Exploring Urban Vitality Characteristics and Interactive Mechanisms at the Community Scale through the Lens of Human Behaviour: A Case Study of Chongqing, China

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Abstract

Exploring urban vitality characteristics and interactive mechanisms are helpful for formulating policy, advancing urban planning and promoting sustainable development. However, the characteristics and influencing factors of urban vitality have not been thoroughly explored at finer spatial scales, especially for mountainous cities. In this work, the central urban area of Chongqing is selected as a case study, social, economic, cultural and comprehensive urban vitalities are quantitatively assessed at the community scale. Then, the OLS-XGBoost-SHAP model is innovatively utilized to identify the top influencing factors that interact strongly with urban vitality. Incorporating mountain city footpath and terrain factors, the nonlinear interactions among various factors and vitality are elucidated. The results indicate: (1) the central urban area of Chongqing presents a structure of two main areas, five subareas, and seven clusters. (2) The interaction between the POI diversity index and vitality exhibits a notable threshold effect. When the POI diversity index reaches 0.7, this factor significantly boosts community vitality. (3) The tolerance of transportation in mountainous cities is higher than that in plain cities. When the distance to the nearest subway station and bus station is less than 2000 meters and 650 meters, respectively, these two indicators have a significantly positive impact on urban vitality. (4) Considering mountain city footpath and DEM factors exhibit a strong interactive relationship with POI density, urban planners need to collaboratively optimize the construction layout of these three elements. These findings may provide important insights for people-oriented urban development and planning.

1. Introduction

Since the reform and opening up, China has experienced the largest and fastest urbanization process in the world. At present, the urban development in China has entered a stage where the focus shifts from large-scale incremental construction to simultaneously improving the quality of existing urban areas and adjusting the urban structure. The level of urban vitality reflects the comprehensive situation of urban operation. Creating vibrant urban spaces is an important part of urban renewal. The rapid and rough urban development in the past has brought about a series of urban problems, such as traffic congestion, imbalance between employment and housing, environmental pollution, etc. These problems further led to the decline in the quality of urban spaces and the loss of urban vitality. Urban vitality plays a key role in meeting people's demands for high-quality living and promoting high-quality development of urbanization. Jacobs first proposed the concept of urban vitality, which refers to the process of interweaving activities and living spaces among people, creating diversity in urban life and making cities vibrant (Jacobs, 1961). Communities are the cells of cities, serving as not only the daily living spaces for people but also the basic units of public services and social governance. Community vitality is crucial for constructing a vibrant urban environment and is also an important factor in sustainable urban renewal. Therefore, there is an urgent need to develop a comprehensive framework for analyzing community vitality, identifying its influencing factors, and enhancing its level to develop responsive and sustainable urban policies and design interventions.

2. Literature Review

The current conceptual frameworks of urban vitality are primarily constructed from sociological and architectural perspectives(Ye et al., 2016). The conceptual framework of urban vitality from a sociological perspective identifies it as comprising economic vitality, social vitality, and cultural vitality (jalladdini and OKTAY, 2012). Within this framework, economic vitality serves as the foundation, social vitality is the core component, and cultural vitality represents the qualitative standard (Wong and Domroes, 2004). In contrast, the architectural perspective reflects the diverse and complex arrangements of activities and environments, as well as the interactions between urban activities and spaces (Jin et al., 2017). Increasingly, conceptual frameworks of urban vitality based on the interaction between people and space (Liu et al., 2022a). This perspective views spatial vitality as the synthesis of human behaviour. Above all, the conceptual framework of urban vitality defined in this paper is a comprehensive embodiment of economic, social and cultural vitality. It takes the interaction between human and space as the core through the Lens of Human Behaviour.

In recent years, various types of big data, such as Baidu and Tencent heat maps (Li et al., 2019; Shi et al., 2021), nighttime light remote sensing images (YU et al., 2021; Zhang et al., 2022), POI data (Lyu et al., 2023; Yang et al., 2022), mobile phone data (Wang et al., 2024), and social media check-in data (Rizwan et al., 2018), have opened up new avenues for measuring urban vitality. With the development of communication and remote sensing technologies, researchers have turned to leveraging big

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data sources for more dynamic and detailed insights. Hourly Baidu or Tencent heat map (BHM) data is commonly utilized to explore the relationship between the built environment and urban vitality (Lyu et al., 2023). Some scholars employed nighttime light images to quantitatively examine the relationship between the urban landscape and urban vitality at the street block level (Zhang et al., 2020). In addition, mobile phone data and POI (Point of Interest) data are also integrated and applied together for street vitality and diversity (Li and Zhao, 2023). POI data have limitations in measuring urban vitality dynamically (Liu et al., 2022b). Similarly, Park et al. applied mobile signal analysis to Seoul's urban vitality data (Park and Kim, 2023). Compared to POI data, mobile signaling data have wide coverage and temporal-spatial characteristics. Pan et al. discovered that Weibo check-in data possesses similar functional advantages in expressing urban vitality (Pan et al., 2021).

Many scholars have studied various factors from urban built environment is closely related to urban vitality, such as population density (Chen et al., 2023), buildings (Lau, 2011), land use (Ma et al., 2023), road networks (Fu et al., 2021), and public transportation (Wan et al. 2024). Liu et al. argued that POI density has the most significant impact on urban vitality enhancement, while others believe that the impact of commercial types on urban vitality is not consistent (Liu and Shi, 2022). Song found that higher employment density and land value are associated with community vitality in Seoul on weekday and weekend (Kang, 2020). Lu et al. compared the correlation between urban vitality and the built environment in Beijing and Chengdu, finding that POI density and public transportation accessibility are closely related to urban vitality, and the effects of density indicators on urban vitality vary greatly among cities in different development stages (Lu et al., 2019).

3. Study Area and Datasets

3.1 Study Area

In this paper, the main urban area of Chongqing is selected as the research object, covering nine administrative districts. Chongqing is a renowned mountainous city in China. It is the only municipality directly under the central government in western China. Chongqing's main urban area covers an area of 5472.7 square kilometers. Affected by topography, the highly heterogeneous spatial structure within the city leads to significant spatial differences in Chongqing's urban vitality. The main urban area of Chongqing is a typical area to study the urban vitality of mountain cities. The research scope of this paper is shown in Figure 1.

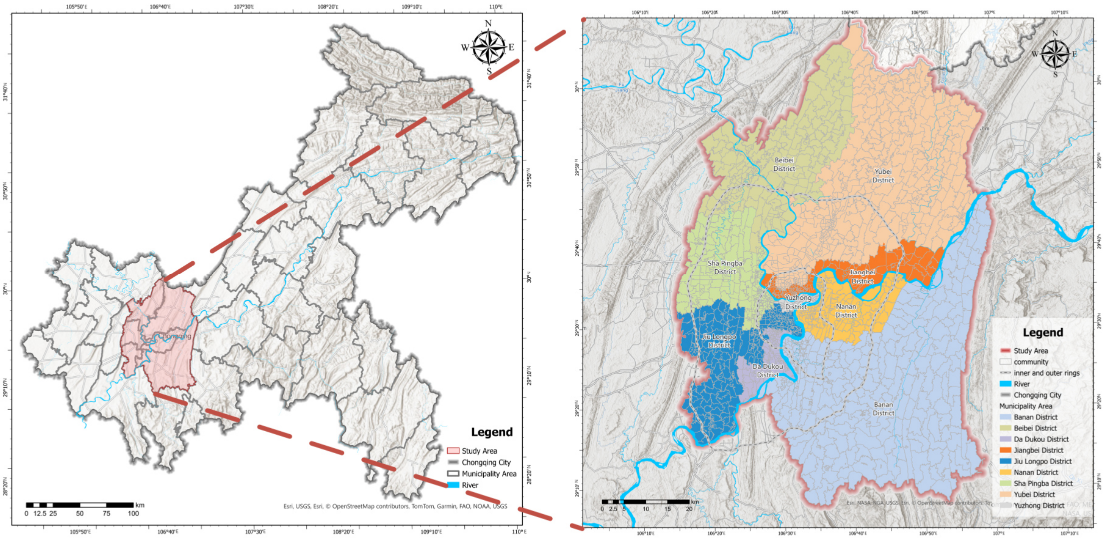

Figure 1. Study area.

3.2 Datasets

Six types of data are utilized in this study (Table 1). China Unicom mobile signaling data is employed in this study to characterize the intensity of urban social vitality. Mobile signaling data records the location information of mobile phone users in the mobile communication network, and the data cover the entire month of May 2022. Nighttime light remote sensing data is obtained from cloud-free, high-resolution DMSP-OLS images acquired during the year of 2022. Due to the difficulty of data acquisition, the cultural interaction data is derived from the Damai website in 2024. Damai is a comprehensive live entertainment ticketing marketing platform in China, covering various events such as concerts, dramas, musicals, and sports events. POI (Point of Interest) generally refers to the Internet electronic map of the point class data, basically including name, address, coordinates, category four attributes. In this paper, the POI data for 2022 from Gaode is utilized. Road network data for Chongqing in 2022 is downloaded from the OpenStreetMap (OSM) website. Road intersections are extracted based on it. Housing price data in 2023 is primarily obtained from the Lianjia website. Basic geographic data from ASTER GDEM included DEM and derived slope and terrain ruggedness data.

Major	Variable	Descrption	Data Source
Socioeconomic	Economic density (ED)	The ratio of total community GDP to community area.	DMSP-OLS.
	Land price (LP)	The average price of second-hand houses.	Lianjia website.
Transportation	Road intersection (RI)	The density of road intersections.	OSM data.
	Road density (RD)	The density of all roads.	OSM data.
	Footpath density (FD)	The density of mountain city footpaths.	OSM data.
	The density of subway stations (MD)	The density of subway stations.	Gaode Map.

	The distance to the nearest subway station (MND)	The distance from each community to its nearest subway station.	Gaode Map.
	The density of bus stops (BS)	The density of bus stops within each community area.	Gaode Map.
	The distance to the nearest bus stop (BSD)	The distance from each community to its nearest bus stop.	Gaode Map.
Function	Points of Interest density (POID)	The density of POI each community area.	Gaode Map.
	Land use mixture(POIM)	Calculate the land use mix within each community boundary based on POI data.	Gaode Map.
	Building density(BD)	Construction land coverage ratio.	Gaode Map.
Human-scale	The proportion of park green space (PG)	Park green space coverage ratio in each community area.	Gaode Map.
	DEM	detailed and accurate description of the Earth's surface topography, including variations in elevation	ASTER GDEM.
	Slope	the gradient or inclination of terrain surfaces.	ASTER GDEM.
	The relief of the terrain(RDLS)	the variation in elevation or altitude.	ASTER GDEM.

Table 1. A detailed description of the data source used in our research.

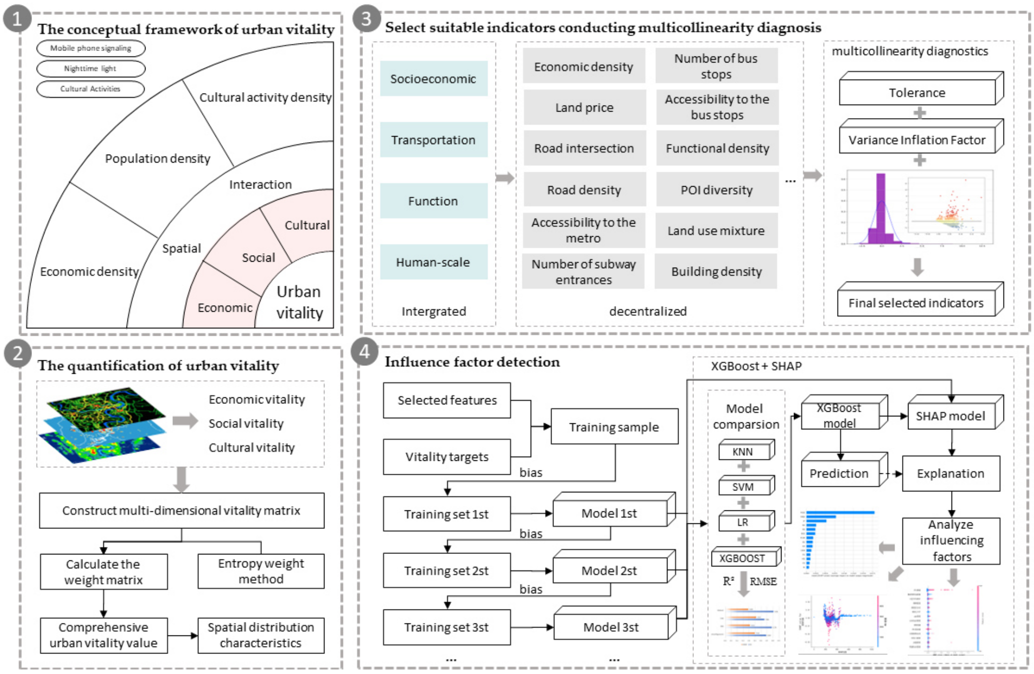

Figure 2. Research framework and technical route.

4. Method

4.1 Conceptual Framework

Figure 2 shows the method structure of the present study. The calculation of urban vitality values is based on the Entropy Weighting Method, which combines the social, economic, and cultural vitality with weighted overlays. Variable collinearity diagnosis is performed based on the Ordinary Least Square Method model. Subsequently, the importance of variables based on XGBoost and SHAP is assessed. Finally, the paper reveals the nonlinear relationship between variables and community vitality based on the SHAP model.

4.2 Entropy Weighting Method

The calculation of urban vitality values is based on the Entropy Weighting Method (EWM), which combines the social, economic, and cultural vitality with weighted overlays. The EWM is an objective method for determining weights by measuring the effective information contained in the data. Firstly, multidimensional vitality indicators need to be standardized first, as shown in Equation (1). Then, the contribution ratio, information entropy, and utility value of the indicators are calculated as Equation (2)(3). Finally, the normalized information utility value is calculated to determine the weight of each indicator. The weighted sum is then obtained as Equation (4), resulting in the weight values of each dimension calculated by the Entropy Weighting Method. The comprehensive vitality of community is integrated as Equation (5).

$$X'_{ij} = \frac{X_{ij} - X_{\min}}{X_{\max} - X_{\min}} \tag{1}$$

$$P_{ij} = \frac{X'_{ij}}{\sum_{i=1}^{n} X'_{ij}} \tag{2}$$

$$e_j = -\frac{1}{ln(m)} \sum_{i=1}^{m} P_{ij} ln(P_{ij}) \tag{3}$$

$$w_j = \frac{1 - e_j}{\sum_{j=1}^{n} (1 - e_j)} \tag{4}$$

$$S_i = \sum_{j=1}^{n} w_j X'_{ij} \tag{5}$$

where X_{ij}, X'_{ij} = The vitality value of the j-th indicator for the i-th community, along with its standardized value

X_{min}, X_{max} = The minimum and maximum values of the j-th indicator across all communities

P_{ij} = The proportion of the j -th indicator of the i -th community to the total value of the j -th indicator across all communities

e_j = The entropy value of the j -th indicator

w_j = The weight of the j -th vitality indicator

s_i = The comprehensive vitality value of the i -th community

4.3 Ordinary Least Square Method

This paper selects the Ordinary Least Square (OLS) method for multicollinearity diagnosis. The comprehensive vitality values calculated in Section 4.1 are used as the dependent variable, while factors such as housing prices are considered as independent variables. Due to the potential strong correlation among the independent variables, the results of the model solution may be distorted or even lead to non-unique solution phenomena. Hence, OLS model between urban vitality and built environment factors is established at a certain moment arbitrarily. Then, by observing the tolerance and Variance Inflation Factor (VIF) values of each independent variable, factors with tolerance less than 0.1 and VIF values greater than 10 are excluded to eliminate collinearity issues among factors. The equations for calculating the values of Variance Inflation Factor (VIF) and Tolerance are introduced as Equation (6)(7).

$$VIF_j = \frac{1}{1-R_j^2}, \quad T_j = 1 - R_j^2 \tag{6}$$

$$R_j = \frac{SSR_j}{SST_j} = \frac{\sum_{i=1}^{i=n-1}\left(\widehat{y_{ij}} - \bar{y}_j\right)^2}{\sum_{i=1}^{i=n-1}\left(y_{ij} - \bar{y}_j\right)^2} \tag{7}$$

where VIF_j = the Variance Inflation Factor of the variable j

T_j = the Tolerance value of the variable j

R_j = The coefficient of determination obtained by conducting linear regression with variable j as the dependent variable and the remaining variables as independent variables

SSR_j = Total sum of squares of the variable j

SST_j = Sum of squares due to regression of the variable j

$\widehat{y_{ij}}$ = The predicted values of variable j after regression

y_{ij} = The observed values of variable j for community i

$\bar{y}_j$ = The mean value of variable j across all communities

4.4 Selection of Machine Learning Models

To scientifically and reasonably select a machine learning model for analyzing the mechanisms influencing urban vitality, this paper utilizes commonly used the coefficient of determination (R^2) and the root mean square error (RMSE) as evaluation metrics. These metrics are employed to assess the performance of KNN, SVM, Linear Regression, and XGBOOST models. As shown in Equation (8)(9). R^2 and RMSE are used to quantify data fitting degree and the deviation between predicted and actual values. The R^2 value ranges from 0 to 1, with a higher R^2 indicating a better fit. The RMSE has a minimum value of 0, and smaller values indicate a smaller deviation represents better model performance.

$$R^2 = 1 - \frac{\sum_{i=1}^{i=n}\left(\widehat{y_i} - \bar{y}\right)^2}{\sum_{i=1}^{i=n}\left(y_i - \bar{y}\right)^2} \tag{8}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{i=n}\left(y_i - \bar{y}\right)^2} \tag{9}$$

where $\hat{y}_i$ = The predicted values of community i after regression

y_i = The observed values of community i

$\bar{y}$ = The mean values of communities

n = The number of communities

4.5 XGBoost Algorithm

XGBoost (eXtreme Gradient Boosting) is an algorithm toolkit based on the Boosting framework. It is a type of boosting tree model, which integrates many CART tree models to form a strong classifier. The important parameters of XGBoost mainly include n_estimator, learning_rate, max_depth, and min_child_weight, and the values of the parameters set are based on previous studies (M. Wang et al., 2023; Z. Wang et al., 2023). n_estimator is the maximum number of trees generated. In this paper, it is set to 100. learning_rate represents the step size of each iteration, set to 0.1. Max_depth is the maximum depth of the tree. In this work, it is set to 15. min_child_weight is the minimum number of samples on the leaf node, and it is set to 1.

4.6 SHAP Method

SHAP is a method inspired by game theory aimed at explaining the predictions of machine learning models. Although XGBoost model outperforms traditional multivariate linear regression models, its interpretability is far inferior to linear models, leading to the black-box problem in the field of machine learning. SHAP generates a SHAP value for each input feature, indicating how the feature contributes to the prediction of a specific data point. The SHAP value expresses the specific impact of each indicator on the prediction result. The essence of SHAP value calculation is to compute the expected marginal contribution of feature j for sample i. The specific process of SHAP is as follows:

$$\varnothing_{ij} = \sum_{S \subseteq N\{j\}} \frac{|S|!\left(N-|S|-1\right)!}{N!}\left(v\left(S \cup \{j\}\right) - v(S)\right) \tag{10}$$

$$y_i = y_{base} + \sum_{j=1}^{m}\varnothing\left(x_{ij}\right) \tag{11}$$

where $v\left(S \cup \{j\}\right) - v(S)$ = The marginal contribution of j to S

S = The subset of features used in the model

$S \subseteq N\{j\}$ = Sum over all possible alliances

$\frac{|S|!\left(N-|S|-1\right)!}{N!}$ = The weight of the alliance

y_i = The predicted result at sample i

y_{base} = The average predicted value of all samples

$\varnothing\left(x_{ij}\right)$ = The SHAP value of sample i at feature j

m = The number of features

5. Results

5.1 Spatial Distribution of Urban Vitality

From the perspectives of economic, social, and cultural vitality, the central urban area of Chongqing presents a structure of multi-

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centers and multi-groups. As shown in Figure 3, regions with vigorous social vitality are mainly distributed within the inner ring, corresponding to the commercial centers of Jiefangbei, Guanyinqiao, Shapingba, Yangjiaping, Shiqiaopu, and Nanping. Areas outside the inner ring, such as Beibei, Jiangbei Airport, Yudong, University City, Dadukou, Aiqinhai, Liangjiatuo cluster, and Chayuan, also exhibit relatively high urban vitality, but are noticeably weaker compared to the inner ring.

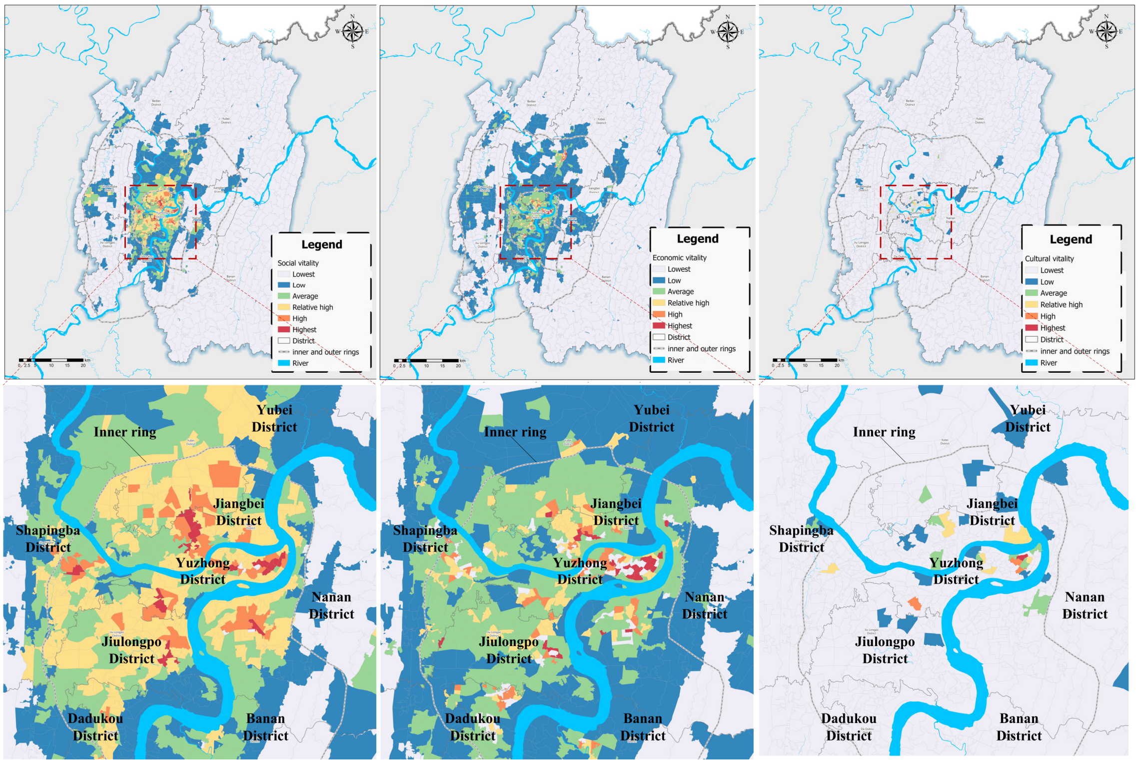


Figure 3. Distribution of social vitality (left), economic vitality (middle), cultural vitality (right) and local details within the inner ring road.

OLS method is used for the independence test of economic, social and cultural vitality variables. It finds that the corresponding VIF values are 1.3, 1.4 and 1.1 respectively. All VIF values are less than 10, and the residual histogram matches the normal curve. Therefore, the comprehensive vitality value is calculated using EWM model. In Figure 4, the central urban area of Chongqing exhibits a "two main, five secondary, seven cluster" structure. It is manifested by Jiefangbei and Guanyinqiao as the high-value areas of vitality, followed by Shapingba, Yangjiaping, Daping, Nanping, and Shiqiaopu. Additionally, areas with relatively high vitality include University City, Dadukou, Jinyu, Konggang near the airport, Aiqinhai, Chiguang, and Dashiba.

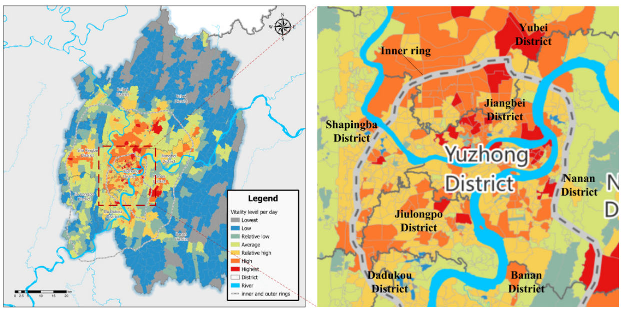


Figure 4. Distribution of community comprehensive vitality.

5.2 Collinearity diagnostics

The reliability of the collinearity results can be verified by the histogram of residual distribution results (HRD) and the residual and prediction graph (RP). Excellent performance of the model shows normal distribution in the HRD, and the scatter structure of RP shows random distribution. According to Figure 5, we can conclude that the OLS results of multicollinearity diagnosis in this paper are reliable. The result of multicollinearity diagnosis shows that the tolerance of almost all variables exceeds 0.1, and the VIF values are all less than 10, except for the slope and relief of terrain variables (Table 2). The tolerance values of the slope and the relief of terrain are 0.08 and 0.1, respectively. Therefore, we removed the slope and relief of terrain indicators. At this point, we constructed a factor detection system including 14 indicators as subsequent input.

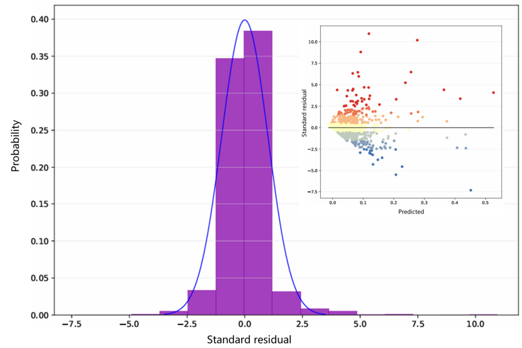


Figure 5. Standardized residual histogram and residual and prediction graph.

Variable	Tolerance	VIF	Variable	Tolerance	VIF
ED	0.95	1.06	BSD	0.59	1.7
LP	0.45	2.24	POID	0.47	2.14
RI	0.63	1.6	POIM	0.88	1.13
RD	0.35	2.88	BD	0.25	4.05

FD	0.77	1.29	PG	0.79	1.27
MD	0.75	1.33	DEM	0.53	1.87
MND	0.39	2.53	SlOPE	0.08	12.6
BS	0.55	1.83	RDLS	0.08	12.45

Table 2. Collinear diagnosis results (The full names of variables can be referenced in Table 1)

5.3 Comparison of machine learning models

In Section 5.2, the selected variables are used to train several machine learning models. The dataset is further divided into training and validation sets, and model selection is based on performance on the validation set. For the SVM, KNN, and Linear Regression models, default parameter values are used. Model performance is analyzed using R-Squared (R^2) and Root Mean Squared Error (RMSE) metrics. In Figure 6, it is evident that the XGBOOST model achieves the highest R^2 and the lowest RMSE, indicating the best performance. Hence, it can be concluded that using the XGBOOST model for analyzing the mechanisms influencing vitality has distinct advantages.

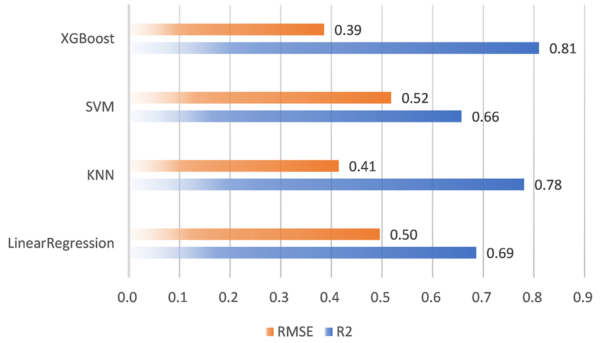
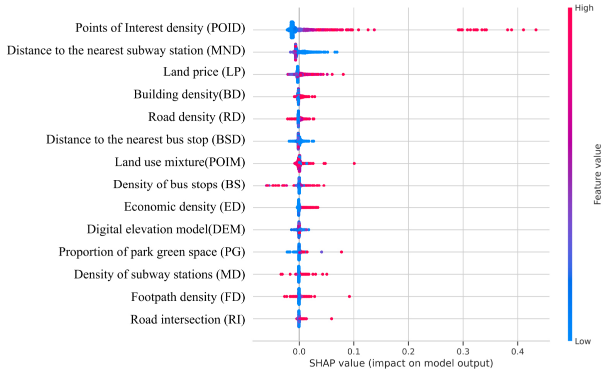


Figure 6. Distribution of community comprehensive vitality.

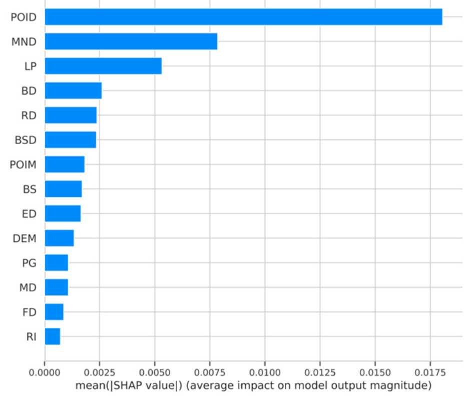
5.4 SHAP Variable Importance

The analysis of the importance of factors affecting community vitality is visualized through both global bar charts and beeswarm plots. Global feature importance plot considers all samples and calculates the average absolute SHAP value for each feature. The beeswarm plot aims to show how the top features in the dataset influence the model output through an information-dense summary. In the left global bar chart, the variable importance of factors affecting community vitality is arranged from top to bottom, and the y-axis represents each variable. In the beeswarm plot as shown in Figure 7(a), the position on the x-axis is determined by the SHAP value of each sample, and the color represents the magnitude of the feature value.

In terms of community vitality, the top six most important variables are POI density, distance to the nearest subway station, average housing price in the community, building density, road network density, and distance to the nearest bus station. As shown in Figure 7(b), the density of POI is positively correlated with community vitality. Additionally, the rankings of distance to the nearest subway station and bus station, as well as road network density, are relatively high, indicating that the convenience and accessibility of community transportation directly affect community vitality. Figure 7(a) illustrates that greater distances to subway and bus stations significantly inhibit community vitality. The influence of road network density on community vitality is complex. A higher road network density tends to enhance community vitality to a certain extent, but sometimes it can also inhibit it. This consideration is mainly due to the fact that an overly dense distribution of road networks can lead to phenomena such as traffic congestion. High-vitality communities tend to have relatively higher housing prices, with the exception of areas such as villa districts characterized by low density and high housing prices. Economic density, park green space ratio, and intersection density have a significant positive impact on community vitality. The impact of mountain city footpaths on community vitality is more complex, due to the fact that some communities with high density of footways are mainly located in areas with relatively poor accessibility.



(a) The beeswarm plot of variables.



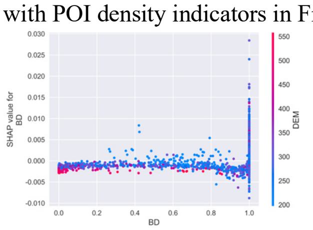
(b) The global feature importance plot.

Figure 7. The importance of variables on community vitality.

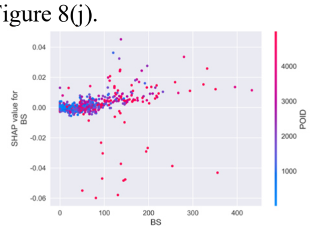
5.5 Nonlinear Variable Relationships

Figure 8 illustrates the marginal effects of different indicators on the predictive outcomes of the machine learning model based on Partial Dependence Plots (PDP) The PDP plot automatically selects a feature with the strongest interaction with the current feature. The colorbar depicts the corresponding values of another variable with the strongest interaction with that variable in each community.

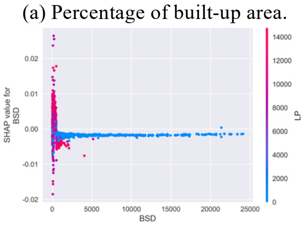
The PDP analysis results confirm the accuracy of previous linear regression model results. Some variables exhibit local impact trends and threshold effects on urban vitality. As shown in Figure 8(k), the overall correlation between POI density and community vitality is positive, with POI density interacting most strongly with POI mix, consistent with previous research findings. Figure 8(l) shows that when the POI mix value is low, it has little impact on community vitality. However, when the POI mix reaches 0.6, the impact of POI mix on community vitality begins to rise. When the POI mix exceeds 0.7, community vitality increases rapidly. Community vitality is negatively correlated with the distance to the nearest subway and bus stations. As shown as Figure 8(c)(i), we can conclude indicators on community vitality is almost negligible when the distance to the nearest subway station and bus stop exceeds 2 kilometers and 625 meters, respectively. The density of subway stations is directly related to housing prices, while housing prices have a strong interaction with POI density, reflecting the strong and close relationship between housing prices and transportation and supporting facilities. Figure 8(a) presents building density is strongly correlated with DEM indicators, and the terrain directly affects urban development. When the built-up area ratio reaches 1, most communities generally have high vitality. When the built-up area ratio reaches 25%, there is a significant increase in community vitality. Road network density shows a changing relationship with community vitality in Figure 8(m), with strong interaction with DEM indicators. When the road network density within the community is less than 35 km/km², it is positively correlated with community vitality. When the road network density exceeds 35 km per kilometers, the community is prone to congestion and other traffic problems, leading to a negative correlation between road network density and community vitality. According to Figure 8(f), the vitality of the community increases, when the density of footways exceeds 3 km per kilometers. As DEM value increases, community vitality gradually decreases in Figure 8(d). The proportion of park green space is significantly positively correlated with community vitality, with the strongest interaction with POI density indicators in Figure 8(j).



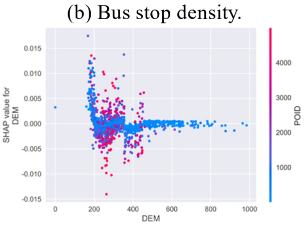
(a) Percentage of built-up area.



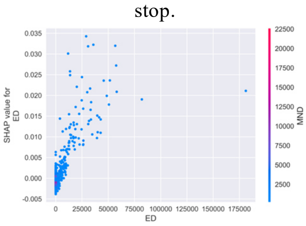
(b) Bus stop density.



(c) Distance to the nearest bus stop.

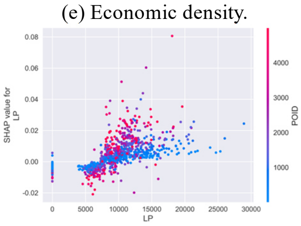


(d) DEM

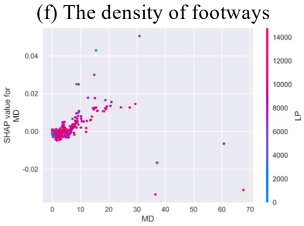


(e) Economic density.

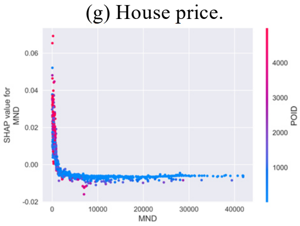
(f) The density of footways



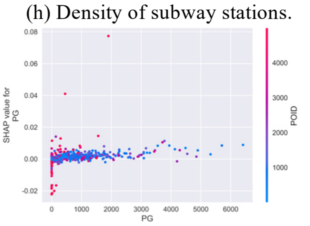
(g) House price.



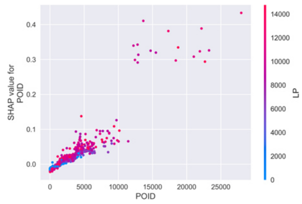
(h) Density of subway stations.



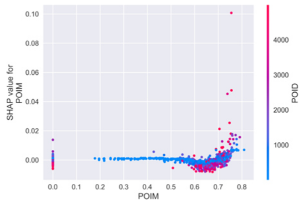
(i) Distance to the nearest subway station.



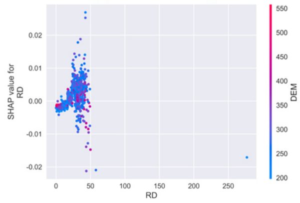
(j) Proportion of park green space.



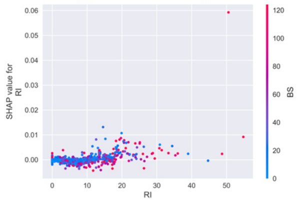
(k) POI density.



(l) POI mix degree.



(m) Density of roads.



(n) Density of intersections

Figure 8. The partial dependence plot between variables and community vitality.

6. Conclusions

Through the Lens of human behaviour, three multidimensional spatial vitality sub-items are evaluated in the central urban area of Chongqing, including social vitality, economic vitality, and cultural vitality. The OLS-XGBoost-SHAP model is innovatively utilized to identify the top influencing factors that interact strongly with urban vitality. Incorporating mountain city footpath and terrain factors, the nonlinear interactions among various factors and vitality are elucidated. The contributions of the study are outlined as follows:

Overall, the study area presents a vitality structure of two main areas, five subareas, and seven clusters. We proposed the OLS-XGBoost-SHAP model to identify 14 influence factors. POI density, distance to the nearest subway station, average housing price, building density, road network density, and distance to the nearest bus stop are the top six variables that interact strongly with urban vitality. POI mix has a significant threshold effect. The promotion effect on community vitality begins when the POI mix reaches 0.6, and it becomes significant when the POI mix reaches 0.7. The transportation tolerance in mountainous urban areas is higher than that in plain cities. When the distance to the nearest rail station is less than 2000 meters and the distance to the bus stop is around 650 meters, it significantly promotes community vitality. Road network density exhibits a clear nonlinear effect on community vitality, with the turning point mainly appearing around 35 km per squared kilometers. Regarding the footways and DEM factors that must be considered in mountainous cities, planners should emphasize the construction of supporting functions to attract more community vitality.

In urban studies, it addresses the challenge of quantitatively analyzing community vitality on a human scale. Meanwhile, our workflow can help urban researchers explore the distribution characteristics and influencing factors of community vitality in multiple dimensions and scales.

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