EXPLORING NONLINEAR RELATIONSHIP BETWEEN BUILT ENVIRONMENT AND STREET VITALITY USING MACHINE LEARNING

A Case Study of Ding Shu, China

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Abstract. Urban vitality serves as the linchpin for sustainable urban development. Being the most extensively utilized public space within cities, augmenting street vitality bears paramount importance in accelerating design in human-centric habitats. This study employs spatial analysis and machine learning methods to explore the potential nonlinear relationships and local threshold effects between the built environment (BE) and street vitality based on multi-source data. This investigation provides support for the quantitative assessment and optimization of street vitality. Initially, using collected street view images, street spatial elements are extracted through deep learning algorithms. Subsequently, integrating multiple data sources, machine learning methods are employed to quantify the impact and interactions of the built environment on street vitality. Illustrated with the case of Dingshu, the feasibility of this process is demonstrated. By examining the correlation and underlying mechanisms between the built environment and street vitality, this study aids decision-makers in leveraging technological means to expedite design processes and create human-centric cities.

Keywords. Nonlinear Relationship, Built Environment, Street Vitality, GBDT-SHAP, Interaction Effect.

1. Introduction

Urban vitality constitutes the bedrock of sustainable urban development and is crucial

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in creating high-quality spaces. Streets, regarded as the primary "organs" of a city and vital public spaces, play a pivotal role in enhancing the living environment of urban residents. During the wave of technological advancements, design processes have been accelerated. However, the lack of understanding about the objective patterns of the correlation between street-level built environment (BE) elements and individual daily activities, resulting in a series of issues, such as declining urban spatial quality, uncontrolled urban sprawl, and environmental pollution. Therefore, we need to uncover the complex relationships between BE and urban vitality to support human-centric urban design and develop liveable cities.

Jacobs initially conceptualized urban vitality as "street life over a 24-h period". From a perspective rooted in urban sociology, Lynch suggested that vitality reflects a place's capacity to fulfil individual survival and development. Gehl emphasized that urban vitality transcends mere population count on a street; it primarily concerns how people utilize street spaces. Montgomery further proposed that a vibrant place entails diverse activities and a continuous flow of people on streets over a 24-hour cycle. Fundamentally, the core of street vitality resides in the presence of people on the streets.

Prior research has indicated a close relationship between street vitality and built environment elements such as street morphology and functionality (Marcus, 2010; Oliveira, 2013; Ye and van Nes, 2014). Traditional research methodology using linear regression models does not cater to the need of uncovering the complex relationships between street vitality and the built environment variables. With the evolution of emerging computational analysis techniques, there is a growing trend in using machine learning models to explore the non-linear relationship between street vitality and the built environment. Compared to traditional models, machine learning methods have exhibited superior performance and effectiveness in predicting vitality based on the built environment. However, the "black box" nature of this approach, where the reasons remain unclear, has faced criticism due to inherent limitations. The emergence of eXplainable Artificial Intelligence (XAI) models, particularly the Shapley Additive exPlanations (SHAP), offers a new pathway to enhance the interpretability of machine learning. SHAP can identify variable importance in predictions and analyse non-linear relationships and interaction effects. Presently, interpretable machine learning methods have not been fully employed to examine the non-linear relationships and interaction effects between street vitality and the built environment.

To bridge this gap, this study primarily focuses on the vitality of liveable streets, closely linked to residents' daily lives. It begins by collecting data from multiple sources and integrating 3D street spatial elements, urban morphology and functionality data. Subsequently, a set of BE indicators are extracted from the multi-source data. The GBDT model is utilized to quantify the relationship between street vitality (1532 streets in Dingshu, in this case) and the built environment factors. This aims to apply machine learning interpretative algorithms from existing literature to identify key influencing factors and capture potential influencing factors. Following this, the SHAP model is used to explain the non-linear relationships and interactions between the built environment elements. Specific research inquiries focus on: 1) applying interpretative machine learning models to identify influential factors and capture potential influencing factors; 2) investigating the driving factors dominating street vitality; 3) uncovering the potential nature and threshold of BE elements impacting street vitality.

2. Study Area and Data

2.1. STUDY AREA

Dingshu Town, located in the city of Wuxi in the eastern part of Jiangsu Province, China, represents a typical small Chinese city. Through natural growth and a long historical evolution, Dingshu has developed a complex and diverse street space. The streets exhibit a rich variety of forms and functions, serving as a representative case for studying street vitality. This study focuses on around the central area of Dingshu, covering a total of 1,532 streets.

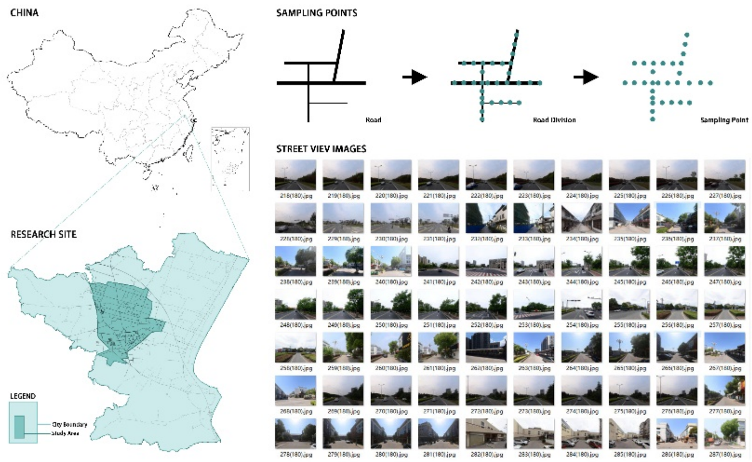

Figure 1. Study area and Baidu Street View Image acquisition

2.2. DATA

2.2.1. Morphological Data

Morphological data primarily encompass street network morphology and architectural fabric morphology. The morphological data is mainly sourced from OpenStreetMap (OSM). Considering potential delays in data updates in certain regions of China, Baidu Map (one of the most prevalent map service platforms in China) was utilized for verification and supplementation purposes. The original street network data underwent cleansing, topological verification, and processing, resulting in a total acquisition of 1,532 streets.

2.2.2. Functional Data

Functional data pertains primarily to Point of Interest (POI) data. The distribution of POIs on both sides of the roads can effectively reflect the functional characteristics of the streets.

On May 10, 2022, via Python, requests were sent to the Baidu Map API, gathering 12,920 POIs across 15 categories. Each POI data includes the name, latitude, longitude, address, category, and other pertinent information of the geographic entity.

2.2.3. Street View Images

Street View Images (SVI) have recently been widely accepted as an effective means to quantify the built environment of streets (Kelly et al., 2013; Shen et al., 2018; Ye et al., 2019).

Based on street network data, sampling points were generated at 20m intervals along the road centrelines. Following cleansing and organization, the central area of Dingshu Town comprised a total of 17,720 sampling points. Geographic coordinates of each point can be obtained in GIS platforms. Additionally, the image size is set to 960×720 pixels. Post data cleansing, this study could utilize 16,250 valid SVIs.

3. Methodology

3.1. VARIABLES

3.1.1. Extraction of Street Spatial Elements

To extract street spatial elements corresponding to each sampling point from the street view images, we employed a convolutional neural network (CNN)-based semantic segmentation method. The spatial elements extracted in this study include nine categories, which are road, sidewalk, building, wall, vegetation, sky, person, bicyclist and car.

First, we selected 50 street view images covering various types of streets in Ding Shu as experimental samples and manually annotated spatial elements on these samples, using them as ground truth. Subsequently, we employed three neural network models pre-trained on the Cityscapes Data dataset for urban street view semantic segmentation: Dilated ResNet-105, Ademxapp Model A1, and Multi-scale Context Aggregation Net. Further comparison between the pixel quantities of various spatial elements in the sample images and the ground truth allowed the determination of the recognition accuracy of each neural network model.

As can be seen in Figure 2, the Ademxapp model exhibited weaknesses in sky recognition, while the multi-scale context aggregation model inaccurately identified distant individuals. Consequently, we selected the Dilated ResNet-105, achieving the highest accuracy among the 50 sample images, for final SVI segmentation.

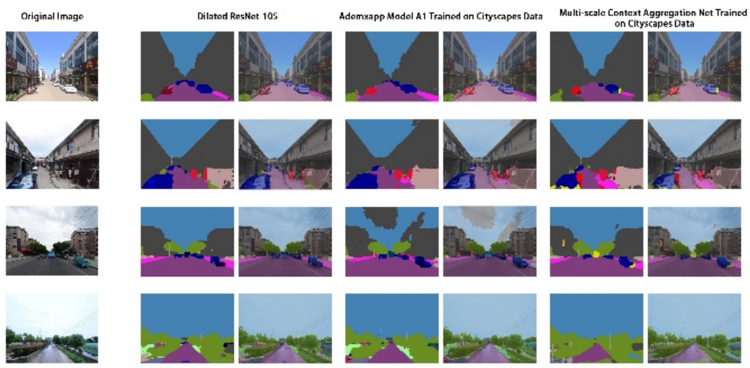

Figure 2. Comparison of neural network recognition of street view images

3.1.2. Construction of Built Environment Indicator Set

Jacobs believes street vitality comes from enough people on the street (Jacobs, 1961). We employed the number of individuals to represent street vitality. The count of individuals was derived from street view images, which were mapped to each sampling point.

The key to constructing an index system lies in effectively representing the elements of the built environment. Referring to the "5D" index system proposed by Ewing et al., which includes Density, Diversity, Design, Destination accessibility, and Distance to transit across five dimensions, this study comprehensively considers the existing research on the construction of indicators related to the built environment. In total, 12 indicators have been selected for the measurement of the built environment, as shown in Table 1.

Table 1. Independent variables and description

Indicators	Formula	Description
Density		
Population density	$PopulationDensity = \frac{Pop_i}{Area_i}$	Pop_i The population of the administrative district where the street is located $Area_i$ The area of the administrative district where the street is located
Diversity		
Functional mixture	$Number\ of\ categories = -\sum_{x=1}^{n} \frac{p\_num_x}{sum\_fuc} \log \frac{p\_num_x}{sum\_fuc}$	p_num_x Number of POIs of category x n The number of category of POIs
Design		
Pedestrian	$Pedestrian = pixr\_sw$	$pixr\_sw$ The pixel ratio of the pavements
Vegetation	$Vegetation = pixr\_gre$	$pixr\_gre$ The pixel ratio of the plants
Street length	$StreetLength = L_i$	L_i The length of a single street segment
Street width	$StreetWidth = pixr\_rd + pixr\_sw$	$pixr\_rd$ The pixel ratio of the roads
Spatial enclosure	$SpatilEnclosure = \frac{pixr\_ver}{pixr\_hor}$	$pixr\_ver$ The pixel ratio of vertical elements, including buildings, walls and plants $pixr\_hor$ The pixel ratio of horizontal elements, including roads and pavements
Spatial openness	$SpatialOpenness = pixr\_sky$	$pixr\_sky$ The pixel ratio of the sky
Destination accessibility		
Distance to city centre	$Dis_{centre} = \min Dis_{centre}$	Dis_{centre} The path distance between the street and the central part of city
Functional density	$FunctionalDensity = \frac{sum\_fuc}{L_i}$	sum_fuc The total number of POIs within 55 m on both sides of the street segment
Distance to transit		
Distance to the nearest bus stop	$Dis_{bus} = \min Dis_{POI\_bus}$	Dis_{poi_bus} The Euclidean distance between the street and the bus stop
Street density	$StreetDensity = \frac{\sum_{i=1}^{n} L_i}{S_A}$	L_i The length of a single street segment S_A The buffer area of 300 m on both sides of the road section

3.2. MODELLING APPROACH

To avoid errors associated with individual sampling points, including white noise/data errors, the obtained sampling points were mapped onto the corresponding road segments. The average values of the built environment indicators corresponding to each sampling point were used to represent the built environment element values of the respective road segment. Here, road segments were considered as basic units segmented by road intersections, while segments with wider roadways, including both forward and backward bidirectional sampling points, were encompassed.

3.2.1. GDBT

The Gradient Boosting Decision Tree (GBDT) model is employed to address issues with highly concentrated data feature distributions, demonstrating higher accuracy compared to algorithms such as Support Vector Machines and Random Forests. Moreover, GBDT can be used to capture any irregular relationships among variables, and modelers are not required to pre-specify these relationships in advance.

3.2.2. SHAP

Although the GBDT model surpasses traditional linear regression models in accuracy and generalization, its interpretability falls far short compared to linear models. Therefore, this study integrates the SHAP (SHapley Additive exPlanations) method to address this "black box" issue.

SHAP, a unified approach, aims to explain the output of any machine learning model. The SHAP method, grounded in cooperative game theory, revolves around computing the marginal contributions of feature observation points when introduced into the model.

4. Results and Discussion

Initially, a Pearson correlation coefficient test was conducted to determine the influence of the considered feature variables on the parameters of street vitality. Variables with significant correlations ($P < 0.5$) were selected from the initial variable pool.

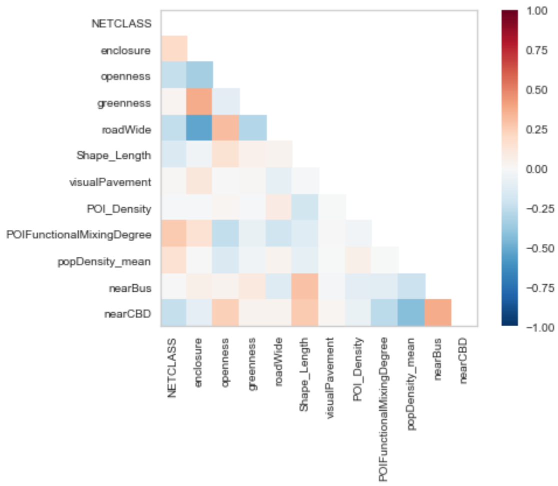

Figure 3. Pearson correlation coefficient test

After variable filtration and data processing, all samples were randomly divided into a training dataset (80%) and a testing dataset (20%) for modelling purposes. Post-testing, the GBDT model achieved a Model Accuracy of 0.935, making it a suitable model for predicting Dingshu street vitality.

Subsequently, for immediate comprehension and interpretation of the entire model, we require global interpretability. Firstly, a feature importance analysis was conducted on the model to gauge the model's dependency on specific features. The SHAP contribution analysis utilized Shapley values to determine the degree of contribution of the built environment to street vitality. Factors with higher contribution values are crucial in predicting street vitality values. The globally established SHAP analysis results are depicted in the figure 4 for immediate understanding.

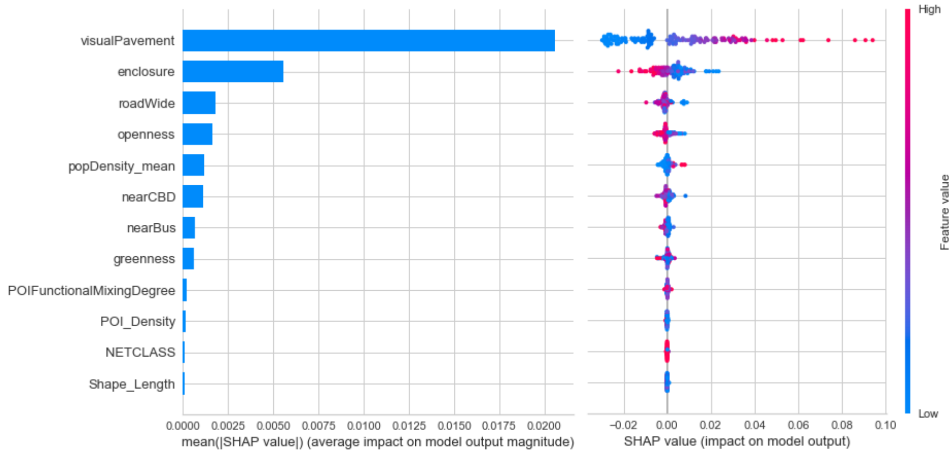

Figure 4. Importance ranking diagram and density scatter diagram of built environment feature

As we can see from figure 4, the built environment indicators that exert the greatest influence on predicting street vitality, listed in descending order, are visual pavement rate, enclosure, road width, openness, population density, and distance from the nearest CBD.

This outcome is relatively intuitive. For instance, a larger proportion of pedestrian pathways provides more space for human activities, thus contributing to the enhancement of street vitality. Similarly, reduced enclosure in streets enhances the sense of safety, encouraging individuals to linger longer. However, there are exceptions, for instance, if the top-ranked indicators significantly impact the predictive outcomes, their effects might be dispersed. Furthermore, the distribution of points on the graph isn't entirely symmetrical along the central axis. Hence, delving deeper into their inherent reasons is imperative.

To achieve this objective, we selected the top 9 indicators in the global feature importance ranking and analysed how individual indicator features influence the overall predictive outcomes based on their SHAP partial dependence plots.

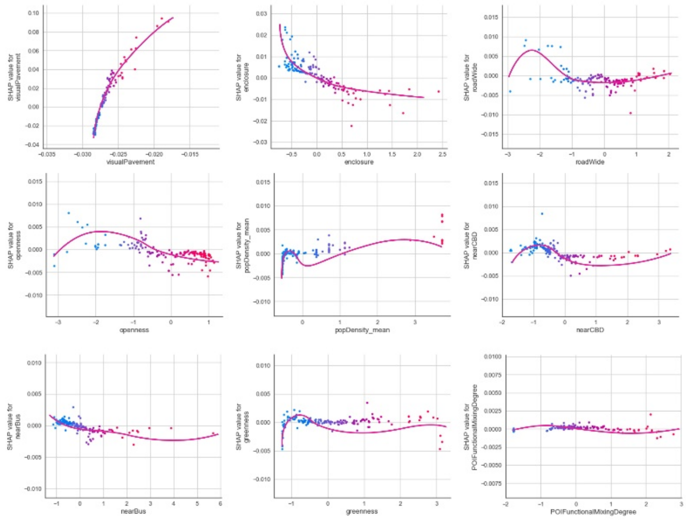

Figure 5. Nonlinear relationships between built environment and street vitality

Based on the partial dependence plot (PDP), marginal effects of various features on the predictive outcomes of machine learning models are depicted. As shown in the figure 5, these plots illustrate the nonlinear relationships between the dependent variable (street vitality) and the top 9 important variables in terms of their significance.

Furthermore, we aim to more precisely comprehend the impact thresholds of these crucial influencing factors on street vitality. To achieve this, we conducted individual PDP tests for each element. This exploration allows for a more in-depth investigation into the specific interrelationships among the key driving factors influencing street vitality.

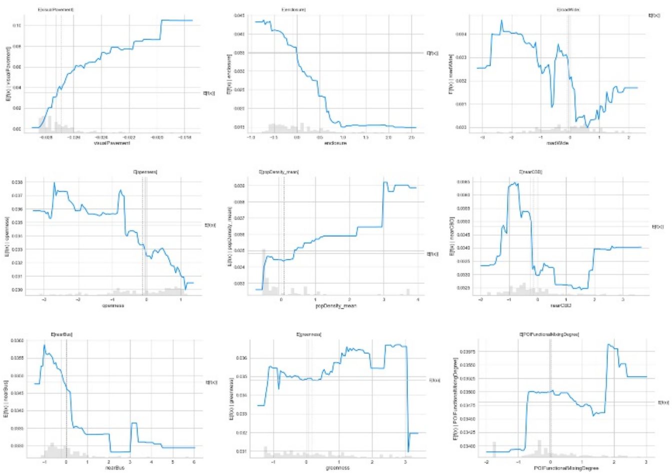

Figure 6. PDPs of Top 9 built environment features

As illustrated in the figure 6, we observed localized impact trends and threshold effects among certain built environment elements concerning street vitality. Notably, there exists a positive correlation between "visual pavement" and street vitality, indicating that wider sidewalks correspond to higher street vitality. However, this growth reaches a threshold after a sidewalk width of 10 meters, suggesting that sidewalk widths exceeding 10 meters do not further enhance street vitality. This might be due to an excessive width ratio of sidewalks, which often accommodate non-motorized traffic, thereby restricting actual pedestrian behaviour within these spaces.

"Openness," on the other hand, demonstrates an overall negative correlation with street vitality but exhibits a specific threshold effect. When openness falls within the range of 0.1 to 0.2, there is a significant increase in street vitality. However, when openness exceeds 0.25, street vitality significantly decreases. This suggests that while increasing openness at lower levels can enhance safety, surpassing a certain threshold in openness leads to reduced enclosure, subsequently decreasing human interaction.

The influence of "near CBD" and "near Bus" on vitality is similar. Within a 500-meter range, vitality increases with distance, reaching a peak around the 500-meter threshold. Within the range of 500 to 2000 meters, street vitality decreases as the distance increases. Beyond 2000 meters, street vitality slightly increases and stabilizes near 2500 meters. It is evident that an increase in population density and green space ratio generally leads to higher street vitality values.

5. Conclusion

This study employed the machine learning model GBDT-SHAP to analyze the nonlinear effects and threshold impacts of the built environment on street vitality. It explored the latent relationship between urban built environments and urban vitality, monitored the marginal benefits of each urban built environment factor, and derived empirical thresholds. These findings offer scientific references for urban planners aiming to enhance street space vitality and ensure residents' mobility and quality of life.

However, several limitations persist in this research:

The study primarily focused on Dingshu as an example for empirical research and analysis. The conclusions drawn might not universally apply to all similarly scaled small cities. Future studies should encompass more cases to ensure the generalizability of the conclusions.

This study mainly explored the nonlinear relationship between street vitality and related built environment indicators from a global perspective. Different types of streets may exhibit distinct patterns. Future plans include categorizing streets based on their characteristics and conducting local feature research for different street types.

Street vitality in this study was characterized solely by the number of people extracted from street view images, lacking analysis regarding temporal and spatial dynamics. We are currently exploring vitality representation using continuous spatial metrics, planning to integrate various data sources to ensure the objectivity and credibility of vitality representation.

Acknowledgements

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