

Article

Beyond Homogenization: Spatio-Temporal Dynamics of Urban Vitality and the Nonlinear Role of Built Environment in Shenyang's Historic Urban Area

Zijing Wang, Yanpeng Gao, Xinrui Wei, Chang Lyu and Li Li *

Jangho Architecture College, Northeastern University, Shenyang 110169, China; 2301574@stu.neu.edu.cn (Z.W.); gaoyanpeng@mail.neu.edu.cn (Y.G.); weixr1@mails.neu.edu.cn (X.W.); lvc1@mails.neu.edu.cn (C.L.)

* Correspondence: lili1118@mail.neu.edu.cn

Abstract

The vitality dynamics of historic urban areas under high tourism pressure and their underlying mechanisms remain not fully understood, posing a challenge to sustaining their uniqueness against homogenized redevelopment. To explore this issue, this study utilises human mobility data and an XGBoost-SHAP model to examine the spatio-temporal dynamics of block-level vitality and to uncover the nonlinear effects of built environment factors in Shenyang, China. The results indicate that: (1) Diverging from the commuting patterns of general urban areas, the vitality of historic urban areas presents unique spatio-temporal shifts, transitioning from commercial centers on weekdays to a commercial-cultural mix during holidays. (2) The determinants of vitality vary temporally, shifting from accessibility-oriented (subway) on weekdays to heritage-oriented (state historic sites) during holidays. (3) By applying the 'Three-Factor Theory' from satisfaction research to decode nonlinear effects, the study classifies factors into Performance (functional density), Basic (proximity to water bodies), and Excitement (distance to subway and state historic sites). The findings guide urban renewal to prioritize systemic and sustainable vitality across the historic urban areas rather than maximizing vitality in specific locations.

Keywords: historic urban area; built environment; urban vitality; nonlinear relationship; three-factor theory; spatial temporal dynamics

1. Introduction

As global urbanization shifts from outward expansion to internal consolidation, urban renewal has become a key strategy for high-quality development. Historic urban areas act as guardians of urban heritage, preserving unique spatial memories and cultural values. However, early renewal efforts often relied on large-scale demolition and the construction of imitation architecture that ignored the local context [1–4]. This approach caused a loss of internal momentum, leading to scattered communities, divided spaces, and cultural hollowing out [5–7]. Ultimately, these areas risk becoming artificial commercial zones without authentic life. Existing studies mostly focus on general urban areas. However, the mixed land use and diverse populations of historic urban areas create vitality patterns that are very different from those found in general areas [8,9]. Therefore, this study aims to uncover the spatio-temporal patterns, as well as the nonlinear drivers, of vitality in historic urban areas. The findings are intended to support sustainable vibrancy and add to the theory of urban vitality.



Academic Editor: Soheil Sabri

Received: 29 January 2026

Revised: 26 February 2026

Accepted: 3 March 2026

Published: 6 March 2026

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The vitality of historic urban areas and their driving factors show great complexity and vary significantly across different time periods. While vitality in general urban districts is mostly driven by commuting and daily commerce, which creates predictable rhythms [10,11], historic urban areas experience unique fluctuations. These variations come from the interaction of cultural significance, tourism, and local identity. Specifically, week-day activity is shaped by the daily lives of residents and the local community culture. In contrast, weekends attract visitors from surrounding regions, and holidays are dominated by inbound tourism and festive events. Therefore, this study examines the similarities and differences in vitality characteristics and their driving factors across these distinct time periods within historic urban areas.

The built environment is considered a key determinant of urban vitality [12,13]. Liu and Shi [14] employed binary regression and eigenvector spatial filtering (ESF) models to investigate the link between built environment factors and block-level vitality. Their findings showed that job–housing balance, floor area ratio, open space, and road density positively influence vitality, though the intensity varies across spatial scales. Similarly, Fan et al. [15] utilized a multiscale geographically weighted regression model to analyze spatial heterogeneity and identified ten key determinants of neighborhood vitality. However, these studies typically assume linear relationships, potentially overlooking nonlinear associations and threshold effects. Recent applications of machine learning suggest that these relationships are often nonlinear and vary across variables [16–19]. Despite this, few studies have used machine learning to specifically examine nonlinear influences on vitality within historic urban areas.

This study uses Baidu Heat Map data to provide a refined measurement of neighborhood vitality within the historic district of Shenyang. By employing the eXtreme Gradient Boosting-Shapley Additive exPlanations (XGBoost-SHAP) framework, it investigates the impact of built environment characteristics on urban vitality, specifically focusing on nonlinear effects. This research contributes to the literature in three ways. First, it reveals that vitality and its determinants exhibit distinct spatio-temporal patterns across week-days, weekends, and holidays. Second, it identifies pervasive nonlinear relationships between vitality and the built environment, offering nuanced insights for the planning of historic urban areas. Third, it integrates the three-factor theory with the XGBoost-SHAP method to analyze the primary drivers of vitality and their nonlinear interactions in historic urban contexts.

The paper is organized as follows. Section 2 reviews the relevant literature. Section 3 introduces the study area, data, and methods. Section 4 shows the empirical results comprehensively. Section 5 discusses the findings and their implications for urban vitality. The final section presents the conclusions and limitations.

2. Literature Review

This section establishes the theoretical framework for the study by reviewing the evolution of urban vitality research. First, it traces the transition from traditional surveys to multisource big data (Section 2.1), laying the foundation for the application of Baidu Heat Map data to quantify urban vitality in this paper. Second, it synthesizes the environmental correlates of vitality (Section 2.2), directly informing the selection of built environment indicators used in the subsequent analysis. Third, by pairing the superior nonlinear modeling capabilities of the XGBoost algorithm with the “three-factor theory” (Section 2.3), this study interprets asymmetric relationships and translates threshold effects into actionable renewal strategies, thereby addressing the theoretical disconnect between quantitative models and planning strategies. This synthesis frames critical research gaps regarding

temporal heterogeneity in historic urban areas and the absence of a prioritized strategy framework for urban renewal, justifying the proposed research design.

2.1. Theory and Measurement of Urban Vitality

The concept of vitality originated in the biological and physical sciences and has since been adopted across diverse disciplines, leading to varied interpretations. Urban vitality was first proposed by Jacobs [20] as a fundamental attribute of vibrant and livable cities. It reflects the intensity of human interaction and activity within urban spaces. Lynch [21] defined vitality as the degree to which spatial settlement patterns support the biological requirements and capabilities of human beings.

The measurement of urban vitality varies significantly based on the research focus [22–25]. Traditional studies primarily relied on field surveys, such as activity logs and questionnaires. However, these methods often involved small sample sizes and struggled to capture broader vitality patterns. With the rise of big data and information technology, the quantification of urban vitality now benefits from richer data sources, larger sample sizes, and expanded analytical scales ranging from micro to macro levels [26–29]. For instance, Ratti [30] pioneered the use of mobile phone signaling data to represent urban activity intensity by examining pedestrian flows in Milan. Hasan et al. [31] extracted location and sociodemographic data from Twitter to classify individual behaviors and propose a daily activity model. Similarly, Xia et al. [32] used Baidu Heat Map data as a foundation for studying the vitality of urban streets.

2.2. Environmental Correlates of Vitality

Existing research has extensively examined the influence of the built environment on urban vitality. Studies suggest that vitality arises from the combined effects of multiple environmental attributes [33,34]. Jacobs [20] proposed that concentration, diversity, opportunities for encounter, and a mixture of old and new buildings constitute favorable conditions for street vitality. In her view, a lively urban environment requires six key elements: density, mixed land use, small block size, varied building ages, accessibility, and the avoidance of border vacuums. Building on these foundational theories, the quantitative evaluation of urban vitality has progressed rapidly in recent years. The widespread use of big data and machine learning has allowed researchers since 2018 to combine traditional variables with new, detailed indicators that offer better spatio-temporal accuracy. Following this trend, our study selects representative research to balance findings from both general urban areas and historic districts. As summarized in Table 1, the selected indicators were categorized into seven attribute groups: socioeconomics, location and transportation, spatial form, functional character, building scale, ecological environment, and historic attractiveness [35–38].

Table 1. Indicator associated with urban vitality in selected empirical studies since 2018.

Dimension	Indicator	Sources
Socioeconomics	Population density	Delclòs-Alió et al. [39], Lee et al. [40]
	Block house prices	Lee et al. [40], Fan et al. [15], Gómez-Varo et al. [41]
Location and transportation	Betweenness	Gómez-Varo et al. [41], He et al. [42]
	Distance to public transport	Shao et al. [43], Lee et al. [40]
	Distance to border vacuums	Delclòs-Alió et al. [39], Gómez-Varo et al. [41]
	Road network density	Jin et al. [44], Fan et al. [15], Long et al. [45], Shao et al. [40], He et al. [42]
	Intersection density	Shao et al. [43], He et al. [42]

Table 1. *Cont.*

Dimension	Indicator	Sources
Spatial form	Block size	Delclòs-Alió et al. [39], Lee et al. [40]
	Form compactness	Fan et al. [15]
	Fragmentation degree	Fan et al. [15], Lee et al. [40], He et al. [42]
Functional character	Functional density	Jin et al. [44], Fan et al. [15], Zhang et al. [46], Long et al. [45], Shao et al. [40], Doan et al. [47]
	Functional diversity	Jin et al. [44], Liu et al. [48], Fan et al. [15], Long et al. [45], Shao et al. [43]
	Residential and non-residential mix	Delclòs-Alió et al. [39], Gómez-Varo et al. [41]
	Mixture of commercial and public facilities	Gómez-Varo et al. [41]
	Basic and non-basic commercial balance	Gómez-Varo et al. [41]
Building scale	Building density	Delclòs-Alió et al. [39], Jin et al. [44], Fan et al. [15], Shao et al. [43], Lee et al. [40], He et al. [42]
	Floor area ratio	Jin et al. [44], Fan et al. [15], Doan et al. [47], He et al. [42]
	Average years of construction of buildings	Delclòs-Alió et al. [39], Gómez-Varo et al. [41]
	Build Year diversity	Delclòs-Alió et al. [39], Gómez-Varo et al. [41]
Ecological environment	Green space ratio	Jin et al. [44], Fan L et al. [15], Lee et al. [40]
	Distance to parks	Gómez-Varo et al. [41], Liu et al. [48], Shao et al. [43], He et al. [42]
	Proximity to water bodies	Fan et al. [15]
Historic attractiveness	Historical feature concentration	Long et al. [45]
	Grade of cultural heritage site	Zhang et al. [46]

2.3. Asymmetric Relationships Between Vitality and Built Environment

Prior studies frequently assumed a linear relationship between the built environment and urban vitality [14,15,44]. However, the recent literature demonstrates that built environment factors exert complex nonlinear and asymmetric effects [16–19]. Urban vitality is effectively enhanced only when these factors are maintained within specific optimal ranges. To capture these intricate dynamics, researchers increasingly rely on machine learning. For example, Lee et al. [40] compared Random Forest (RF), Gradient Boosting Decision Trees (GBDT), and XGBoost models. They ultimately selected XGBoost as the optimal algorithm to explore the nonlinear associations, threshold effects, and interactions between the Street Built Environment (SBE) and urban vitality.

While machine learning accurately models these statistical relationships, a robust theoretical framework is needed to interpret their asymmetric nature. To achieve this, our study applies the three-factor theory, which originated in satisfaction research [49–52], to explain how built environment factors influence urban vitality. This theory builds upon importance-performance analysis (IPA) [53]. Traditional IPA evaluates quality attributes based on performance and importance to set improvement priorities, but it assumes that these relationships are strictly linear and symmetric [54]. As shown in Figure 1, the three-factor theory overcomes this limitation by showing how an attribute impacts overall vitality asymmetrically [55]. Basic factors reduce vitality when they underperform but offer no additional benefits once they are adequate. Excitement factors significantly boost vitality at high levels but do not cause harm when they are absent. Performance factors show a direct, linear relationship with vitality [56]. Because of “loss aversion,” the negative impact of underperforming basic factors is much stronger than the positive effects of performance or excitement factors. This makes basic factors the most urgent priority for urban planning [57].

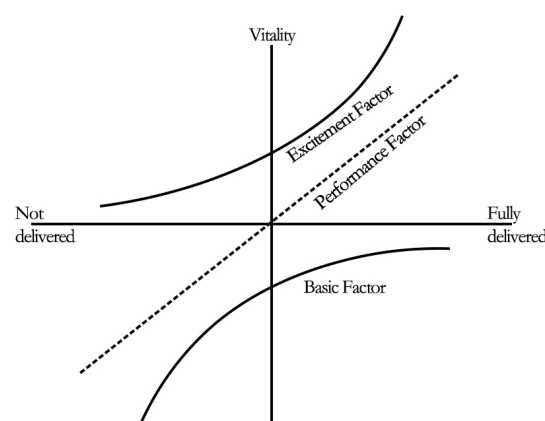


Figure 1. Three factor types and asymmetric effects on urban vitality. (source: Vavra et al. [55]).

To distinguish among these three types of factors, previous studies often used dummy variable regression based on penalty-reward contrast analysis [51]. Researchers typically used high and low performance variables to classify attributes. If only the low performance variable is significant, it indicates a penalty and is labeled a basic factor. If only the high performance variable is significant, it represents a reward and is considered an excitement factor. When both are significant, the attribute is a performance factor.

However, a major limitation of this approach is that it forces researchers to group complex data into three rigid categories [58]. This grouping hides how specific scores affect results and fails to capture the continuous, nonlinear influence of an attribute. Therefore, an ideal approach should evaluate an attribute across its entire performance scale without artificial data grouping. To address these issues, this study combines the nonlinear modeling of XGBoost with the three-factor theory. We aim to systematically classify the environmental elements that affect the vitality of historic urban areas to provide targeted strategies for urban renewal.

2.4. Literature Synthesis and Research Focus

A review of the literature reveals three main trends in the study of urban vitality. First, measurement methods have moved from traditional, small-scale surveys to the use of multisource big data. This change allows researchers to measure urban vitality dynamically and on a large scale. Second, built environment assessments have shifted from looking at isolated variables to using systematic frameworks that capture a wide range of urban features. Third, analytical methods have moved beyond simple linear assumptions. Researchers now frequently use machine learning algorithms to discover complex, nonlinear relationships and threshold effects between environmental factors and urban vitality [16–19].

However, several unexplored issues remain in the current research. First, in terms of timing, most studies focus on typical urban centers that rely on predictable commuter traffic. Historic urban areas, on the other hand, show unique changes driven by tourism and leisure. These irregular patterns are rarely studied. Therefore, we need to analyze vitality patterns in these specific areas across different times, including weekdays, weekends, and holidays. Second, regarding the driving forces, even though evaluation frameworks have become more detailed, they often ignore the specific spatio-temporal variations found in historic districts. Current studies rarely show how the main influencing factors shift from resident-focused weekdays to tourist-focused holidays. As a result, it is important to understand how the impact of built environment features changes over time. Third, there is a gap between research findings and actual urban planning. Even when studies recognize uneven relationships, very few apply the three-factor theory to urban vitality

research. Because of this, we lack a clear framework to turn research results into practical urban renewal strategies. Therefore, built environment indicators must be classified into “Basic,” “Performance,” or “Excitement” factors to help guide evidence-based planning.

To address these gaps, this paper has three main goals. First, it aims to reveal specific spatio-temporal patterns of vitality across weekdays, weekends, and holidays. Second, it seeks to explain time-sensitive, nonlinear mechanisms using a combined XGBoost-SHAP framework to show how the impact of built environment factors changes on different days. Third, the study aims to classify these indicators based on the three-factor theory and suggest prioritized strategies for the adaptive reuse and planning of historic urban areas.

3. Method

The overall analytical framework of this study is shown in Figure 2. It comprises four key stages: (1) collecting and processing multisource data, including Baidu Heat Map data to measure urban vitality (the dependent variable) and various geographic datasets to measure built environment factors (the independent variables); (2) analyzing the spatio-temporal characteristics of vitality while measuring built environment factors across seven dimensions; (3) employing the XGBoost-SHAP model in Python 3.8 to determine the relative importance of variables and explore time-varying nonlinear relationships; (4) integrating findings with the three-factor theory to develop a prioritized planning strategy framework for urban renewal.

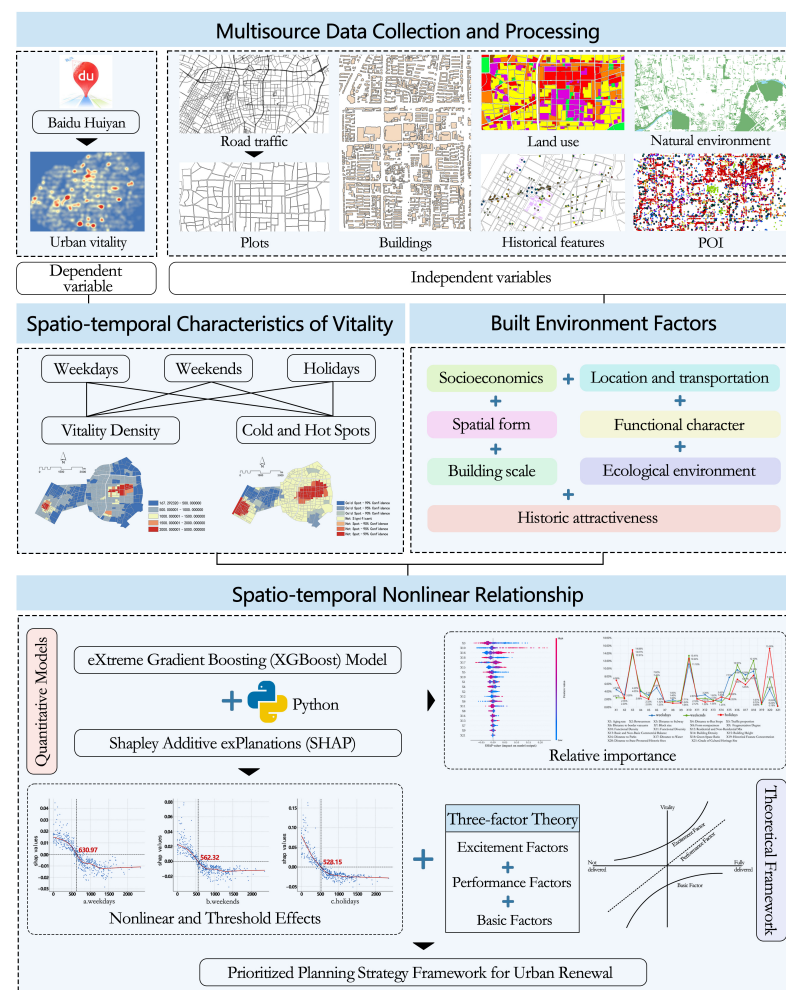


Figure 2. Analytical framework of the research.

3.1. Study Area

Shenyang was designated as a National Famous Historical and Cultural City by the State Council in 1986 [59], reflecting its distinctive cultural heritage and landscape within Liaoning Province. Figure 3 illustrates the boundaries of the historic urban area. According to the Shenyang Historic and Cultural City Protection Plan (2020–2035) [60], this area comprises three major historic layers: the Shengjing City of the Ming and Qing dynasties, the South Manchuria Railway (SMR) Zone, and the Commercial Settlement established during the Republican era. The total area covers approximately 20.7 square kilometers.



Figure 3. Range of the study area. (a) Location of Liaoning Province in China; (b) Location of Shenyang's Historic Urban Area in Liaoning Province; (c) Detailed Boundary of Shenyang's Historic Urban Area.

This specific area was chosen as the research site because of its rich culture, active economy, and typical urban challenges. First, it contains two provincial historic districts and over 100 heritage sites [60–62]. These spaces preserve the city's memory and provide an excellent sample to study how traditional environments impact modern urban vitality. Second, the commercial landscape is highly diverse. It features functional clusters like large supermarkets, department stores, pedestrian streets, and business offices. This lively mix of people and activities creates ideal conditions for analyzing human behavior and vitality patterns. Finally, the district faces common problems shared by historic areas across the country. There is a clear conflict between protecting heritage and upgrading modern infrastructure. Additionally, an uneven distribution of resources has led to local decline and fragmented vitality. By combining deep historical value with typical urban problems, this area serves as a highly representative case. It is an ideal location to explore the drivers of urban vitality and to find sustainable renewal strategies.

3.2. Data Sources

The primary data sources for this study include population heat map data, road networks, Points of Interest (POI), public transit stops, building information, and population statistics. All datasets were obtained from open-access online sources. Before analysis, all datasets underwent strict preprocessing to ensure data quality and spatial consistency.

The specific details and sources of these multisource geographic datasets are summarized in Table 2.

For the population thermal data, we selected 18 days with good weather and normal travel conditions, covering weekdays, weekends, and holidays across different seasons from 2024 to 2025. We collected hourly heat point data from 8:00 AM to 10:00 PM. This selection was based on three main reasons. First, because seasonal changes greatly impact the spatio-temporal vitality of northern Chinese historic districts, we chose days that accurately reflect Shenyang’s distinct four-season climate [63]. Second, within each season, we included a balanced mix of weekdays, weekends, and public holidays to capture variations over time. Third, days with extreme weather, major events, or unusual working arrangements were excluded to prevent outside disruptions.

The road network required detailed topological processing. This included removing duplicate roads, correcting offsets, filling missing segments, extending dead-end roads, and merging roads of different grades. To define spatial plots, we created buffers based on the width of each road type and removed these road areas from the study zone to form distinct spatial units. POI data underwent deduplication, coordinate system conversion, and reclassification into 14 major functional categories. Additionally, historical feature data was carefully filtered, identifying 5 national-level, 31 provincial-level, and 45 municipal-level cultural heritage sites, along with 128 historic buildings within the study area. Finally, population statistics data was extracted from the 2021 Seventh National Population Census. This focused specifically on the total population and the demographic aged 65 and older at the subdistrict level.

Table 2. Multisource geographic data.

Data Name	Information Included	Data Source
Population thermal data	Population distribution locations, times	Baidu Maps Open Platform [64] (https://lbsyun.baidu.com/ , accessed on 15 April 2025)
Road traffic	Road classification, road length, rail transit stations, public transport stops	OpenStreetMap [65] (https://www.openstreetmap.org , accessed on 15 April 2025)
Plots	Plot area, perimeter, land use type, building density, entrance/exit locations	Generated by the authors
Buildings	Building footprint area, building height	China Multi-Attribute Building Dataset (CMAB) on Figshare [66] (https://figshare.com , accessed on 20 April 2025)
Natural environment	Large parks, water bodies, vegetation coverage	OpenStreetMap, Science Data Bank [67] (https://www.scidb.cn/en , accessed on 23 April 2025)
Historical features	Cultural heritage sites, historic buildings	Official websites of the State Council, provincial, and municipal governments [62,68,69]
POI	Functional types, locations	Amap Open Platform [70] (https://lbs.amap.com/ , accessed on 15 April 2025)
Population	Total street population, elderly population	National Bureau of Statistics [61] (https://www.stats.gov.cn/ , accessed on 20 February 2026)

3.3. Variables

This study utilizes population thermal data to represent block vitality, which serves as the dependent variable. To capture the multifaceted nature of the built environment,

the independent variables are structured across seven clear dimensions: socioeconomics, focusing on the aging rate of residents; location and transportation, evaluating regional accessibility and urban fabric continuity; spatial form, capturing the physical layout, scale, and structural features of the block; functional character, assessing the variety and mix of land-use functions using POI data; building scale, examining physical volume and density of buildings; ecological environment, evaluating accessibility to natural amenities; and historic attractiveness, quantifying historical value through the concentration and protection levels of cultural heritage sites. To ensure model reliability, multicollinearity diagnostics were conducted prior to analysis. All selected variables satisfied the Variance Inflation Factor (VIF) requirements, and the specific composition and descriptions of these indicators are summarized in Table 3.

Table 3. Variable description.

Variable	Dimension	Indicator	Description
Dependent variable		Block vitality	Average aggregated heat value within each block over the studied time period
Independent variables	Socioeconomics	Aging rate	Percentage of residents aged 65 and over relative to the total subdistrict population
	Location and transportation	Betweenness	Frequency with which a node appears on the shortest path between other nodes
		Distance to subway	Euclidean distance from the block centroid to the nearest subway station
		Distance to bus stops	Euclidean distance from the block centroid to the nearest bus stop
		Traffic proportion	Combined advantages of driving, public transit, and walking accessibility
		Distance to border vacuums	Euclidean distance to large-scale single-use barriers detrimental to urban vitality
	Spatial form	Block size	Block unit area
		Form compactness	Measurement of spatial planar shape compactness
		Fragmentation degree	The extent of land subdivision within the block
	Functional character	Functional density	Density of POI
		Functional diversity	Diversity ratio of different POI functional types
		Residential and non-residential mix	Residential and Non-Residential Use Balance
	Building scale	Basic and non-basic commercial balance	Balance between essential and non-essential commercial facilities
		Building density	Ratio of building footprint area to the site area
		Building height	Mean height of buildings
	Ecological environment	Distance to parks	Euclidean distance from the block centroid to the nearest park
		Proximity to water bodies	Euclidean distance from the block centroid to the nearest water body
		Green space ratio	Ratio of vegetation coverage area to total area
	Historic attractiveness	Historical feature concentration	Ratio of historic building POIs
		Distance to state protected historic sites	Euclidean distance from the block centroid to the nearest state protected historic sites
		Grade of Cultural Heritage Site	Weighted score based on the protection level of cultural heritage sites and historic buildings

While Table 3 provides a summary of all variables, several specific indicators regarding location and transportation, spatial form, and functional character require detailed methodological elaboration.

Regarding the location and transportation dimension, we employed betweenness with a 5000-m search radius to measure vehicular accessibility in historic urban areas. High values typically identify vibrant urban cores, while low values indicate gated communities or cul-de-sacs that may require improved connectivity. Methodologically, a road topology network was generated in ArcGIS 10.2, with block entrances identified at intersections. We

used the Urban Network Analysis (UNA) toolkit from the City Form Lab (MIT/SUTD) for the calculation [71]. This tool surpasses standard space syntax methods by incorporating parcel features, using geometric distance metrics, and allowing weighted building attributes. The specific formula is as follows [39]:

$$BTW^r[i] = \sum_{j,k \in -\{i\}; d[j,k] \leq r} \frac{n_{jk[i]}}{n_{jk}} \times W[j] \quad (1)$$

The betweenness of node i is defined as the number of times node i appears on the shortest path between all other node pairs within a given radius r . Specifically, n_{jk} denotes the number of shortest paths from node j to node k within radius r , while $n_{jk[i]}$ represents the subset of these paths passing near i . $W[j]$ indicates the weight assigned to each node.

Furthermore, within the same dimension, traffic proportion is evaluated by combining multiple dimensions. Vehicular convenience is measured using betweenness, while walkability is assessed based on road network and intersection density. Accessibility to public transit is determined by the distance to the nearest subway stations and bus stops [15]. In parallel, functional diversity is calculated using the Shannon–Wiener Diversity Index, with the specific formula as follows:

$$TD[i] = -\sum_{i=1}^n p_i \ln p_i \quad (2)$$

Among these, $n = 3$ and p_i represent the proportion of each transportation mode's accessibility within the study unit relative to the total accessibility value. Values closer to $\ln 3$ indicate greater balance among the three modes, while values closer to 0 indicate accessibility is concentrated in a single mode.

In *The Death and Life of Great American Cities*, Jacobs [20] argued that certain urban designs and land uses undermine city vitality by creating “border vacuums” that obstruct the natural flow of human activity. In this study, selected border vacuums include three categories [38,72]: large, single-function buildings exceeding 5000 square meters (e.g., theaters, hospitals, museums, shopping malls, bath centers, and hotels); single-use plots larger than 5000 square meters (e.g., green spaces, sports fields, and vacant lots); and major linear infrastructures, such as highways, railway lines, and dedicated parking lots.

Moving to the spatial form dimension, which captures the physical configuration, scale, and structural attributes of the block itself, two key metrics require explanation as they reflect how the density of the urban fabric influences vitality. First, the formula for calculating form compactness is as follows [15]:

$$SC[i] = \frac{\sqrt{\pi S}}{V} \quad (3)$$

where $SC[i]$ represents spatial compactness, S denotes the block area, and V indicates the total study area. A compactness value of 1 corresponds to a circular block, while all other shapes yield values less than 1.

Second, the formula for calculating fragmentation degree is as follows [15,39]:

$$SFI[i] = (F - 1) \times \frac{\text{Min}(P_u)}{S} \quad (4)$$

where F represents the aggregate of all patches within block i , $\text{Min}(P_u)$ denotes the area of the smallest land parcel within the block, and S indicates the total area of block i .

The functional character dimension assesses the variety and mix of land-use functions within a block. When residential areas are integrated with office and commercial facilities,

residents can access work, shopping, education, and other daily necessities within walking distance. This integration aligns with the “15-min neighborhood” planning concept, which emphasizes proximity to essential services. The formula for calculating the residential and non-residential mix is as follows [72]:

$$\text{RNR}[i] = 1 - \left| \frac{\text{Res}_i - \text{NonRes}_i}{\text{Res}_i + \text{NonRes}_i} \right| \quad (5)$$

where Res_i represents the number of residential POIs and NonRes_i represents the number of non-residential POIs. When residential and non-residential functions are perfectly balanced, $\text{RNR}[i] = 1$. When one function dominates completely, $\text{RNR}[i]$ approaches 0.

Following the same mathematical approach, we also calculated the basic and non-basic commercial balance. Departing from conventional urban geography categorizations, this study classifies living service facilities, public facilities, and transportation services as essential commercial facilities. Conversely, catering, finance and insurance, retail, and sports and leisure services are grouped as non-essential commercial facilities. Essential commerce primarily supports the daily needs of local residents, whereas non-essential commerce largely attracts external consumption. An imbalance between these two types can lead to inadequate service provision or commercial instability, making an area particularly vulnerable to fluctuations in tourism.

3.4. Analysis Methods

3.4.1. XGBoost

XGBoost is an optimized machine learning model based on gradient boosting. Its core principle involves the iterative addition of classification and regression trees. These trees are used to fit the residuals between the predictions of previous models and the true values of the training samples [73]. Compared to traditional linear regression, XGBoost is much better at capturing complex, nonlinear relationships and detailed variable interactions. It does this without needing strict assumptions about data distribution [74]. Furthermore, unlike traditional Gradient Boosting Decision Trees (GBDT), XGBoost includes built-in regularization techniques. These techniques penalize model complexity, which helps prevent overfitting and improves overall predictive reliability [75]. The objective function is formulated as follows [73,76]:

$$L(\phi) = \sum_i l(y_i, \hat{y}_i) + \sum_k \Omega(f_k) \quad (6)$$

where $L(\phi)$ represents the objective function value, which is minimized during computation; y_i denotes the original vitality value of the i th sample x_i ; $\hat{y}_i$ is the predicted value for x_i ; $l(y_i, \hat{y}_i)$ is the loss function for a single sample; and $\sum_k \Omega(f_k)$ is the complexity of the k th tree.

The data was randomly divided into training and testing sets in a 7:3 ratio to rigorously evaluate model configurations [77,78]. During the tuning process, several key hyperparameters were adjusted to balance computation time and predictive accuracy. Specifically, the learning rate controls the step weight during the fitting process, where a smaller value enhances accuracy but necessitates a larger number of decision trees. The maximum tree depth dictates the complexity of individual decision trees, while the minimum child weight determines the minimum sum of instance weights required in a terminal node; both parameters are crucial for constraining overall model complexity and preventing overfitting. Additionally, the Gaussian distribution was utilized as the objective function to appropriately model the continuous variable of urban vitality. Through systematic comparative testing of validation strategies and parameter grids, the results demonstrated that a 5-fold

cross-validation approach outperformed 10-fold cross-validation. Ultimately, the XGBoost model achieved its highest R^2 score and optimal predictive performance when employing the 5-fold cross-validation framework alongside a tree count of 5000, a learning rate of 0.01, a maximum tree depth of 5, and a minimum child weight of 0.8.

As a nonlinear model, XGBoost demonstrates higher accuracy and better generalization than traditional multiple linear regression. However, it lacks interpretability, presenting the common “black box” challenge in machine learning [26,79]. To address this limitation, the SHAP method was introduced in this study.

3.4.2. SHAP

SHAP is a game theory-based approach widely used to interpret the output of machine learning models. It uses Shapley values from cooperative game theory to establish a connection between optimal credit allocation and local model interpretability [80–82]. The core idea of the SHAP method is to compute the marginal contribution of adding a specific feature value to the model. For a given sample x_i , the predicted value y_i is calculated as follows [76]:

$$\hat{y}_i = y_{\text{base}} + \sum_{m=1}^K \text{SHAP}(x_{im}) \quad (7)$$

where y_{base} is the mean predicted value of the sample, $\text{SHAP}(x_{im})$ is the SHAP value of the sample x_i at feature m , and K is the number of sample features. The SHAP method calculates the contribution of each feature based on the prediction results of the machine learning model, thereby addressing the black-box nature of the model.

4. Results

4.1. Spatio-Temporal Characteristics of Vitality in Shenyang's Historic Urban Area

The spatial analysis of vitality density revealed that overall distribution patterns were broadly consistent across weekdays, weekends, and holidays, despite distinct variations in spatial intensity. Block-level vitality for each period was categorized using specific value intervals (500, 1000, 1500, and 2000). These classification results are illustrated in Figure 4.

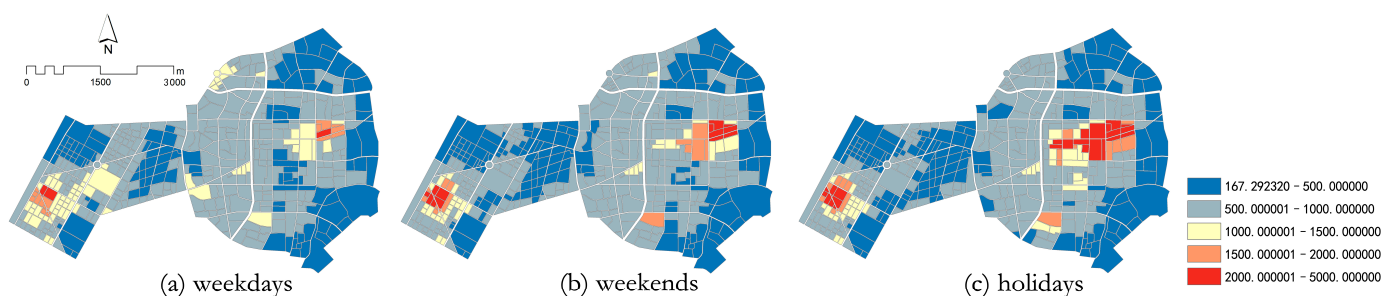


Figure 4. Spatial distribution map of vitality density. (a) Weekdays; (b) Weekends; (c) Holidays.

A Getis-Ord Gi hotspot analysis was employed to statistically evaluate the spatial clustering of neighborhood vitality density. Based on P-values and Z-values, significant clusters of high vitality (hot spots) and low vitality (cold spots) were identified, as illustrated in Figure 5. These clusters were subsequently classified into three confidence levels (Level 1, Level 2, and Level 3). Blocks that did not exhibit statistically significant clustering were categorized as non-significant areas.

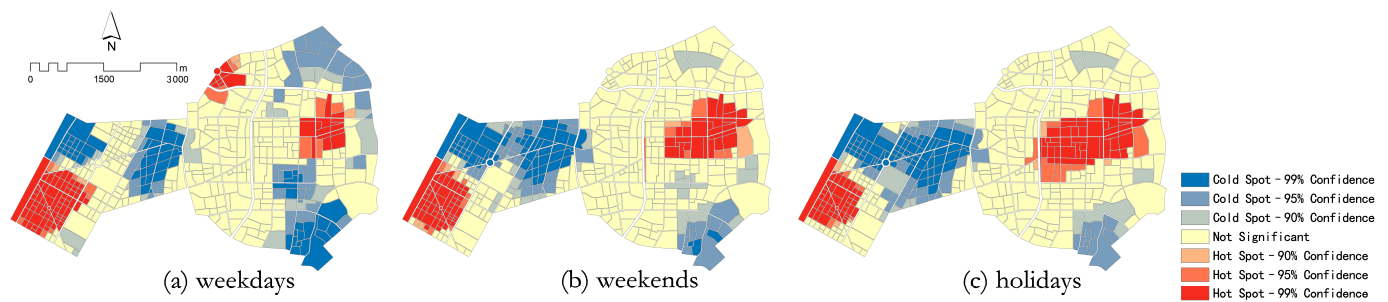


Figure 5. Spatial distribution map of vibrant cold and hot spots. (a) Weekdays; (b) Weekends; (c) Holidays.

The spatio-temporal distribution of vitality in Shenyang's historic urban area exhibits significant heterogeneity. Spatially, a dual-core concentric pattern characterizes weekdays, anchored by two primary commercial clusters. The first, centered on Middle Street (Zhongjie), integrates modern commercial developments—such as Joy City, Wuyue Plaza, and Commercial City—with historic landmarks like the Official Bank of the Three Northeast Provinces. The second cluster, centered on Taiyuan Street, combines commercial complexes (e.g., Parkson, Impression City) with the Shenyang Railway Station transportation hub and the historic China Eastern Railway Building Complex. Both cores function as high-vitality zones underpinned by deep historical foundations. In contrast, lower vitality is concentrated in residential neighborhoods within the northwest and central sectors, as well as in Wanliutang Park to the southeast.

Temporally, the vitality pattern evolves dynamically as leisure time extends, transitioning from 'dual-core clustering' on weekdays to a state of 'cultural integration and diffusion' during holidays. This progression unfolds sequentially: on weekends, the primary hotspot begins to expand westward from the Zhongjie commercial core toward the Shenyang Imperial Palace, marking an initial phase of commerce–culture integration. During holidays, this diffusion intensifies, with the hotspot extending further west to Shuncheng Street. Concurrently, the configuration of cold spots transforms; holiday cold spots in the northwest and central areas diffuse outward from Zhongshan Square, while former secondary cold spots centered on the Zhang's Military Government Mansion and Shenyang First People's Hospital gradually weaken or dissipate.

4.2. Temporal Variations in Built Environment Impacts on Vitality

The predictive performance of the XGBoost model was evaluated using the coefficient of determination (R^2), yielding values of 0.652 (weekdays), 0.615 (weekends), and 0.624 (holidays). To assess the relative importance of built environment features, the mean absolute SHAP value was employed. This metric quantifies the average magnitude of a feature's contribution to model predictions, where a higher value indicates greater importance.

As shown in Figure 6, the analysis identified seven built environment indicators that consistently exhibited high importance across all time periods: distance to subway, functional density, distance to parks, proximity to water bodies, green space ratio, distance to border vacuums, and distance to state protected historic sites. Collectively, these indicators accounted for 62.34%, 72.33%, and 71.59% of the total importance on weekdays, weekends, and holidays, respectively. A key temporal variation was observed in the dominant factors. Distance to subway emerged as the most influential factor for weekday and weekend vitality. In contrast, distance to state protected historic sites became the primary factor during holidays. This shift reflects the temporal interaction between visitors' primary activity purposes and the built environment. Additionally, building height demonstrated a

strong, weekday-specific influence, likely attributed to the concentration of work-related activities in high-rise areas.

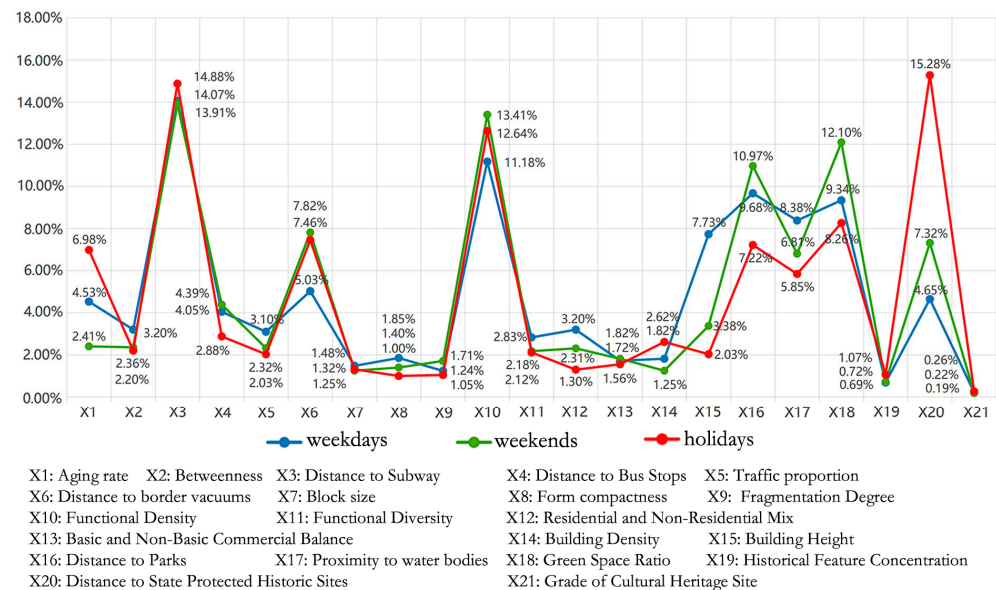


Figure 6. Importance of built environmental characteristics.

4.3. Nonlinear and Threshold Effects of Built Environment on Vitality

SHAP dependence plots visualize the nonlinear relationships between built environment indicators and vitality in the historic urban area. These plots reveal that most indicators exhibit distinct threshold effects. The direction of influence is interpreted based on the SHAP value, where a value greater than 0 indicates a positive impact on neighborhood vitality and a negative value signifies a negative impact. Consequently, the threshold for a given feature is defined as the specific value at which its SHAP values cross zero. This crossing point marks a reversal in the direction of the feature's effect on model predictions.

As illustrated in Figure 7, these nonlinear relationships are interpreted through the performance–basic–exciting factors framework [56,57]. Performance factors, exemplified by functional density, exhibit an approximately linear and positive association with vitality. This relationship is particularly pronounced on weekends and holidays, confirming that higher values reliably predict greater block vitality.

Basic factors demonstrate a complex and non-monotonic relationship where the attribute is expected until a critical threshold is breached. Proximity to water bodies typifies this category. While a general public affinity for water exists, vitality is surprisingly suppressed at very close distances of 600 to 900 m. It remains stable until a second threshold of 2000 to 2200 m and then declines precipitously beyond that point. This indicates a fundamental disadvantage when accessibility is excessively poor.

Exciting factors contribute positively only after exceeding a neutral point. Three indicators fall into this category: distance to subway, distance to border vacuums, and distance to state protected historic sites. Their shared characteristic is an initial negative correlation within a specific range. For example, metro stations show a threshold of approximately 340 m. Vitality is suppressed within these specific ranges. Only beyond these thresholds do these factors cease their negative effect and begin to enhance the urban vitality.

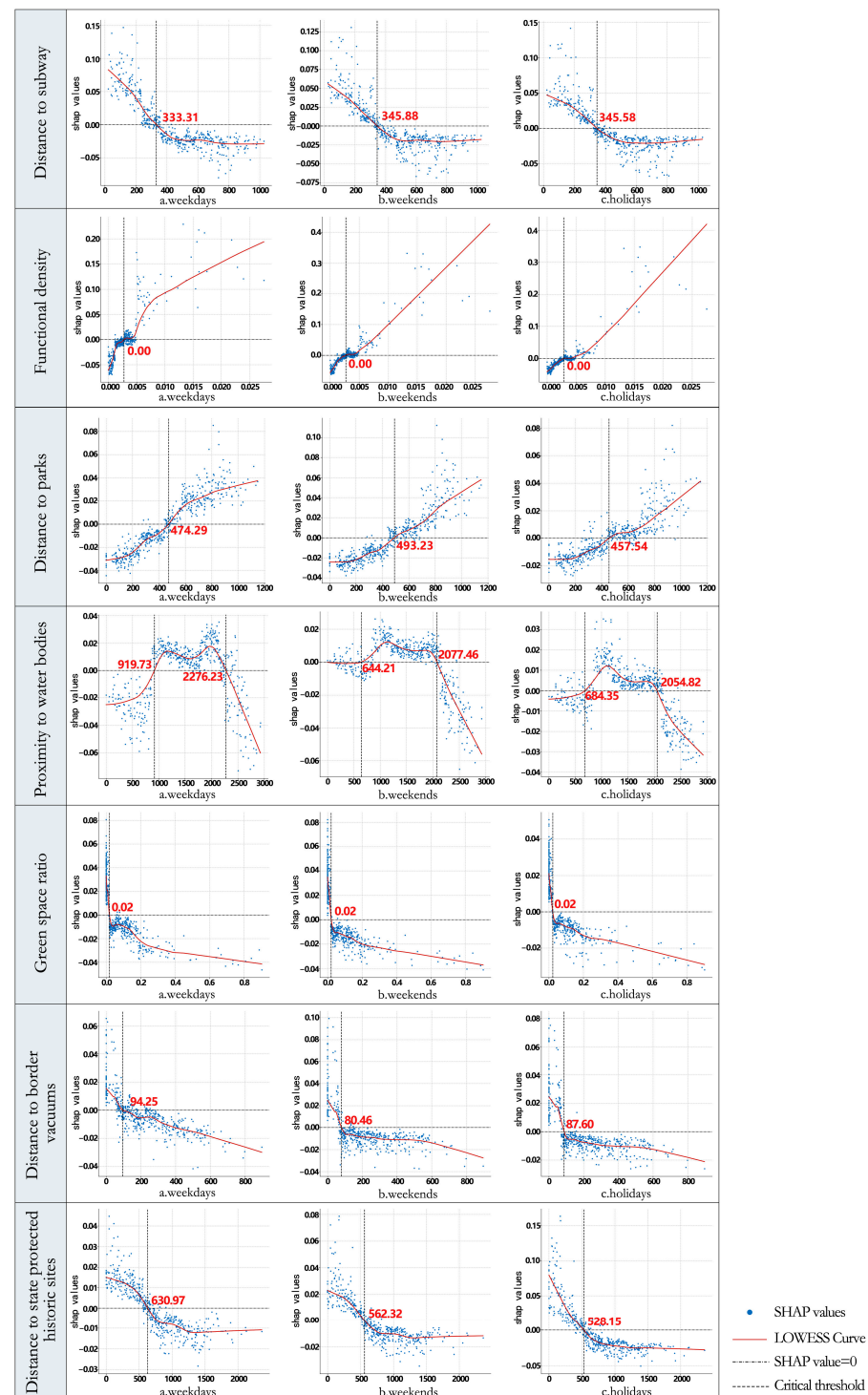


Figure 7. Nonlinear effects of built environment indicators on block vitality.

5. Discussion

5.1. Spatial Distribution of Vitality in Shenyang's Historic Urban Area

The spatial vitality distribution within Shenyang's historic urban area exhibits distinct polycentric characteristics. This observation aligns with Zhang et al. [83], who noted that high-vitality zones in historic contexts like Chongqing are often spatially dispersed, with commercial districts typically exhibiting higher activity levels. This phenomenon is primarily driven by the high concentration of POIs for commercial, cultural, and entertainment functions, coupled with dense building and transit networks. These factors collectively am-

plify human activity and spatial vitality in central zones. However, while this “dual-center” structure fosters localized high vitality, it also reinforces spatial imbalances. Both Zhongjie and Taiyuan Street are characterized by a high concentration of traditional commerce, such as retail and dining. Despite internal business diversity, this results in a monofunctional agglomeration where activities for tourists and residents are largely confined to consumption, lacking richer urban experiences. Consequently, historical elements like the Zhang’s Mansion are often relegated to the status of scenic “backdrops” for commerce, explaining their role as secondary vitality zones. Furthermore, these two core areas face severe overcrowding and capacity overload. In stark contrast, peripheral areas suffer from inferior built environment quality and limited functional diversity, creating a fractured vitality gap. This sharp disparity ultimately undermines the spatial integrity and experiential continuity of the historic urban area as a whole.

Further analysis reveals that the spatial vitality of Shenyang’s historic urban area exhibits distinct temporal dynamics. Vitality patterns undergo significant shifts between weekdays and weekends or holidays, a transition driven primarily by changes in dominant user groups and activity purposes. On weekdays, vitality is defined by the commuting and daily service activities of local residents. It predominantly clusters around commercial centers and transportation hubs, forming a dual-core pattern driven by functional necessity. In contrast, weekends and holidays witness a substantial influx of tourists, shifting the core demand toward historical–cultural experiences and leisure recreation. Consequently, high-vitality hotspots expand and integrate, extending from purely commercial zones into adjacent cultural heritage sites such as the Shenyang Imperial Palace and Zhang’s Mansion. This transition from a commercially driven gravity to a culturally driven gravity highlights the area’s multifaceted appeal. However, it also poses significant challenges, including the risk of crowding out local living spaces, subjecting public services to tidal pressures, and triggering excessive commercialization that may destabilize the local community ecosystem. These factors make achieving sustainable development across all temporal and spatial dimensions a complex challenge.

Based on the empirical findings regarding spatial imbalances and temporal dynamics, several strategies are proposed to enhance the vitality of the historic urban area. To mitigate the observed backdrop effect where historical sites remain secondary to commercial hubs, functional integration is suggested through the establishment of physical and cultural linkages. For instance, creating exploration routes that connect Zhongjie with the Imperial Palace could redistribute peak holiday demand from saturated commercial streets into underutilized cultural buffer zones. Furthermore, to bridge the vitality gap between the dual cores and the periphery, micro-regeneration focusing on functional diversification is recommended. The introduction of community-scale services such as creative workshops and neighborhood amenities may stabilize weekday vitality, which currently relies too heavily on concentrated commercial hubs. These strategies ultimately contribute to a networked, balanced, and sustainable vitality for the entire historic area.

The distribution of vitality in Shenyang is heavily dominated by traditional commercial streets like Zhongjie and Taiyuan Street. This pattern often appears in cities such as Xi’an, Nanjing, and Chengdu, all of which share a mix of deep historical roots and intense commercial development. As a result, the “backdrop effect” identified in this study is a common challenge in these large cities, where historical sites are often reduced to mere commercial add-ons. This shared problem makes our proposed strategies for functional integration and networking highly applicable to similar urban areas. However, applying these strategies to cities with different social and spatial traits requires a more careful approach. In smaller or less commercialized historic towns, for instance, vitality typically centers around a single cultural street or a spread-out network of boutique inns and craft

shops. For these towns, the main issue is rarely the spatial crowding caused by over-commercialization. Instead, they are more likely to face a “vitality hollowing-out” caused by a lack of commercial support.

5.2. Nonlinear Impact of Built Environment on Urban Vitality

The findings of this study are broadly consistent with previous literature, demonstrating both temporal variations and nonlinear characteristics in the built environment’s influence on urban vitality. Seven indicators consistently influenced vitality across all temporal modes (weekdays, weekends, and holidays): distance to subway, functional density, distance to parks, proximity to water bodies, green space ratio, distance to border vacuums, and distance to state protected historic sites.

Transportation services emerged as a dominant driver of regional vitality, particularly emphasizing the critical role of subway accessibility. The distance to the nearest subway station is identified as the most critical determinant of vitality during weekdays and weekends. This reflects the dependence of essential daily activities, such as commuting, on basic functional facilities. However, with the temporal shift to holidays, the impact of subway proximity on vitality is observed to diminish, as travel patterns transition from routine commuting to diverse leisure activities. Furthermore, identified as an exciting factor, closer proximity to subway leads to a disproportionate and significant increase in vitality intensity, consistent with previous studies [39,42]. However, the impact exhibits a distance-decay threshold. When the distance to subway is considerable, the impact of proximity on urban vitality is found to be limited. This aligns with findings by Doan et al. [47], as people are often drawn to areas with greater facility convenience.

The analysis reveals the dual nature of water bodies: they function as regional attractors but local barriers. At a regional scale, water functioned as a fundamental natural amenity that positively correlated with vitality, aligning with research by Fan et al. [15]. However, at close proximity, water bodies appeared to suppress local vitality. This finding is attributed to the conflict between ecological protection and urban connectivity. Pedestrian networks are often interrupted by green buffers around water bodies. Despite being visually attractive, these areas lack the necessary access to support vibrant street activity.

From a design perspective, border vacuums are observed to significantly enhance urban vitality in this context. This observation contrasts with the findings of Delclòs-Alió et al. [38] and Gómez-Varo et al. [40], who proposed that such barriers have negative impacts. This phenomenon is explained by the specific urban form of the study area. In Shenyang’s historic urban area, large shopping malls act as the primary border vacuums. Although street connectivity is interrupted by their massive scale, these malls also function as concentrated centers of vitality. People are willing to accept detours to reach such attractive destinations. Consequently, the mall acts not as a void, but as a centralized pump of vitality that reorganizes local flows around itself. Furthermore, similar to subway stations, a threshold effect is observed in these border vacuums, where a positive influence takes effect only after the initial physical distance is overcome. This reflects an urban layout where large commercial complexes serve as core landmarks and activity hubs.

Regarding cultural heritage, this study challenges the focus on aggregated indicators found in previous works [45,46]. It implies that in a historic district, the density of resources is less impactful than the specific accessibility to high-value nodes. The influence of accessibility is observed to vary over time. It increases significantly from weekdays to weekends, becoming the most critical factor during holidays. As an exciting factor, the boost in vitality is most pronounced near the state historic sites, which serve as primary anchors for the experience economy. The temporal surge observed on weekends and holidays

further validates their role as drivers of leisure destinations, effectively transforming surrounding areas into core zones for tourist consumption.

5.3. Renewal Strategies for Shenyang's Historic Urban Area

Based on our findings regarding time-based changes and the nonlinear impacts of the built environment, this section offers specific renewal strategies for Shenyang's historic urban area. By addressing the unique roles of transit hubs, natural features, commercial centers, and heritage sites, the following strategies aim to create a balanced and sustainable urban vitality. These recommendations also provide a framework for other high-density historic cities struggling to blend modern functions with heritage preservation.

The observed nonlinear threshold effect of subway proximity on urban vitality suggests a potential role for adaptive TOD that focuses on the last-mile experience in historic areas. Given that subway access appears to be a primary driver of vitality during regular days, planning efforts could benefit from targeting specific distance ranges to maximize the impact of transit hubs. Improving pedestrian paths and slow-traffic environments around these stations may help cities anchor daily activities and reduce reliance on private cars. This approach could be considered for transit-dependent, high-density historic cities worldwide, as it may offer spatial guidelines for prioritizing public space improvements where they are most likely to yield vitality returns.

Water bodies often display a dual nature, acting as regional attractions but local barriers. This dynamic suggests that a decentralized, multifunctional green space system might be more effective than large, isolated parks in crowded historic areas. While water features naturally draw people in, the ecological buffers around them can frequently block pedestrian paths and reduce local street activity. To potentially transform these spatial barriers into active areas for daily use, planners might consider shifting toward open waterfront designs that prioritize clear views and physical access. This insight appears relevant for historic cities built around rivers or canals, where balancing ecological protection with continuous urban spaces remains a universal challenge.

The analysis indicates that large commercial complexes can act as centralized “vitality pumps” rather than traditional border vacuums. This finding carries implications for high-density, rapidly growing cities, particularly in Asia. In these settings, massive structures are often built into historic neighborhoods, where they absorb large crowds and reshape local activity. Therefore, spatial strategies might focus on mitigating the barrier effects of these complexes by improving entrance access and pedestrian flow. Such interventions have the potential to better connect the indoor activity of malls with the outside street network, leveraging their massive draw to support a more continuous urban vitality. It is worth noting, however, that this dynamic may have limited applicability in strictly preserved European historic centers, where tight street networks and continuous street-level shops are heavily protected against large enclosed developments.

The finding that easy access to high-value heritage sites correlates with surges in holiday vitality offers a potential roadmap for the experience economy. By improving service quality and building a supportive commercial environment around these protected sites, planners might enhance their overall reach. This approach could help transition the surrounding neighborhoods into core zones for sustainable leisure and tourism. While this strategy may be particularly instructive for tourism-driven historic cities aiming to use key historical nodes to boost broader economic vitality, it remains important to monitor social and economic risks. Over-commercialization, for example, can disrupt the local community, which is a common challenge for globally recognized heritage destinations.

6. Conclusions

Unlike the predictable, commuting-driven rhythms of general urban districts, the spatio-temporal vitality of historic urban areas exhibits unique fluctuations primarily driven by high tourism pressure. To advance the understanding of these complex mechanisms, this study introduces a key methodological innovation by integrating the superior nonlinear modeling capabilities of the XGBoost-SHAP algorithm with the three-factor theory. This approach effectively decodes the built environment drivers and their nonlinear impacts on vitality in Shenyang's historic urban area. The analysis reveals that block-level vitality exhibits distinct spatio-temporal heterogeneity. During weekdays, vitality predictably concentrates in commercial centers to support local routines. However, under the high tourism pressure of weekends and holidays, this vitality diffuses outward toward cultural landmarks. This dynamic shift is driven by specific built environment indicators, capturing a critical transition in their influence. Seven factors are identified as particularly influential, including distance to subway, functional density, distance to parks, proximity to water bodies, green space ratio, distance to border vacuums, and distance to state-protected historic sites. While proximity to subway infrastructure has the strongest impact on vitality for daily commuters on weekdays and weekends, proximity to national cultural relics becomes the paramount factor during holidays. Furthermore, the influence of the built environment on vitality is nonlinear and characterized by pronounced threshold effects, effectively differentiated by the 'Performance-Basic-Exciting' framework. It establishes a robust analytical paradigm that serves as a valuable theoretical reference for evaluating spatio-temporal vitality dynamics and spatial optimization in other historically rich, plain-based cities.

Building upon these empirical and theoretical insights, the findings offer vital implications for urban policy and planning practice. The proposed classification framework provides a robust, evidence-based foundation for planners to translate analytical results into prioritized urban renewal strategies. By understanding which spatial elements act as basic necessities versus exciting attractors under varying temporal pressures, policymakers can implement targeted micro-regeneration and adaptive spatial management. These interventions can effectively balance the competing demands of local residents and high tourist volumes, thereby mitigating spatial imbalances, achieving a spatio-temporal vitality equilibrium, and promoting the long-term sustainable development of historic urban areas.

However, this study has certain limitations that offer clear directions for future research. First, due to data constraints, Baidu Heat Map data lacks the precision required for individual-level tracking, so future studies could integrate multisource big data such as mobile signaling or GPS trajectories to better capture granular spatio-temporal behaviors. Second, the current analysis focuses on broad periods including weekdays, weekends, and holidays without examining finer intraday temporal variations. To address this, conducting intraday dynamic analyses of morning peaks and evening surges will be a key direction to complete the temporal spectrum of urban vitality. Finally, while this research focuses on the flat, historically rich urban area of Shenyang, it remains unclear if these nonlinear thresholds apply to cities with different landscapes, such as mountainous regions. Therefore, future comparative studies across diverse geographical settings are necessary to make the evaluation framework more universally applicable and reliable.

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

Funding: This research was funded by the National Natural Science Foundation of China (No. 42301256), Fundamental Research Funds for the Central Universities (No. N25LPY056), and Liaoning Provincial Social Science Planning Fund Project (No. L25BJY017).

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

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

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