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EXPLORING THE ASSOCIATION BETWEEN BUILT ENVIRONMENT AND URBAN VITALITY USING DEEP LEARNING METHODS

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Research Paper

Abstracts*: Urban vitality is a critical element in the development of cities. The built environment of a city plays a pivotal role in shaping urban vitality. Using Yinchuan City as a case study, this research employs the Baidu heat map to assess urban vitality. Simultaneously, the built environment variables serve as independent variables. We utilize Ordinary Least Squares (OLS), Moran's I, and Geographically Weighted Regression (GWR) models to explore the relationship between urban vitality and the built environment on weekdays and weekends in Yinchuan City. Finally, we apply the Gradient Boosting Decision Tree (GBDT) model to analyze the importance of variables influencing different time periods of urban vitality. The research findings indicate that: (1) The built environment in Yinchuan City significantly influences urban vitality on both weekdays and weekends. (2) There is positive spatial autocorrelation between the built environment and urban vitality on both weekdays and weekends. (3) GWR model analysis reveals that urban vitality on weekdays and weekends exhibits different spatial distribution characteristics. (4) GBDT model analysis indicates that variables influencing urban vitality during weekdays and weekends have different importance rankings. Finally, tailored strategies to enhance urban vitality are proposed for different urban areas and time periods. This study provides crucial reference points for urban planning and sustainable development in Yinchuan City.*

Keywords*: Built Environment, Baidu Heat Map, Urban Vitality, Deep Learning, GBDT.*

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1. Introduction

Over the past few decades, China has experienced a substantial surge in its urbanization levels. According to data sourced from the National Bureau of Statistics, China is underscoring a remarkable upswing in the nation's urbanization landscape[1]. Despite the remarkable strides in urbanization, persistent challenges have emerged, including issues of lower urbanization quality, traffic congestion, imprudent spatial land utilization, insufficient public spaces, and the emergence of "Ghost Cities" (Shepard, 2015). Urban vitality reflects a city's vitality, creativity, and attractiveness. Therefore, researching urban vitality and its influencing factors holds crucial significance for enhancing the quality of urban management, fostering sustainable urban development in Chinese cities (Zheng et al., 2017).

The measurement of urban vitality has been a central focus of research. The traditional method used to perceive urban vitality is mainly questionnaires. Spatial vitality can be accurately understood through respondents' evaluations of the space in which they live. With the advancement of technology, more big data for urban research can be obtained. For instance, Becker elucidated the dynamic shifts in urban crowd activities within Morristown, USA, over a two-month period, leveraging mobile phone data and employing statistical analysis and mapping techniques (Isaacman et al., 2011). Wang delved into the distribution characteristics of spatial vitality across the dimensions of time, space, and function using mobile phone signaling data (Zhang et al., 2016). Additionally, Zhang investigated the evolving patterns of spatial vitality in central Hangzhou by employing multi-source data, including the Baidu heat map and Points of Interest (POI) data (Zhang et al., 2017).

Another area of research on urban vitality is its influencing factors. It has been shown that the role of the built environment on urban vitality cannot be ignored. The built environment is the part of the physical environment in a city that is made up of human activities, including land, buildings, transport systems, roads, pavements, carriageways, and other infrastructures. A well-developed transportation facility not only provides convenient mobility for residents but also acts as a catalyst for the generation of activities, fostering a vibrant urban environment. Therefore, it is important to investigate the effect of built environment on urban vitality. Sung used multiple linear regression model to study the urban vitality and built environment in Seoul (Kim, Choi, & Kim, 2013). De Nadai measured Jane Jacobs' theory by using data such as mobile phone signaling, Open Street Map, land use and other data to measure the extent to which Jane Jacobs' four urban diversity conditions explain urban vitality (De Nadai et al., 2016).

Yinchuan is one of the important central cities in Northwest China. In the process of industrialization and urbanization, the city has generated many problems, such as over-concentration of population, urban traffic congestion, irrational layout of urban functions, and environmental pollution. Therefore, this paper focuses on the built environment on urban vitality in Yinchuan City. Through a comprehensive study of urban vitality in Yinchuan City on weekdays and weekends, Baidu heat map is used as an indicator to measure urban vitality. Using Point of Interest (POI) data and street view data, we construct a comprehensive framework that integrates the OLS, GWR model, and the GBDT model. This framework is designed to deeply explore the intricate mechanisms.

[1] https://www.stats.gov.cn/sj/ndsj/2022/indexch.htm

2. Literature Review

The built environment refers primarily to the planned and transformed man-made environment. Urban vitality is a component of basic quality of life. The influence of built environment on urban vitality has been researched more. Cervero and Ewing formed 5D theory (Density, Diversity, Design, Distance, Destination) (Ewing & Cervero, 2010) based on 3D theory (Density, Diversity, Design) (Ewing & Cervero, 2001). Some study uncovered a meaningful connection between urban vitality and the 5D elements of the built environment (Chen et al., 2019; He et al., 2018; Xu et al., 2018). Previous studies on physical indicators of urban vitality and built environment are usually traditional quantitative studies (Yue et al., 2017). Nevertheless, conventional data remains static, and quantitative analyses fail to capture ongoing spatiotemporal dynamics.

The built environment has an important impact on urban vitality, and different buildings and facilities can have different impacts on urban vitality (Brownson et al., 2009; Lin & Moudon, 2010; Shach-Pinsly, 2019). For example, the construction of urban functional areas such as commercial districts and office areas can enhance the economic vitality of a city (Xia, Yeh, & Zhang, 2020), while the construction of public spaces such as parks and squares can enhance the social vitality of a city (Alex de Freitas, 2010). Quantitative research plays an important role in the study of urban vitality and built environment. The relationship between urban vitality and built environment can be more accurately described and explained through quantitative research methods (De Nadai et al., 2016; Park, Kim, Choi, & Seo, 2013; Wu, Ye, Ren, & Du, 2018). Some studies have used quantitative research methods by applying questionnaire survey method, spatial data analysis method, multiple linear regression analysis, principal component analysis and factor analysis, geographically weighted regression analysis and deep learning methods (Chen et al., 2019; Lan, Gong, Da, & Wen, 2020; Lu, Huang, Shi, & Yang, 2019; Tang et al., 2018). Therefore, the use of multiple methods can better describe and explain the relationship between urban vitality and the built environment, providing a scientific basis for enhancing urban vitality and achieving sustainable development (Azmi & Karim, 2012; He et al., 2018; Wu & Niu, 2019).

With the continuous development of information technology, deep learning algorithms have gradually come into the view of many scholars, providing new opportunities for the study of urban vitality. The relationships between variables in the built environment and urban vitality are often complex and non-linear. GBDT excels at capturing intricate patterns and non-linearities in the data, providing a more accurate representation of the relationships (Yang, Cao, & Zhou, 2021). GBDT provides a measure of variable importance. This is valuable in understanding which built environment variables have a more significant impact on urban vitality (Zhang et al., 2020). Identifying key factors can guide urban planning and development strategies. Therefore, this paper chooses to utilize the GBDT method.

Studies on residents' activities and the built environment primarily center around the built surroundings, residents' living spaces, their health, lifestyle choices, and overall living experiences (Chen, Hui, Lang, & Tao, 2016; Lan et al., 2020; Wu et al., 2018). Most of the results focus on the study of residents' travel mode and physical and mental health at the community scale (Chen et al., 2016; Kooshki, Mollatabar, &

Masumi, 2015; Lan et al., 2020). The choice of residents' traveling mode is one of the more concerned topics in the field of urban built environment, and most of the empirical research on the urban built environment and residents' traveling are more 5D theories (Kim, 2018; Koohsari et al., 2014; Li, Li, Yuan, & Li, 2019; Wu et al., 2018). In traditional research on residents and the built environment, questionnaires, in-depth interviews, or participatory observation by the researcher are more often used (Schönfelder & Axhausen, 2003). This approach is more subjective and entails significant time and capital investment. However, in recent years, the rise of big data has facilitated the extensive utilization of datasets like cell phone records, smart cards, and travel records for examining the spatiotemporal behavioral characteristics of urban residents (Soto & Frías-Martínez, 2011). Residents' spatio-temporal behavior is influenced by demographic characteristics, time, location, and other factors (Luo, Cao, Mulligan, & Li, 2016). Residents' spatio-temporal behavior differs between weekdays and weekends (Zhang, Xu, Tu, & Ratti, 2018). However, there are relatively few studies on the relationship between urban space and population movement.

3. Data and Methodology

3.1. Study Area

The case of this study is Yinchuan City, China (Figure 1). Yinchuan is the capital city of the Ningxia Hui Autonomous Region, and it is a famous historical and cultural city in China, with a history of more than 2,100 years since it was founded. In the evaluation of China's top ten livable cities, Yinchuan City ranks fifth in transportation accessibility and third in environmental health. The areas studied in this paper are the three districts of Xingqing District, Jinfeng District, and Xixia District in Yinchuan City. This study uses administrative streets as the unit of analysis, which is a total of 112 research units.

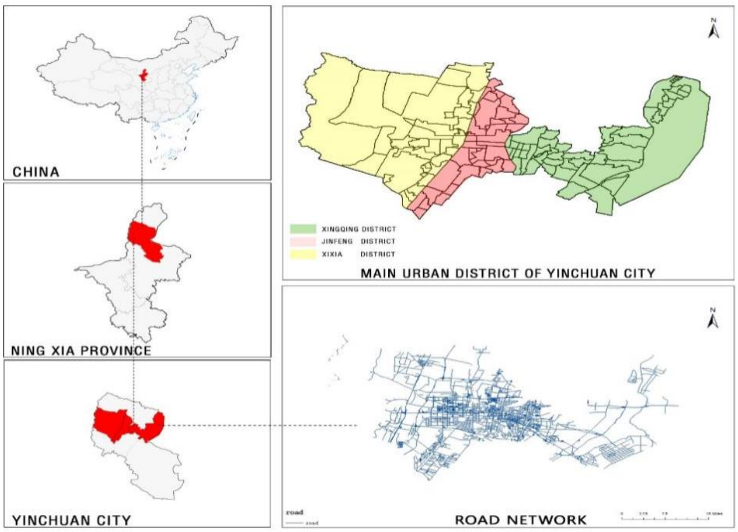

Figure 1: Study area（http://www.ngcc.cn/）.

3.2. Data Sources

Five types of data are used in this study. Geographic information data is from (http://www.ngcc.cn/).POI data is from Gaode Map(https://ditu.amap.com/). Road network data is from Open Street Map(https://www.openstreetmap.org). Baidu Heat Map is from Baidu Online Map(http://map.baidu.com/). Baidu street view is from (https://map.baidu .com). This study utilizes Baidu Heat Value to measure crowd activity density. The Baidu Heat Value is derived from the Baidu Heat Map, which is based on geographic data from mobile users on the Baidu Location-Based Service (LBS) platform. The Baidu Heat Map data uses various colors and brightness levels to reflect the population concentration in different regions. Brighter red areas indicate higher population density, while more pronounced blue areas indicate lower population density. The Baidu Heat Map is updated every 15 minutes. As a big data application with millions of users, the Baidu Heat Map holds significant value for urban research (Wu & Ye, 2016). It serves as a valuable tool to measure people's mobility in urban spaces or the vitality of different areas within a city (Wu et al., 2018b; Wu & Ye, 2016; Yue, Chen, Zhang, & Liu, 2019).

3.3. Conceptual Framework

Taking Yinchuan City as the research object, this study conducted comprehensive research on weekday and weekend urban vitality in Yinchuan City by collecting relevant information such as geographic information data of Yinchuan City and real-time Baidu heat map data. As shown in Figure 2, the data processing process in this paper is to extract the factors influencing urban vitality from three stages: data collection, feature extraction, and influence factor analysis. Firstly, during the data collection phase, we utilized the Baidu Maps Open Platform API interface to gather urban network data, Points of Interest (POI) data, population density data, and street view image data. Secondly, factors influencing urban vitality were identified through Geographic Information System (GIS) analysis and machine learning. The steps to obtain the influence factors are as follows:

(1) Extract the heat data of the active population on weekdays and weekends through Baidu Heat Map and measure the crowd density indexes.
(2) Use the Gaode POI data, and derive six indexes, namely, public facilities, food, landscape, transport, shopping, and hotel, through GIS kernel density analysis.
(3) Open Street Map extracts the structure of the road network of Yinchuan City from Baidu Maps to obtain Baidu Street View (Baidu Street View) images, using DeepLabV3 to extract elements from the street view image, to realize image segmentation, and to obtain the openness, greenness, enclosure, walkability, imageability and other five Measurement factors.
(4) Obtain bus stops and bus routes through Baidu map and get distance to transit indicator.
(5) Extract the road network structure of Yinchuan City through Open Street Map and analyze the traffic accessibility using sDNA in GIS platform and get destination indicator.

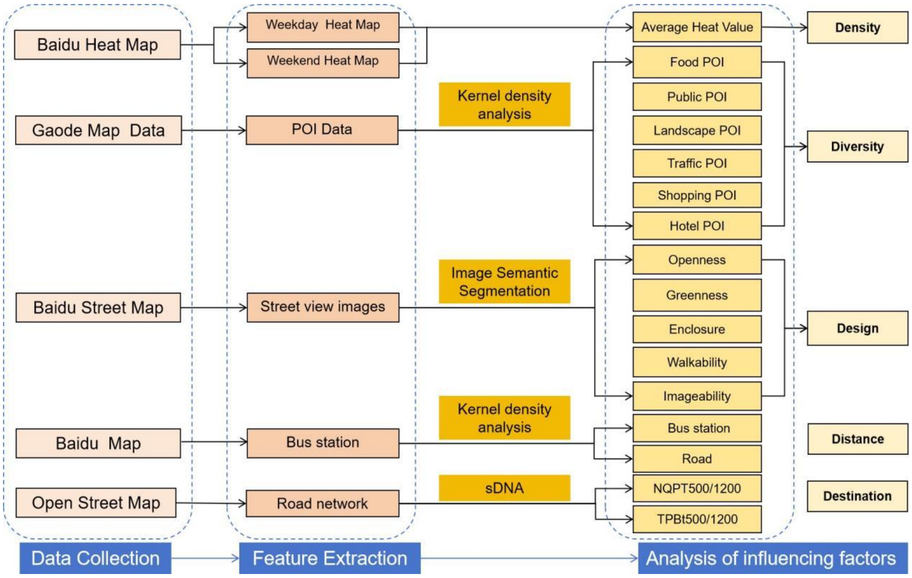

Figure 2: Data Collection and Processing.

This paper employed the Ordinary Least Squares (OLS) regression model to assess the influence of 5D variables on urban vitality. Additionally, global autocorrelation analysis using Moran's I index was applied to unveil the overall spatial correlation of urban vitality. To enhance the realism of the findings, Geographically Weighted Regression (GWR) was utilized to scrutinize the spatial heterogeneity in the impact of study variables on urban vitality. Lastly, the Gradient Boosting Decision Tree (GBDT) machine learning method was employed to rank the significance of factors influencing urban vitality on both weekdays and weekends, as depicted in Figure 3 .

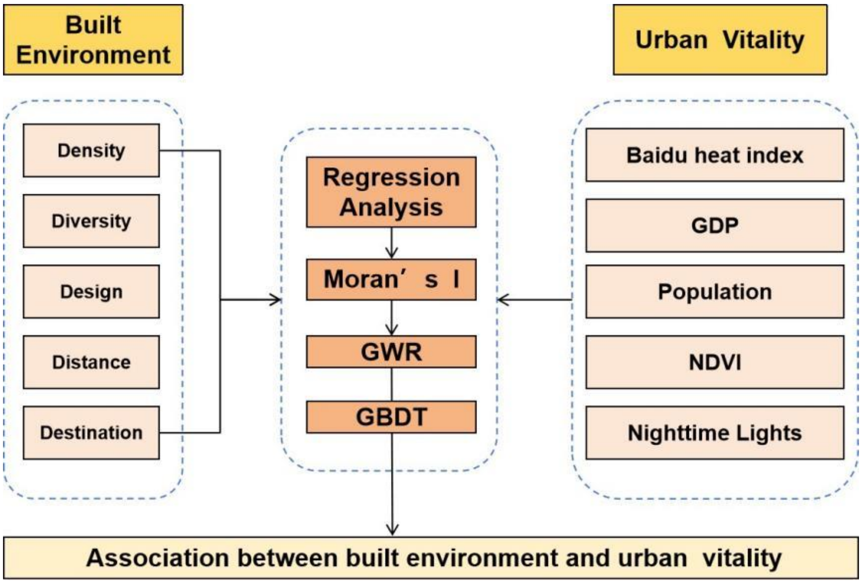

Figure 3: Conceptual Framework.

3.4. Select Variables

This paper focuses on urban vitality as the dependent variable during both weekdays and weekends, with the independent variables being the 5D factors. Density is the intensity of the spatial distribution of an element. This paper focuses on population density as a measure of urban vitality. Areas with higher population densities are relatively active in terms of urban vitality. For example, Saelens concluded that higher population density promotes walking and cycling activities (Saelens, Sallis, & Frank, 2016). Diversity is the complexity of utilization change of land use functions. Many researchers have utilized Point of Interest (POI) data for characterizing the built environment. Design serves as the factor that delineates the features and attributes of the built environment. Scholars in related fields often characterize urban design elements through parameters such as green coverage, road width, and various physical space elements that collectively shape the urban environment. Destination accessibility is a crucial factor, denoting the ease with which travelers can navigate from their starting point to their destination. According to Gehl and Gemzøe (2008), a well-connected and dense road network, coupled with efficient public transport organization, is essential for spatial vitality (Gehl & Gemzøe, 2008). Destination accessibility evaluates how easily individuals in an urban area can reach transportation hubs. This is often quantified by the density of public transport stations, including bus stops and metro stations. Vance and Hedel (2007) integrated public transport accessibility as a crucial indicator when examining the impact of the built environment on residents' reliance on motorized transportation. (Vance & Hedel, 2007). They observed that the walking distance to a public transport station significantly affects the distance traveled by residents using motorized transport.

This paper examines urban vitality as the dependent variable during both weekdays and weekends, employing the Baidu Heat Map to gauge the mobility of individuals within urban spaces. In this study, Baidu heat map is used as an indicator to measure the vitality of the city, and the collected heat map data are processed and analyzed using ArcGIS 10.7 to extract the vitality data of the city in different time periods. This paper takes Yinchuan city as an example. On the Baidu heat map, the population heat value of Wednesday, July 19, 2023, is selected, and the value is taken every two hours from 8:00 to 20:00, totaling seven times. The population heat value for Saturday, July 22, 2023, was selected and again taken every two hours from 8:00 to 20:00, for a total of seven times. Thus, the population heat values were taken for a total of 14 data occasions. The Baidu heat values for July 19 and July 22 were averaged through ArcGIS 10.7 software, followed by a comparative analysis to investigate urban vitality distinctions between weekends and weekdays.

As depicted in Table 1, the independent variables encompass a total of 17 factors. For Diversity, six Point of Interest (POI) data points were selected through density analysis. Design independent variables were derived from Baidu Street View, where DeepLab V3+ and ADE20K facilitated semantic segmentation of images. Drawing from previous research, five indices, namely Openness, Greenness, Enclosure, Walkability, and Imageability, were extracted and the equation was computed based on Rui (2023). Distance to transit variable was gauged using Bus Station density and Road density, following established literature. For Destination accessibility, the sDNA (Spatial Design Network Analysis) tool was employed, utilizing NQPDA and TPBt as the primary indicators (Rui, 2023).

Table 1: Explanations for The Indices' Scores Related to The Variables.

Variables	Name	Max	Min	Mean	S.D.
Density	Weekday Average Baidu heat	17.558	0	4.025	4.007
	weekend Average Baidu heat	18.064	0	4.576	3.642
Distance	Road	16.711	0	3.825	3.935
	Bus station	639457.334	0	81976.72	144763.808
Diversity	Landscape POI	19051.867	0	3307.122	4362.686
	Food POI	1364966.315	0	120618.457	257062.106
	Public POI	58628.231	0	5484.378	8849.809
	Hotel POI	171376.493	0	15460.55	36465.489
	Shopping POI	2644474.75	0	235377.049	479076.135
	Traffic POI	380486.446	0	36721.758	69577.989
Design	Openness	46.394	0	28.414	12.723
	Enclosure	0.499	0	0.277	0.143
	Walkability	44.533	0	16.775	10.378
	Greenness	7.343	0	1.324	1.676
	Imageability	0.141	0	0.007	0.025
Destination	NQPDA-500	0.066	0	0.009	0.014
	NQPDA-1200	0.099	0	0.012	0.019
	TPBt-500	0.881	0	0.386	0.24
	TPBt-1200	2.687	0	0.761	0.699

4. Results and Analysis

4.1. Regression Model of Urban Vitality

This study employs Ordinary Least Squares (OLS) linear regression, with built environment 5D variables as independent variables, and weekday and weekend urban vitality as dependent variables. Through stepwise regression, eight linear regression models were derived. The variable "Public" was excluded due to a Variance Inflation Factor (VIF) exceeding 7.5, while all other variables exhibited VIF values below 7. The results in Table 2 highlight the significance of Landscape POI, Public POI, Hotel POI, Shopping POI, Openness, Greenness, Imageability, Road, Bus station, TPBt -500, NQPTA-500, and TPBt-1200 variables in influencing urban vitality. Moreover, Landscape POI, Public POI, Hotel POI, Shopping POI, Openness, Greenness, Imageability, Road, Bus station, NQPTA-500, TPBt-1200 variables were found to be significant contributors to urban vitality specifically during weekends.

Table 2: The Relationship Between the Built Environment and Urban Vitality on Weekdays and Weekends Using OLS.

Variable	Variable Name	Weekday Urban Vitality						Weekend Urban Vitality					
		Standard Error	T	P	VIF	R^2	Adjust R^2	Standard Error	T	P	VIF	R^2	Adjust R^2
Diversity	Landscape POI	0.073	6.546	0.000***	1.988			0.062	9.919	0.000***	1.988		
	Food POI	0.159	-0.364	0.716	6.404			0.136	-1.184	0.239	6.404		
	Public POI	0.235	-1.968	0.052*	9.077	0.69	0.674	0.202	-1.982	0.050**	9.077	0.708	0.693
	Hotel POI	0.092	5.442	0.000***	2.753			0.079	5.523	0.000***	2.753		
	Shopping POI	0.099	2.989	0.003***	2.291			0.085	2.205	0.029**	2.291		
	Traffic POI	0.138	1.528	0.129	4.55			0.118	0.777	0.439	4.55		
Design	Openness	0.07	1.873	0.064*	1.037			0.062	2.845	0.005***	1.037		
	Enclosure	0.123	0.927	0.356	3.436			0.108	0.98	0.329	3.436		
	Walkability	0.148	0.247	0.806	3.306	0.19	0.155	0.13	-0.002	0.998	3.306	0.202	0.168
	Greenness	0.089	-2.987	0.003***	1.154			0.078	-2.76	0.007***	1.154		
	Imageability	0.114	3.539	0.001***	1.098			0.1	3.503	0.001***	1.098		
Distance	Road	0.059	3.827	0.000***	1	0.556	0.549	0.041	5.866	0.000***	1	0.726	0.722
	Bus station	0.061	11.574	0.000***	1			0.043	16.726	0.000***	1		
Destination	TPBt-500	0.113	-2.452	0.016**	5.443			0.097	-1.45	0.150	5.443		
	NQPTA-500	0.099	-2.281	0.024**	2.55			0.085	-2.96	0.004***	2.55		
	NQPTA-1200	0.118	0.023	0.982	2.983	0.607	0.594	0.102	0.46	0.646	2.983	0.63	0.617
	TPBt-1200	0.131	7.935	0.000***	6.73			0.113	7.467	0.000***	6.73		

Note: ***, **, * represent 1%, 5%, and 10% significance levels, respectively.

4.2. Spatial Autocorrelation of Urban Vitality

In this study, ArcGIS was utilized to compute the Moran's I index for each variable. Notably, Walkability, Greenness, Imageability, and NQPDA-500 variables exhibited p-values > 0.001, necessitating their exclusion in subsequent analyses. Conversely, all other independent variables demonstrated Moran's I indices, Z-scores, and p-values above zero, with p-values below 0.05. This suggests a higher degree of spatial clustering for these variables, making them suitable for a GWR model. The Moran's I value for urban vitality on weekday and weekend were 0.742 and 0.721, respectively, indicating a positive correlation with a clustered spatial distribution. This implies a discernible spatial relationship between urban vitality and the built environment. Across most variables, Moran's I values ranged from 0.063 to 0.828, signifying positive spatial autocorrelation at the significance level of $p = 0.01$.

4.3. GWR Model

Based on Moran's I statistics, a majority of both dependent and independent variables exhibit noteworthy and positive spatial autocorrelation. Variables displaying significant correlations with urban vitality were chosen for a GWR model analysis to discern variation in space. The findings indicate a substantial enhancement in model performance with the GWR approach as opposed to the Ordinary Least Squares (OLS) regression (Figure 4).

The GWR model analysis indicates a positive correlation between the 'Road' variable on weekdays and the central areas of 3 districts, specifically in locations like Shengli Street and Jiefangxi Street (Figure 4(a)(b)). Conversely, it shows a negative correlation in most of the corresponding areas in Xixia District. On weekends, the 'Road' variable exhibits a negative correlation in more picturesque rural or outskirts areas of the city. In simpler terms, higher road density in the city center corresponds to a more pronounced impact on urban vitality. Conversely, in the peripheral areas of the central city, increased road density is associated with diminished urban vitality.

As depicted in Figure 4(c)(d), the 'Bus station' variable on weekdays exhibits predominantly positive correlations in the central urban regions of the three districts. Conversely, it demonstrates negative correlations in the center of Xingqing District. On weekends, the 'Bus station' variable is largely negatively correlated in the central urban areas of the three districts, particularly in regions characterized by an overall negative correlation, often indicative of more bustling commercial areas. This suggests that a higher density of bus stations is associated with weaker urban vitality.

As illustrated in Figure 4(e)(f)(g)(h)(i)(j), on weekdays, the variables 'Food,' 'Traffic,' and 'Shopping' demonstrate positive correlations with urban vitality in the central city areas of the three districts. On weekends, streets with high pedestrian traffic exhibit a robust positive correlation, while most other areas display a negative correlation. Many locations with negative correlations are situated at a considerable distance from the city center. This pattern suggests that excessive concentration of food and shopping activities in the central city contributes to traffic congestion, thereby diminishing the overall vitality of the city.

Illustrated in Figure 4(k)(l)(m)(n), 'Openness' and 'Enclosure' variables on weekdays exhibit a positive correlation in the central city and a negative correlation in peripheral areas. Increasing urban open space and enhancing the enclosure of buildings on both sides of the road can increase urban vitality and attract more people. The ‘Openness’ and ‘Enclosure’ on weekends show a negative correlation with most of the suburban areas. This may be because people tend to go to the suburbs on weekends.

As depicted in Figure 4(o)(p)(q)(r)(s)(t), on weekdays, the variables 'TPBt-500,' 'TPBt-1200,' and 'NQPTA-1200' exhibit a positive correlation in the central area and a negative correlation in other regions with high pedestrian flow. On weekends, these variables show a negative correlation in the city's suburbs. Urban centers during weekdays attract population clusters primarily due to work demands, and transportation plays a crucial role in facilitating trips to workplaces in these areas, leading to a positive relationship between transportation and vitality. However, the expansion of areas positively correlated with rest days aligns with the trend of people relocating away from the city center during leisure periods.

In summary, based on the Geographically Weighted Regression (GWR) analysis, the central region of Xingqing District in Yinchuan City emerges as the locale with the highest urban vitality, followed by the central area of Jinfeng District in the second position, and the central area of Xixia District ranking third. These areas with heightened urban vitality are characterized by a concentration of high-quality shopping, residential, dining, and transportation services, affirming findings from prior research.

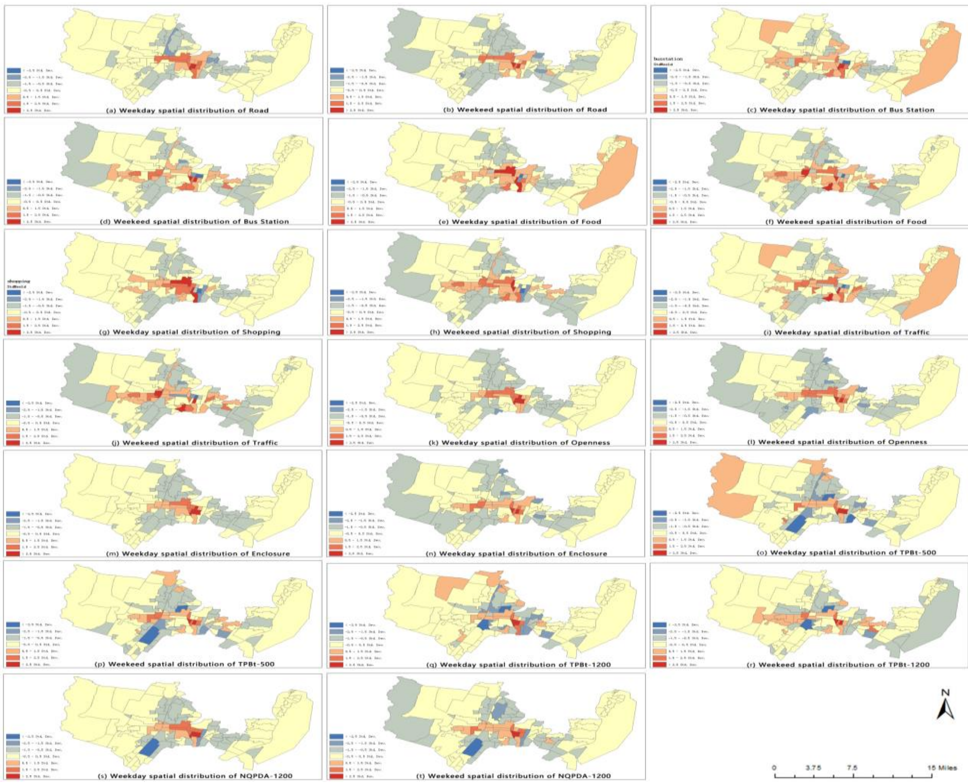

Figure 4: Regression Coefficients for Influencing Factors in A GWR Model Across Different Spatial Locations.

4.4. GBDT Model

As illustrated in Figure 5 and Figure 6 , the importance of features calculated by GBDT reveals that, on weekdays, the top five factors are TPBt-1200, Greenness, Imageability, Landscape, and Food. TPBt-1200 takes the lead with a significance of 60.6%, followed by Greenness at 11.7%, Imageability at 8.3%, Landscape at 4.0%, and Food at 3.3%, respectively. On weekends, the highest-ranking factors are TPBt-1200, Bus Station, Imageability, Traffic, and Landscape. TPBt-1200 holds the highest importance at 61.6%, followed by Bus Station at 13.9%, Imageability at 8.0%, Traffic at 4.1%, and Landscape at 3.1%. The analysis indicates that, during working days, significant factors include traffic accessibility (TPBt-1200) and green visibility, while on weekends, transport accessibility and public transport density are predominant. This study suggests that prioritizing these highly ranked indicators can be instrumental in the urban planning or urban regeneration process.

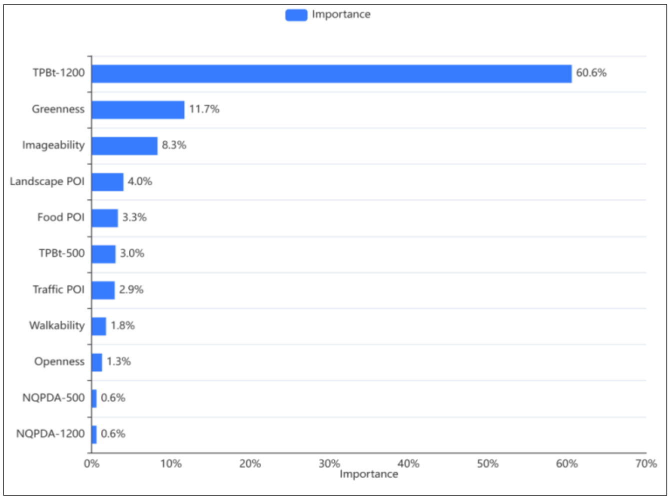

Figure 5: Feature Importance of Weekday's Ranking Results.

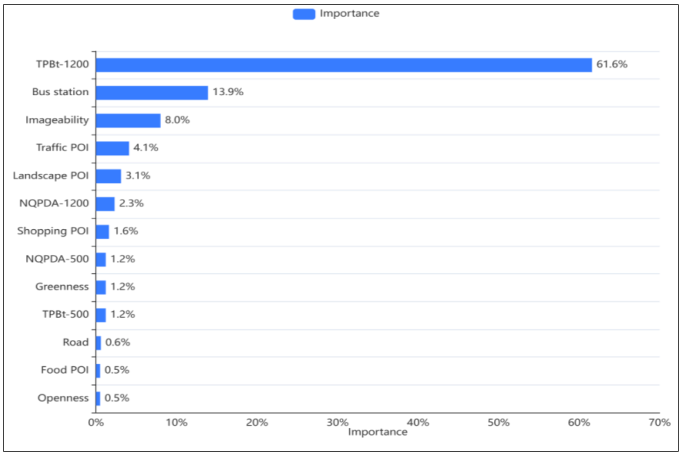

Figure 6: Feature Importance of Weekend's Ranking Results.

5. Discussion

5.1. Variations In the Spatial Patterns of Urban Vitality During Weekdays and Weekends

This study delves into the analysis of urban vitality distribution in Yinchuan City during weekdays and weekends, revealing discernible differences in spatial patterns (Wu et al., 2018; Xu et al., 2018). Such disparities arise from varying activities and functions across different areas of the city during working and non-working hours. The subsequent section provides a detailed breakdown of the spatial distribution of urban vitality on weekdays and weekends in Yinchuan City.

5.2. The Spatial Patterns of Urban Vitality During Weekdays

The distribution of weekday urban vitality shows obvious Morning and Evening peak characteristics (Fang, Li, & Wang, 2016; Liao & Wong, 2015; Liu et al., 2017). Weekday urban vitality is mainly concentrated in commercial areas, office areas and transportation hubs in the central urban areas of the three districts. The vitality of these areas' peaks during 8:00-12:00 and 14:00-18:00 when people from residential areas commute to commercial and office areas. While at 12:00-14:00 and 18:00-20:00, people return from commercial and office areas to residential areas, and the vitality of these areas will decrease, as identified in the research by He et al. (2018) and Lu et al. (2019). These districts are the commercial, cultural, and administrative centers of Yinchuan, concentrating many commercial facilities such as shopping malls, supermarkets, restaurants and cafes, as well as offices such as government agencies, banks and law offices. These facilities attract people to come to work and live in the area, making this area a high level of urban vitality. The main commercial areas in Yinchuan include areas such as Xinhua Street, Gulou Street, and Nanmen Square. These areas have numerous stores, restaurants, entertainment facilities, etc., which attract many consumers and tourists to come to shop, dine and play. These activities further enhance the urban vitality of these areas.

5.3. The Spatial Patterns of Urban Vitality During Weekends

During weekends, the spatial distribution of urban vitality is more diversified and decentralized, as mentioned in the research by Azmi and Karim (2012). Moreover, the distribution of urban vitality on weekends is more balanced than on weekdays, as mentioned in the research by Guo, Chen, and Yang (2021). People are no longer constrained by the need to commute and are free to organize their activities. As a result, urban vitality may be more decentralized, including a wide range of activities such as shopping, tourism, and entertainment. Some public places, such as parks, shopping malls and museums, may become busier on weekends as more people have time to visit them. In addition, some leisure and entertainment venues and tourist attractions may become hotspots of urban vitality.

Weekend urban vitality is concentrated in areas such as parks, tourist attractions and shopping centers (Tang et al., 2018). These areas include Zhongshan Park, Haibao Park and Nanfeng Park. These parks and squares are good places for people to relax and have fun, especially on weekends, where people engage in a variety of outdoor activities, such as walking, running, playing ball games, singing, dancing, etc., which makes urban vitality higher in these areas. Yinchuan is a city full of history and culture, with many tourist attractions, such as the Mausoleum of the Xixia Kings, the rock paintings on Helan Mountain, and the Zhenbeibao Movie Town. On weekends, these attractions attract many tourists to visit and learn from them, further enhancing the urban vitality of these areas. There are many shopping centers in Yinchuan, such as Wanda Plaza, Century Golden Flower Shopping Center and Xinbai supermarket. These shopping centers attract many consumers to shop and dine on weekends, making the urban vitality of these areas higher.

Overall, the distribution of urban vitality in Yinchuan demonstrates variations between weekdays and weekends. During weekdays, heightened urban vitality is primarily centered around the city core and major business districts. In contrast, on weekends, areas with elevated urban vitality shift to parks, squares, tourist attractions, and shopping centers. This discrepancy underscores the diverse functions and activities of the city throughout different times of the week, playing a pivotal role in shaping the city's development and planning considerations.

5.4. Strategies to Enhance Urban Vitality on Weekdays and Weekends

Through an examination of the built environment factors and their correlation with weekday and weekend urban vitality in Yinchuan, it was observed that Diversity, Design, Distance to transport, and Destination accessibility play pivotal roles in influencing urban vitality. To augment both weekday and weekend urban vitality, strategic interventions can be formulated by leveraging the 5D variables of the built environment. Presented below are specific recommendations for implementing such strategies.

5.5. Strategies for Enhancing Urban Vitality from Diversity

Enhancing the diversity of the cityscape proves instrumental in drawing more individuals for work and leisure visits. On weekdays, fostering the growth of diverse commercial and office spaces—ranging from technology and finance to arts—can attract talents and businesses across various sectors. During weekends, amplifying the variety of entertainment and recreational amenities, such as cinemas, museums, and parks, contributes to a vibrant city atmosphere. Moreover, organizing a spectrum of cultural activities and festivals, including music festivals, art exhibitions, and food festivals, adds to the city's allure and diversity (Lu et al., 2019).

5.6. Strategies for Enhancing Urban Vitality from Design

Effective urban design plays a pivotal role in elevating a city's charm and vitality (Xia, Yeh, & Zhang, 2020). In this design process, careful consideration must be given to the creation and utilization of public spaces. Parks, squares, and streets, among others, not only serve as places for relaxation but also stand as significant symbols and attractions within the city. Designing distinctive and unique public spaces contributes to further enhancing the city's image and appeal. These spaces serve as havens for office workers seeking relaxation on weekdays and transform into destinations for individuals to unwind and enjoy activities such as walking, exercising, and gathering on weekends. Additionally, improving the city's environmental quality can be achieved by enhancing greenery and beautification. Planting flowers, plants, and trees along streets or incorporating artworks like fountains and sculptures in public spaces enhances the aesthetic appeal. In conclusion, thoughtful urban design holds the potential to significantly enhance a city's charm and vitality.

5.7. Strategies for Enhancing Urban Vitality from Distance to Transit

Transit stations constitute vital infrastructure in a city, playing a crucial role in facilitating people's travel and fostering urban development (Maas, Attard, & Caruana, 2020). On weekdays, optimizing the public transport network by increasing the number and frequency of bus stops and metro stations enhances the convenience of daily commuting and travel for residents. Simultaneously, promoting the use of low-carbon transportation modes like bicycles or walking contributes to sustainable mobility. During weekends, enhancing accessibility to urban tourist attractions becomes a priority, which can be achieved by establishing special tourist lines or providing free buses around these attractions. Additionally, encouraging travelers to utilize free travel options such as bike sharing, or car rental further promotes sustainable and flexible transportation choices.

5.8. Strategies for Enhancing Urban Vitality from Destination Accessibility

Improving the accessibility of destinations is crucial for enhancing the attractiveness and vibrancy of a city (Li et al., 2017). On weekdays, optimizing the accessibility of commercial and office areas can be achieved through the installation of clear signage or the provision of map navigation services. This ensures people can effortlessly reach their destinations and find suitable parking spaces (Mouratidis & Poortinga, 2020). During weekends, a further improvement in accessibility to the city's entertainment and recreational facilities is essential. Establishing special tour routes or sightseeing buses that connect various attractions and activity venues is a viable solution. Additionally, providing convenient services such as free Wi-Fi and charging facilities enhances the overall visitor experience. By implementing these measures, the city can ensure that individuals, regardless of their mode of transportation, can easily access its diverse attractions, fostering a dynamic and lively urban environment (Tang et al., 2018).

In summary, through the implementation of measures such as rational planning of urban density, increasing urban diversity, optimizing urban design, and improving accessibility to transportation stations and destinations, we can effectively enhance urban vitality on weekdays and weekends. These measures need to be coordinated and supported to maximize the combined benefits and ultimately achieve a comprehensive increase in urban vitality.

6. Conclusion and Future Work

6.1. Conclusion

Utilizing Yinchuan City as a case study, this research extensively explores the temporal and spatial patterns of the relationship between urban vitality and built environment. The study employs the 5D theory of the built environment and utilizes OLS, GWR, and GBDT methodologies to conduct a comprehensive investigation. The results not only uncover the intricate temporal and spatial patterns of urban vitality but also confirm the varied degrees of impact exerted by elements of the built environment on urban vibrancy. The key findings include:

(1) The built environment's 5D variables exert a substantial impact on urban vitality in Yinchuan City, evident on both weekdays and weekends.
(2) Utilizing the Moran's Index, the study uncovers a positive spatial autocorrelation between the built environment and urban vitality, observed consistently on both weekdays and weekends.
(3) Analysis using the GWR model highlights unique spatial distribution features of urban vitality during weekdays and weekends. In the central city area of Yinchuan, neighborhoods with higher urban vitality tend to cluster. Specifically, on weekdays, urban vitality is primarily influenced by commercial districts, office areas, and transportation hubs. On weekends, urban vitality is more influenced by leisure and entertainment facilities such as parks, tourist attractions, and shopping centers.
(4) Utilizing the GBDT model, it is observed that the variables influencing urban vitality during different time periods exhibit different orders of importance.

6.2. Limitations of the Study and Future Research

Despite achieving relatively positive outcomes, this study has certain limitations. Firstly, the research predominantly concentrated on the central area of Yinchuan City, neglecting the suburbs and surrounding regions. Subsequent studies could broaden their scope to encompass various areas, considering distinctions in urban vitality and its influencing factors across diverse regions. Secondly, the study primarily focused on the direct impact of the built environment on urban vitality, neglecting possible contributing factors such as social culture and policy institutions.

Future research can further explore the mechanisms by which these factors influence urban vitality. Future research can also be carried out in the following areas. Firstly, conduct a comprehensive examination of the dynamics of urban vitality and the factors influencing it across various time periods. Secondly, exploring how to integrate urban vitality enhancement strategies with urban planning to achieve sustainable urban development. Thirdly, conducting quantitative research to further verify and assess the effectiveness and feasibility of urban vitality enhancement strategies.

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