expand upon these findings by incorporating a longitudinal data dimension, analyzing from a spatiotemporal perspective to explore causal relationships. Concurrently, machine learning algorithms (e.g., GBDT, Random Forest) could be employed to identify specific impact thresholds, providing a quantitative, index-based regulatory basis for renewal planning. Overall, notwithstanding these areas for improvement, this research provides a beneficial empirical study focused on an internationally famous historical city, offering critical evidence and a

methodological reference for similar urban contexts seeking to enhance vitality through built environment interventions.

Author Contributions: Conceptualization, J.Y. and D.W.; methodology, J.T. and X.J.; software, J.T. and W.L.; validation, J.L., D.Y. and W.L.; formal analysis, J.T. and X.J.; resources, J.T. and J.L.; data curation, J.T., X.J. and N.T.; writing—original draft preparation, X.J., W.L., J.T. and N.T.; writing—review and editing, N.T. and J.Y.; visualization, J.T. and J.L.; supervision, J.Y. and D.W.; funding acquisition, J.Y. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Xi'an University of Architecture and Technology Talent Research Initiation Project (Program NO. 1960324011), Natural Science Basic Research Program of Shaanxi (Program No. 2025JC-YBMS-373), Social Science Foundation Program of Shaanxi (Program No. 2025J003) and National Natural Science Foundation of China (Program No. 52378073), and Shanghai Key Laboratory of Urban Renewal and Spatial Optimization Technology (Program No. 20230204).

Data Availability Statement: The original contributions presented in the study are included in the article; further inquiries can be directed to the corresponding authors.

Conflicts of Interest: The authors declare no conflicts of interest.

References

- Martinez-Fernandez, C.; Audirac, I.; Fol, S.; Cunningham-Sabot, E. Shrinking Cities: Urban Challenges of Globalization. *Int. J. Urban Reg. Res.* **2012**, *36*, 213–225. [\[CrossRef\]](#)
- Long, Y.; Wu, K. Shrinking Cities in a Rapidly Urbanizing China. *Environ. Plan. A* **2016**, *48*, 220–222. [\[CrossRef\]](#)
- Haase, A.; Rink, D.; Grossmann, K.; Bernt, M.; Mykhnenko, V. Conceptualizing Urban Shrinkage. *Environ. Plan. A* **2014**, *46*, 1519–1534. [\[CrossRef\]](#)
- Jacobs, J. *The Death and Life of Great American Cities*; Vintage Books: New York City, NY, USA, 1961; ISBN 978-0-679-74195-4.
- Batty, M. *The New Science of Cities*; The MIT Press: Cambridge, MA, USA, 2013; ISBN 978-0-262-31823-5.
- Wu, C.; Ye, X.; Ren, F.; Du, Q. Check-in Behaviour and Spatio-Temporal Vibrancy: An Exploratory Analysis in Shenzhen, China. *Cities* **2018**, *77*, 104–116. [\[CrossRef\]](#)
- Mouratidis, K.; Poortinga, W. Built Environment, Urban Vitality and Social Cohesion: Do Vibrant Neighborhoods Foster Strong Communities? *Landsc. Urban Plan.* **2020**, *204*, 103951. [\[CrossRef\]](#)
- Pan, C.; Guo, J.; Li, H.; Wu, J.; Qiu, N.; Wu, S. Study on the Influence Mechanism of Machine-Learning-Based Built Environment on Urban Vitality in Macau Peninsula. *Buildings* **2025**, *15*, 1557. [\[CrossRef\]](#)
- Lyu, G.; Angkawisittpan, N.; Fu, X.; Sonasang, S. Investigating the Relationship between Built Environment and Urban Vitality Using Big Data. *Sci. Rep.* **2025**, *15*, 579. [\[CrossRef\]](#) [\[PubMed\]](#)
- Roof, K.; Oleru, N. Public Health: Seattle and King County's Push for the Built Environment. *J. Environ. Health* **2008**, *71*, 24–27. [\[PubMed\]](#)
- Handy, S.L.; Boarnet, M.G.; Ewing, R.; Killingsworth, R.E. How the Built Environment Affects Physical Activity: Views from Urban Planning. *Am. J. Prev. Med.* **2002**, *23*, 64–73. [\[CrossRef\]](#)
- Ewing, R.; Cervero, R. Travel and the Built Environment: A Meta-Analysis. *J. Am. Plan. Assoc.* **2010**, *76*, 265–294. [\[CrossRef\]](#)
- Mehaffy, M. *A New Pattern Language for Growing Regions*; Sustasis Foundation: Portland, OR, USA, 2020.
- Moreno, C.; Allam, Z.; Chabaud, D.; Gall, C.; Pratlong, F. Introducing the “15-Minute City”: Sustainability, Resilience and Place Identity in Future Post-Pandemic Cities. *Smart Cities* **2021**, *4*, 93–111. [\[CrossRef\]](#)
- Wu, W.; Niu, X. Influence of Built Environment on Urban Vitality: Case Study of Shanghai Using Mobile Phone Location Data. *J. Urban Plan. Dev.* **2019**, *145*, 04019007. [\[CrossRef\]](#)
- Li, M.; Pan, J. Assessment of Influence Mechanisms of Built Environment on Street Vitality Using Multisource Spatial Data: A Case Study in Qingdao, China. *Sustainability* **2023**, *15*, 1518. [\[CrossRef\]](#)
- Lu, S.; Shi, C.; Yang, X. Impacts of Built Environment on Urban Vitality: Regression Analyses of Beijing and Chengdu, China. *Int. J. Environ. Res. Public Health* **2019**, *16*, 4592. [\[CrossRef\]](#)
- Li, Q.; Cui, C.; Liu, F.; Wu, Q.; Run, Y.; Han, Z. Multidimensional Urban Vitality on Streets: Spatial Patterns and Influence Factor Identification Using Multisource Urban Data. *ISPRS Int. J. Geo-Inf.* **2022**, *11*, 2. [\[CrossRef\]](#)
- Wu, W.; Liu, X.; Zhou, Y.; Zhao, K. Spatial Heterogeneity of Built Environment's Impact on Urban Vitality Using Multi-Source Big Data and MGWR. *Sci. Rep.* **2025**, *15*, 23459. [\[CrossRef\]](#)

20. Wu, W.; Ma, Z.; Guo, J.; Niu, X.; Zhao, K. Evaluating the Effects of Built Environment on Street Vitality at the City Level: An Empirical Research Based on Spatial Panel Durbin Model. *Int. J. Environ. Res. Public Health* **2022**, *19*, 1664. [\[CrossRef\]](#)
21. Lin, J.; Zhuang, Y.; Zhao, Y.; Li, H.; He, X.; Lu, S. Measuring the Non-Linear Relationship between Three-Dimensional Built Environment and Urban Vitality Based on a Random Forest Model. *Int. J. Environ. Res. Public Health* **2023**, *20*, 734. [\[CrossRef\]](#) [\[PubMed\]](#)
22. Liu, W.; Yang, Z.; Gui, C.; Li, G.; Xu, H. Investigating the Nonlinear Relationship Between the Built Environment and Urban Vitality Based on Multi-Source Data and Interpretable Machine Learning. *Buildings* **2025**, *15*, 1414. [\[CrossRef\]](#)
23. Zhan, D.; Wang, Y.; Wu, Q.; Zhang, W. Nonlinear Effects of the Urban Built Environment on Urban Vitality: A Case Study of Hangzhou, China. *J. Geogr. Sci.* **2025**, *35*, 1183–1203. [\[CrossRef\]](#)
24. Li, Z.; Zhao, G. Revealing the Spatio-Temporal Heterogeneity of the Association between the Built Environment and Urban Vitality in Shenzhen. *ISPRS Int. J. Geo-Inf.* **2023**, *12*, 433. [\[CrossRef\]](#)
25. Li, J.; Lin, S.; Kong, N.; Ke, Y.; Zeng, J.; Chen, J. Nonlinear and Synergistic Effects of Built Environment Indicators on Street Vitality: A Case Study of Humid and Hot Urban Cities. *Sustainability* **2024**, *16*, 1731. [\[CrossRef\]](#)
26. Lee, S.; Cho, N. Nonlinear and Interaction Effects of Multi-Dimensional Street-Level Built Environment Features on Urban Vitality in Seoul. *Cities* **2025**, *165*, 106145. [\[CrossRef\]](#)
27. Wang, J.-F.; Li, X.-H.; Christakos, G.; Liao, Y.-L.; Zhang, T.; Gu, X.; Zheng, X.-Y. 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. [\[CrossRef\]](#)
28. Wang, J.-F.; Zhang, T.-L.; Fu, B.-J. A Measure of Spatial Stratified Heterogeneity. *Ecol. Indic.* **2016**, *67*, 250–256. [\[CrossRef\]](#)
29. Mehaffy, M.W.; Salinger, N.A. *Design for a Living Planet: Settlement, Science, and the Human Future*; Sustasis Foundation: Portland, OR, USA, 2015; ISBN 978-0-9893469-5-5.
30. 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. [\[CrossRef\]](#)
31. He, Q.; Yan, M.; Zheng, L.; Wang, B. Spatial Stratified Heterogeneity and Driving Mechanism of Urban Development Level in China under Different Urban Growth Patterns with Optimal Parameter-Based Geographic Detector Model Mining. *Comput. Environ. Urban Syst.* **2023**, *105*, 102023. [\[CrossRef\]](#)
32. Fotheringham, A.S.; Yang, W.; Kang, W. Multiscale Geographically Weighted Regression (MGWR). *Ann. Am. Assoc. Geogr.* **2017**, *107*, 1247–1265. [\[CrossRef\]](#)
33. Sung, H.; Lee, S. Residential Built Environment and Walking Activity: Empirical Evidence of Jane Jacobs' Urban Vitality. *Transp. Res. Part D Transp. Environ.* **2015**, *41*, 318–329. [\[CrossRef\]](#)
34. Chiaradia, A.; Hillier, B.; Schwander, C.; Wedderburn, M. Spatial Centrality, Economic Vitality/Viability. In Proceedings of the 7th International Space Syntax Symposium, Stockholm, Sweden, 8–11 June 2009.
35. Fang, C.; He, S.; Wang, L. Spatial Characterization of Urban Vitality and the Association with Various Street Network Metrics from the Multi-Scalar Perspective. *Front. Public Health* **2021**, *9*, 677910. [\[CrossRef\]](#) [\[PubMed\]](#)
36. Aoki, T. Activity Space Compactness Index from the Viewpoint of Trip Arrival Point by Lifestyle Activity Purpose in a Mature Conurbation. *Sustain. Cities Soc.* **2023**, *88*, 104302. [\[CrossRef\]](#)
37. Wang, T.; Wang, L.; Ning, Z.-Z. Spatial Pattern of Tourist Attractions and Its Influencing Factors in China. *J. Spat. Sci.* **2020**, *65*, 327–344. [\[CrossRef\]](#)
38. 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. [\[CrossRef\]](#)
39. Min, M.; Lin, C.; Duan, X.; Jin, Z.; Zhang, L. Spatial Distribution and Driving Force Analysis of Urban Heat Island Effect Based on Raster Data: A Case Study of the Nanjing Metropolitan Area, China. *Sustain. Cities Soc.* **2019**, *50*, 101637. [\[CrossRef\]](#)
40. Oldenburg, R. *The Great Good Place: Cafes, Coffee Shops, Bookstores, Bars, Hair Salons, and Other Hangouts at the Heart of a Community*; Hachette Books: New York, NY, USA, 1999; ISBN 978-0-7867-5241-6.
41. Jeffres, L.W.; Bracken, C.C.; Jian, G.; Casey, M.F. The Impact of Third Places on Community Quality of Life. *Appl. Res. Qual. Life* **2009**, *4*, 333–345. [\[CrossRef\]](#)
42. Mehta, V.; Bosson, J.K. Third Places and the Social Life of Streets. *Environ. Behav.* **2010**, *42*, 779–805. [\[CrossRef\]](#)
43. Li, Z.; Chen, B.; Huang, Y.; Wang, H.; Wang, Y.; Yuan, Y.; Li, X.; Chen, J.M.; Xu, B.; Gong, P. Enhanced Mapping of Essential Urban Land Use Categories in China (EULUC-China 2.0): Integrating Multimodal Deep Learning with Multisource Geospatial Data. *Sci. Bull.* **2025**, *70*, 3029–3041. [\[CrossRef\]](#)
44. Chen, Y.; Xu, C.; Ge, Y.; Zhang, X.; Zhou, Y. A 100 m Gridded Population Dataset of China's Seventh Census Using Ensemble Learning and Big Geospatial Data. *Earth Syst. Sci. Data* **2024**, *16*, 3705–3718. [\[CrossRef\]](#)
45. Shrestha, N. Detecting Multicollinearity in Regression Analysis. *Am. J. Appl. Math. Stat.* **2020**, *8*, 39–42. [\[CrossRef\]](#)

46. Wheeler, D.; Tiefelsdorf, M. Multicollinearity and Correlation among Local Regression Coefficients in Geographically Weighted Regression. *J. Geogr. Syst.* **2005**, *7*, 161–187. [\[CrossRef\]](#)
47. Daoud, J.I. Multicollinearity and Regression Analysis. *J. Phys. Conf. Ser.* **2017**, *949*, 012009. [\[CrossRef\]](#)
48. Paköz, M.Z.; Işık, M. Rethinking Urban Density, Vitality and Healthy Environment in the Post-Pandemic City: The Case of Istanbul. *Cities* **2022**, *124*, 103598. [\[CrossRef\]](#) [\[PubMed\]](#)
49. He, Q.; He, W.; Song, Y.; Wu, J.; Yin, C.; Mou, Y. The Impact of Urban Growth Patterns on Urban Vitality in Newly Built-up Areas Based on an Association Rules Analysis Using Geographical ‘Big Data’. *Land Use Policy* **2018**, *78*, 726–738. [\[CrossRef\]](#)
50. Lan, F.; Gong, X.; Da, H.; Wen, H. How Do Population Inflow and Social Infrastructure Affect Urban Vitality? Evidence from 35 Large-and Medium-Sized Cities in China. *Cities* **2020**, *100*, 102454. [\[CrossRef\]](#)
51. Liu, L.; Dong, Y.; Lang, W.; Yang, H.; Wang, B. The Impact of Commercial-Industry Development of Urban Vitality: A Study on the Central Urban Area of Guangzhou Using Multisource Data. *Land* **2024**, *13*, 250. [\[CrossRef\]](#)
52. Long, Y.; Huang, C. Does Block Size Matter? The Impact of Urban Design on Economic Vitality for Chinese Cities. *Environ. Plan. B Urban Anal. City Sci.* **2019**, *46*, 406–422. [\[CrossRef\]](#)
53. Wang, F.; Liu, Z.; Shang, S.; Qin, Y.; Wu, B. Vitality Continuation or Over-Commercialization? Spatial Structure Characteristics of Commercial Services and Population Agglomeration in Historic and Cultural Areas. *Tour. Econ.* **2019**, *25*, 1302–1326. [\[CrossRef\]](#)
54. Zeng, C.; Song, Y.; He, Q.; Shen, F. Spatially Explicit Assessment on Urban Vitality: Case Studies in Chicago and Wuhan. *Sustain. Cities Soc.* **2018**, *40*, 296–306. [\[CrossRef\]](#)
55. Xia, C.; Yeh, A.G.-O.; Zhang, A. Analyzing Spatial Relationships between Urban Land Use Intensity and Urban Vitality at Street Block Level: A Case Study of Five Chinese Megacities. *Landsc. Urban Plan.* **2020**, *193*, 103669. [\[CrossRef\]](#)
56. Jiang, Y.; Han, Y.; Liu, M.; Ye, Y. Street Vitality and Built Environment Features: A Data-Informed Approach from Fourteen Chinese Cities. *Sustain. Cities Soc.* **2022**, *79*, 103724. [\[CrossRef\]](#)
57. Wang, S.; Deng, Q.; Jin, S.; Wang, G. Re-Examining Urban Vitality through Jane Jacobs’ Criteria Using GIS-sDNA: The Case of Qingdao, China. *Buildings* **2022**, *12*, 1586. [\[CrossRef\]](#)
58. He, S.; Yu, S.; Wei, P.; Fang, C. A Spatial Design Network Analysis of Street Networks and the Locations of Leisure Entertainment Activities: A Case Study of Wuhan, China. *Sustain. Cities Soc.* **2019**, *44*, 880–887. [\[CrossRef\]](#)
59. Gómez-Varo, I.; Delclos-Alio, X.; Miralles-Guasch, C. Jane Jacobs Reloaded: A Contemporary Operationalization of Urban Vitality in a District in Barcelona. *Cities* **2022**, *123*, 103565. [\[CrossRef\]](#)
60. Gordon, P.; Ikeda, S. Does Density Matter? In *Handbook of Creative Cities*; Edward Elgar Publishing: Cheltenham, UK, 2011.
61. Zhang, Z.; Liu, J.; Wang, C.; Zhao, Y.; Zhao, X.; Li, P.; Sha, D. A Spatial Projection Pursuit Model for Identifying Comprehensive Urban Vitality on Blocks Using Multisource Geospatial Data. *Sustain. Cities Soc.* **2024**, *100*, 104998. [\[CrossRef\]](#)
62. Li, X.; Li, Y.; Jia, T.; Zhou, L.; Hijazi, I.H. The Six Dimensions of Built Environment on Urban Vitality: Fusion Evidence from Multi-Source Data. *Cities* **2022**, *121*, 103482. [\[CrossRef\]](#)
63. Fu, C.; Huang, Z.; Scheuer, B.; Lin, J.; Zhang, Y. Integration of Dockless Bike-Sharing and Metro: Prediction and Explanation at Origin-Destination Level. *Sustain. Cities Soc.* **2023**, *99*, 104906. [\[CrossRef\]](#)
64. Yan, Y.; Chen, Q. Spatial Heterogeneity and Nonlinearity Study of Bike-Sharing to Subway Connections from the Perspective of Built Environment. *Sustain. Cities Soc.* **2024**, *114*, 105766. [\[CrossRef\]](#)
65. De Nadai, M.; Staiano, J.; Larcher, R.; Sebe, N.; Quercia, D.; Lepri, B. The Death and Life of Great Italian Cities: A Mobile Phone Data Perspective. In Proceedings of the 25th International Conference on World Wide Web, Montréal, QC, Canada, 11 April 2016; pp. 413–423.
66. Wang, J.; Liao, Y.; Liu, X. *Tutorial on Spatial Data Analysis*; Science Press: Beijing, China, 2019; ISBN 978-7-03-060789-8.
67. Ma, W.; Wang, N.; Li, Y.; Sun, D.J. 15-Min Pedestrian Distance Life Circle and Sustainable Community Governance in Chinese Metropolitan Cities: A Diagnosis. *Humanit. Soc. Sci. Commun.* **2023**, *10*, 364. [\[CrossRef\]](#)
68. Wu, H.; Wang, L.; Zhang, Z.; Gao, J. Analysis and Optimization of 15-Minute Community Life Circle Based on Supply and Demand Matching: A Case Study of Shanghai. *PLoS ONE* **2021**, *16*, e0256904. [\[CrossRef\]](#)
69. He, M.; Li, J.; Shi, Z.; Liu, Y.; Shuai, C.; Liu, J. Exploring the Nonlinear and Threshold Effects of Travel Distance on the Travel Mode Choice across Different Groups: An Empirical Study of Guiyang, China. *Int. J. Environ. Res. Public Health* **2022**, *19*, 16045. [\[CrossRef\]](#)
70. Zhu, S.; Bai, Z.; Gan, Z.; Jin, S.; Zhang, C.; Wang, J. Simulation of the Spatial Pattern of Scenic Spots Combining Optimal Scale and Deep Learning. *Front. Earth Sci.* **2022**, *10*, 887043. [\[CrossRef\]](#)
71. Zhu, N.; Zeng, G.; Li, X.; Zhong, Z. Optimum Spatial Scale of Regional Tourism Cooperation Based on Spillover Effects in Tourism Flows. *Tour. Econ.* **2023**, *29*, 409–436. [\[CrossRef\]](#)
72. Yue, Y.; Zhuang, Y.; Yeh, A.G.O.; Xie, J.-Y.; Ma, C.-L.; Li, Q.-Q. Measurements of POI-Based Mixed Use and Their Relationships with Neighbourhood Vibrancy. *Int. J. Geogr. Inf. Sci.* **2017**, *31*, 658–675. [\[CrossRef\]](#)
73. Wu, W.; Niu, X.; Li, M. Influence of Built Environment on Street Vitality: A Case Study of West Nanjing Road in Shanghai Based on Mobile Location Data. *Sustainability* **2021**, *13*, 1840. [\[CrossRef\]](#)

74. Yang, J.; Cao, J.; Zhou, Y. Elaborating Non-Linear Associations and Synergies of Subway Access and Land Uses with Urban Vitality in Shenzhen. *Transp. Res. Part A Policy Pract.* **2021**, *144*, 74–88. [\[CrossRef\]](#)
75. Hu, Y.; Liang, C. Study on the Spatial Relationship between Road Network and the Diversity of Urban Public Facilities: The Case of the Central Area of Changsha City. *J. Eng. Appl. Sci.* **2024**, *71*, 156. [\[CrossRef\]](#)
76. Yue, H.; Zhu, X. Exploring the Relationship between Urban Vitality and Street Centrality Based on Social Network Review Data in Wuhan, China. *Sustainability* **2019**, *11*, 4356. [\[CrossRef\]](#)
77. Kang, C.; Fan, D.; Jiao, H. Validating Activity, Time, and Space Diversity as Essential Components of Urban Vitality. *Environ. Plan. B Urban Anal. City Sci.* **2021**, *48*, 1180–1197. [\[CrossRef\]](#)
78. Huang, J.; Hu, X.; Wang, J.; Lu, A. How Diversity and Accessibility Affect Street Vitality in Historic Districts? *Land* **2023**, *12*, 219. [\[CrossRef\]](#)
79. Huang, B.; Zhou, Y.; Li, Z.; Song, Y.; Cai, J.; Tu, W. Evaluating and Characterizing Urban Vibrancy Using Spatial Big Data: Shanghai as a Case Study. *Environ. Plan. B Urban Anal. City Sci.* **2020**, *47*, 1543–1559. [\[CrossRef\]](#)
80. Downs, A. The Law of Peak-Hour Expressway Congestion. *Traffic Q.* **1962**, *16*, 393–409.
81. Kurniawan, G.J.; Soemardiono, B.; Novianto, D. Cultural Resonance: Enhancing Heritage Identity of Spaces with Digital Engagement. *J. Archit. Des. Urban.* **2025**, *7*, 91–100. [\[CrossRef\]](#)
82. Wangbao, L. Spatial Impact of the Built Environment on Street Vitality: A Case Study of the Tianhe District, Guangzhou. *Front. Environ. Sci.* **2022**, *10*, 966562. [\[CrossRef\]](#)
83. King, K. Jane Jacobs and ‘The Need for Aged Buildings’: Neighbourhood Historical Development Pace and Community Social Relations. *Urban Stud.* **2013**, *50*, 2407–2424. [\[CrossRef\]](#)
84. Buitelaar, E.; Moroni, S.; De Franco, A. Building Obsolescence in the Evolving City. Reframing Property Vacancy and Abandonment in the Light of Urban Dynamics and Complexity. *Cities* **2021**, *108*, 102964. [\[CrossRef\]](#)
85. Yeh, A.G.-O.; Li, X. A Cellular Automata Model to Simulate Development Density for Urban Planning. *Environ. Plan. B Plan. Des.* **2002**, *29*, 431–450. [\[CrossRef\]](#)
86. Pan, C.; Zhou, J.; Huang, X. Impact of Check-In Data on Urban Vitality in the Macao Peninsula. *Sci. Program.* **2021**, *2021*, 7179965. [\[CrossRef\]](#)
87. Wen, L.; Kenworthy, J.; Marinova, D. Higher Density Environments and the Critical Role of City Streets as Public Open Spaces. *Sustainability* **2020**, *12*, 8896. [\[CrossRef\]](#)
88. Cui, G.; Wang, M.; Fan, Y.; Xue, F.; Chen, H. Assessment of Health-Oriented Layout and Perceived Density in High-Density Public Residential Areas: A Case Study of Shenzhen. *Buildings* **2024**, *14*, 3626. [\[CrossRef\]](#)
89. Zhao, Y.; Ponzini, D.; Zhang, R. The Policy Networks of Heritage-Led Development in Chinese Historic Cities: The Case of Xi’an’s Big Wild Goose Pagoda Area. *Habitat Int.* **2020**, *96*, 102106. [\[CrossRef\]](#)
90. Zhao, L.; Fan, X.; Lin, H.; Hong, T.; Hong, W. Impact of Expressways on Land Use Changes, Landscape Patterns, and Ecosystem Services Value in Nanping City, China. *Pol. J. Environ. Stud.* **2021**, *30*, 2935–2946. [\[CrossRef\]](#)
91. Shi, X.; Liu, D.; Gan, J. A Study on the Relationship between Road Network Centrality and the Spatial Distribution of Commercial Facilities—A Case of Changchun, China. *Sustainability* **2024**, *16*, 3920. [\[CrossRef\]](#)
92. Mackett, R.L.; Thoreau, R. Transport, Social Exclusion and Health. *J. Transp. Health* **2015**, *2*, 610–617. [\[CrossRef\]](#)
93. Xie, Z.; Huang, B.; Lee, H.F.; Liu, Y.; Zhen, F. Unraveling the Determinants of Intra-City Commuting Flows with a Spatially Weighted Interaction Model: Nanjing, China as a Case Study. *Cities* **2025**, *162*, 105962. [\[CrossRef\]](#)
94. Niu, X.; Wu, W.; Li, M. Influence of Built Environment on Street Vitality and Its Spatiotemporal Characteristics Based on LBS Positioning Data. *Urban Plan. Int.* **2019**, *34*, 28–37. [\[CrossRef\]](#)
95. Li, M.; Liu, J.; Lin, Y.; Xiao, L.; Zhou, J. Revitalizing Historic Districts: Identifying Built Environment Predictors for Street Vibrancy Based on Urban Sensor Data. *Cities* **2021**, *117*, 103305. [\[CrossRef\]](#)
96. Bernabeu-Bautista, Á.; Serrano-Estrada, L.; Marti, P. The Role of Successful Public Spaces in Historic Centres. *Insights Soc. Media Data. Cities* **2023**, *137*, 104337. [\[CrossRef\]](#)
97. Duan, J.; Lan, W.; Jiang, Y. An Evaluation Approach to Spatial Identity in Historic Urban Areas from a Humanistic Perspective. *Front. Archit. Res.* **2022**, *11*, 806–814. [\[CrossRef\]](#)
98. Pourbahador, P.; Brinkhuijsen, M. Municipal Strategies for Protecting the Sense of Place through Public Space Management in Historic Cities: A Case Study of Amsterdam. *Cities* **2023**, *136*, 104242. [\[CrossRef\]](#)

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.