

Article

Exploring Non-Linear and Synergistic Effects of Street Environment on the Spirit of Place in Historic Districts: Using Multi-Source Data and XGBoost

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Abstract: The fragmented remodeling of historic districts undermines the spirit of place. Understanding the intricate relationship between the neighborhood environment and the spirit of place is essential for sustainable urban development. Current research predominantly relies on case studies and the concept of place, which are subjective and lack specific analysis of how the neighborhood environment shapes the spirit of place. In this study, we examine Chuancheng Street in Handan City as a case study. Utilizing the eXtreme Gradient Boosting (XGBoost) model and multi-source data, combined with SHapley Additive exPlanation (SHAP) and Partial Dependence Plots (PDP), we analyze the non-linear and synergistic effects of the street environment on the spirit of place in historic districts. The findings reveal that (1) the proportion of enduring sociability (PES) on the street significantly shapes the spirit of place, with cultural space elements being less prioritized in perception; (2) PES, green vision index (GVI), Integration_800 m, and mixed land use (MLU) have pronounced non-linear impacts on the spirit of place, with strong threshold effects, and these factors also demonstrate a synergistic effect; (3) There are notable spatial variations in the spirit of place across different blocks, particularly influenced by the authenticity of cultural heritage. This study provides fundamental insights into the spirit of place in historic neighborhoods, enabling a better understanding of complex urban dynamics and informing future street regeneration from a place perspective.

Keywords: street environment; spirit of place; multi-source data; XGBoost; nonlinear effect; historic districts



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1. Introduction

Places are “things that exist” made visible through their connection to human experience. The character of the environment, place, is then determined by these objects when objects with material essence, form, texture and color form a whole [1]. Spatial places are embodied when space is visualized, symbolized and assembled, bringing the environment together. The concept of place arises from the dynamic interaction between life, physical space, people, and creative expression [2]. According to Norberg-Schulz, places are a fusion of people and sites, essentially being the locations where human interactions occur [1]. The spirit of place, rooted in the ancient Roman belief in a unique “guardian spirit” for each being, imbues people and places with identity and essence. The spirit of place is expressed by the clarity of location, spatial form and identity [1]. Vitruvius understood the spirit of place through a sense of direction and identity. The spirit of place is an “intrinsic” value of a particular area [2]. The sense of place is crucial in fostering the spirit of place [3,4]. Indeed, the spirit of place in the streets plays an essential role in shaping the city’s image and citizens’ collective memory [5].

Many cities in China have a history spanning two to three thousand years, with historical and cultural neighborhoods serving as vital components of their cultural heritage and public spaces. These areas encapsulate the city's cultural memory, showcase regional characteristics [6,7], and foster sustainable development while enhancing residents' perception of their city and sense of place [8]. However, rapid urbanization has led to homogenization, threatening the sustainability of these neighborhoods and eroding their unique features [9]. As streets grow more generic, people's attachment to their environments and Indigenous identity wanes [10], with the fragmented transformation of urban spaces severing emotional connections to the historical and cultural heritage. Streets emerged with the formation of cities, providing access and serving as places for social interaction [11], fostering a sense of belonging and community [12]. Streets are the carrier for urban residents to perceive the city and feel urban life [13], an essential urban linear open space. The way residents interact and behave is influenced to some extent by the spirit of the street place [14,15]. The sense of place is instrumental in the successful renewal of historic districts [16]. Therefore, assessing citizens' perceptions of the spirit of street places is a crucial step in urban spatial renewal remodeling and cultural regeneration.

Early research on the relationship between street place perception and environment relied on traditional questionnaires, cognitive experiments and interviews to obtain relevant data [17,18]. The cognitive experimental method merges the fuzzy study of geographical elements with psychology, using questionnaires and other tools to explore subjects' cognition and understanding of geographical concepts or regional boundaries [19–22]. Liu et al. used cognitive experiments combined with support vector regression to study the spatial distribution of fuzzy features [23]. Although cognitive experiments can directly reflect the spatial perceptions of the general public, the problems of high time costs, small coverage and small sample sizes have made place perception research possible only for individual places [24]. Recently, the utilization of geospatial big data and data mining techniques to enhance the semantic attributes of places has emerged as a significant research direction in geographic information science [24]. Purves et al. have shown that the concept of place aligns with existing concepts of spatial information, and that geographic information about places can be expressed in a GIS when the concept of spatial information is componentially developed and combined [25]. Different types of geospatial big data offer socially aware methods for the quantitative analysis of specific populations and places [26]. Dodds utilizes Twitter media data with cognitive and emotional information about individuals to construct semantics and emotional association with different locations at a collective level [27]. On the other hand, crowdsourced mapping services and geotagged imagery offer a wealth of visual information that provides street scenes from a human perspective, which allows for the large-scale quantification of public perceptions of street scenes and places across various scales [28,29]. As artificial intelligence advances rapidly, deep learning applications in urban perception and planning have proven their great potential by several experimental studies [30–32]. For instance, Zhang et al. employed deep learning to measure and evaluate urban perception based on the Place Pulse perceptual evaluation crowdsourced dataset [33].

However, research perspectives on urban perception measures have focused on social, cultural, economic and environmental aspects [34–39], overlooking the influence of behavioral interactions between people and places on place perception [40–42], as well as the impact of various crowd activities on the assessment of urban scenes [43]. Only a few previous studies have employed qualitative methods to explore the spiritual perceptions of urban places, and there has been a lack of quantitative analysis on the spiritual perceptions of street places in relation to the street environment, without considering the city as a place.

In modeling choices, linear models have been widely used, such as ordinary least squares [44]. In addition, logistic regression models have been applied to assess the relationship between residential satisfaction and place attachment [45]. However, these models are limited by their assumption of linear relationships, often missing potential nonlinear relationships and critical impact thresholds. In addition, several studies have

demonstrated that machine learning methods have achieved good results in assessing human emotions [42,46] and are capable of capturing nonlinear and synergistic effects. Advances in Explainable Artificial Intelligence (XAI), such as the XGBoost model, now offer interpretability beyond the “black box” stereotype.

Contemporary XAI methods encompass transparent machine learning (ML) models and advanced post hoc interpretation techniques such as SHAP, PDP and Locally Interpretable Model-Agnostic Explanations (LIME). These techniques are widely used in various fields of urban research [47]. Wang developed a reliable urban inundation depth prediction model using XGBoost, enhanced by SHAP and PDP algorithms to analyze the nonlinear effects of city features on flooding and optimize prediction intervals [48]. Kim integrated the RF model with SHAP to estimate heat-related mortality, achieving high-resolution spatial accuracy and improved model interpretation [49]. Zhang created a transparent and interpretable crime prediction model using XGBoost and SHAP [50]. The key to machine learning technology is model explainability. Post hoc techniques, which are model-independent, are primarily used to interpret “black box” models. SHAP, based on game theory, provides explanations for ML model outcomes from both global and local perspectives by evaluating each input feature’s contribution [49–52]. This technique not only highlights feature importance and interactions but also identifies significant nonlinear effects between independent and dependent variables [53]. SHAP also provides clarity in modeling outcomes and excels in illustrating non-spatial effects [54]. This approach opens a valuable new window for delving into the mechanisms behind the spiritual perception of place. Therefore, in this study, we utilized multi-source data to investigate the spirit of street places in the Chuancheng Street area of Handan City. We developed a comprehensive framework to elucidate the spirit of place perception, focusing on three primary research questions: (1) How can we measure the human perception of the spirit of place in historic districts using streetscape data? (2) How do input variables of the neighborhood spatial environment contribute to the perception of the spirit of place, as investigated using the XGBoost-SHAP technique? (3) Do different administrative subdivisions impact the spirit of place perception? To address these, we initially assessed the study area’s fundamentals and data processing. Next, we introduced the Random Forest ML to measure the spirit of place and analyzed its spatial distribution. Ultimately, we analyzed and explored the non-linear and synergistic effects of the street environment on the spirit of place.

2. Study Area and Dataset

2.1. Study Area

Handan, abbreviated as “Han”, is a prefecture-level city in southern Hebei Province, located between longitudes 114°03′ E and 114°40′ E and latitudes 36°20′ N and 36°44′ N. It is located in the North China Plain, bordered by the Taihang Mountains to the west, and functions as the economic hub for the region that includes the provinces of Shanxi, Hebei, Shandong, and Henan. Handan is a celebrated national historical and cultural city [55]. By the end of 2022, the city comprised six districts, 11 counties and one county-level city, covering a total area of 12,066 square kilometers and housing a population of approximately 9,281,000 [56].

This study area is the Handan Chuancheng Street Historical and Cultural Block Area, located in the densely populated old city of Handan. As shown in Figure 1, the area encompasses eight blocks: West Lianfang, Sijiqing, West Congtai, East Congtai, Heping, Zhonghua, Huomo and Lingyuan Road. The core area is bounded by Lingxi Street to the west, Renmin Road to the north, East Chengnei Street to the east and Chengnan Street to the south. Primarily serving cultural recreation and commercial residence, the block exudes a robust humanistic and residential ambiance across its approximate area of 4.096 km². Abundant Baidu Street View Imagines (BSVIs) data in the study area enhance the accuracy of the research findings [57].

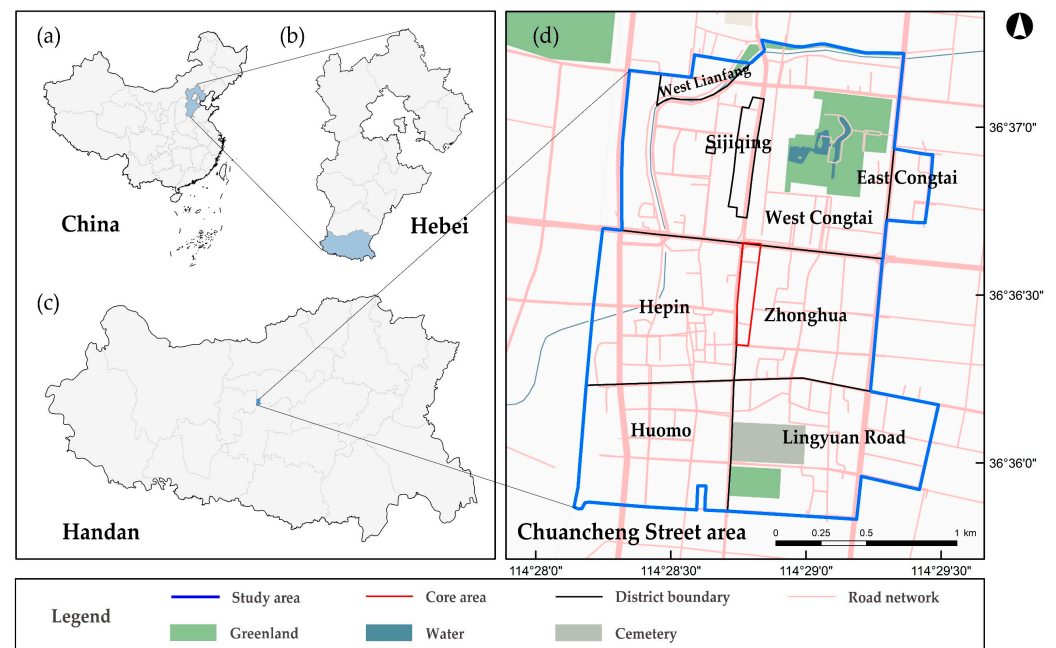


Figure 1. Overview of the study area for the present study: (a) Location of Hebei Province in northern China; (b) Location of Handan within Hebei Province; (c) Administrative districts of Handan, highlighting Chuancheng Street area; (d) Road network in Chuancheng Street area.

2.2. Data Source and Processing

Multi-source data were collected to assess the spirit of place in the Chuancheng Street Block Area. The underlying data included the road network, Points of Interest (POI), street imagery, cultural and behavioral data. All of these data were collected for 2023. (1) The urban road network data were obtained from the BaiduMaps platform (<https://map.baidu.com/>, accessed on 12 November 2023). (2) The POI data were obtained from the Amap online map service platform (<https://www.amap.com/>, accessed on 6 October 2023). The POI data were analyzed and filtered to contain nine first categories. (3) The streetscape data were collected from BaiduMaps open platform (<https://lbsyun.baidu.com/>, accessed on 9 August 2023), BSVIs data included collection time and orientation. (4) The cultural and behavioral data were collected from field research, with cultural data supplemented by street view images and satellite imagery maps. In addition, the historical elements data of Chuancheng Street were derived from the “Handan Famous Historical and Cultural City Protection Plan (2020–2035) Exposure Draft” [58]. After acquiring the above data, the data were cleaned and filtered. The data name, data source, number of records and time of acquisition are shown in Table 1.

Table 1. A detailed description of the study data.

Data	Source	Number of Records	Time
Road	BaiduMaps	38	2023
POI	Amap	6690	2023
Streetscape	BaiduMaps	5090	2023
Culture	Field research, BSVIs,	1641	2023
Behavior	Handan Natural Resources and Planning Bureau on-site recording	3387	2023

3. Methods

3.1. Workflow

Figure 2 shows the workflow of the entire analytical process, which includes the following steps: (1) Collecting multi-source data—road network, POI, streetscape, cultural,

and behavioral—for streets as the unit of analysis. (2) Establishing an index system for assessing the spirit of street places in historical and cultural blocks using four indicators: behavioral categories, convenience, city culture, and spatial features. (3) Employing the XGBoost model to investigate the non-linear and synergistic relationship, with SHAP and PDP techniques for model interpretation. (4) Examining the impact of key features and cultural heritage authenticity on the spiritual perception of street places.

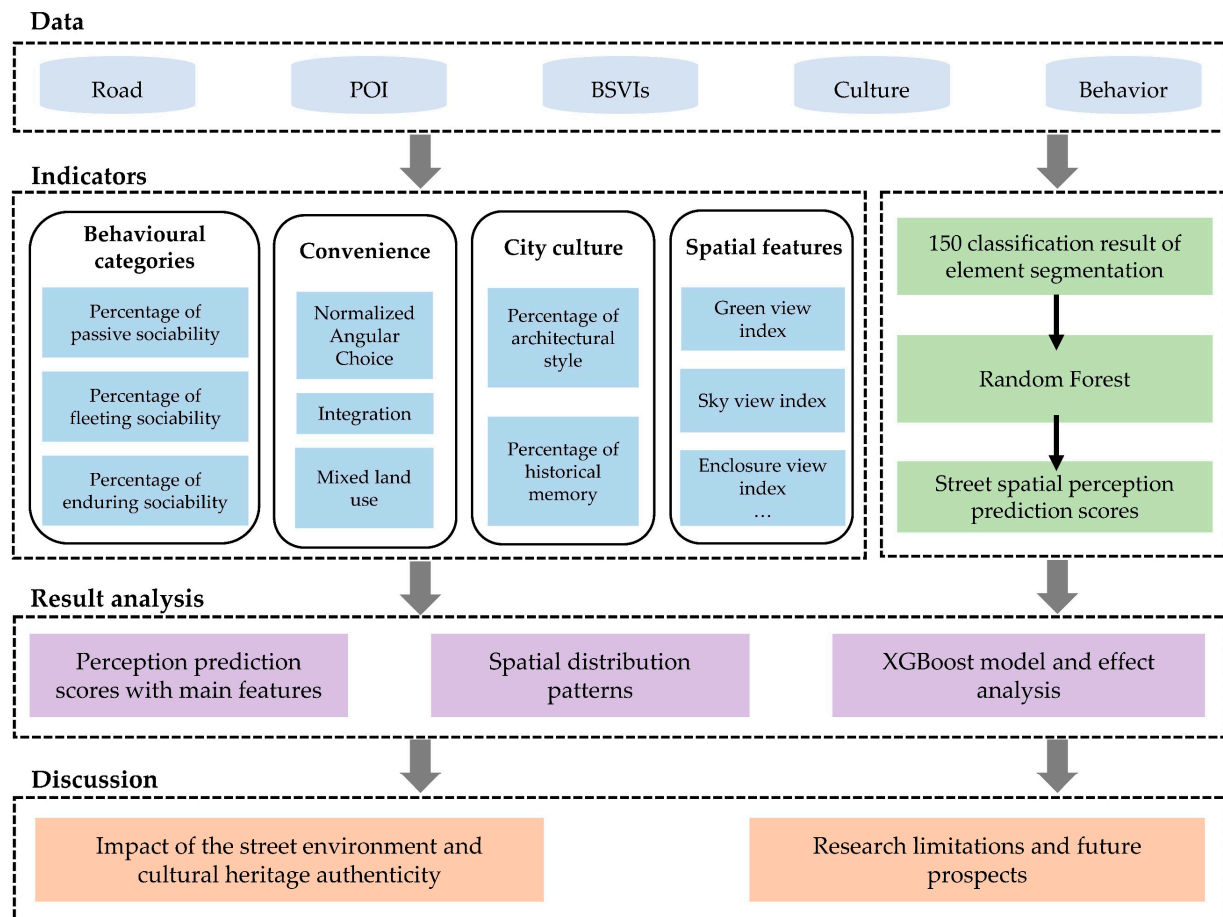


Figure 2. Research framework for the present study.

3.2. Street Generation

This study uses the living street as the basic unit of analysis. Living streets, characterized by activities that draw people to linger and engage, such as local interactions, daily commerce, leisure, and public performances, are selected as the focus due to their high usage and diverse social behaviors. The process for identifying living streets is as follows:

Firstly, the highest precision road network data of the Baidu map is captured by Baiducapture_1.2 V, and the roads are topologized and interrupted at intersections. Secondly, we analyze the interrelationships and mechanisms of social behavior and place perception in the street over 12 h, from 8:00 to 20:00, on both weekdays and weekends. Meanwhile, we utilize a method that filters street features by the weight of POI types [59]. Finally, by combining user activities with the occupation and use of space, we identify 38 streets or segments that have been consistently popular in residential neighborhoods, categorizing them as living streets. Some actual environmental photos of the area and characters are shown in Figure 3.



Figure 3. Presentation of urban place in the Chuancheng Street districts: (a) Children on the square; (b) Roads in the historical district; (c) Handan Art Museum; (d) Aerial view of the historical district; (e) Street vendors in the old city; (f) The aged enjoying the cool breeze on the roadside.

3.3. Index System Construction

Building upon previous research [43,60], four indicators and 17 variables covering three dimensions (i.e., physical space elements, cultural space elements and human behavioral elements) were defined to assess the spiritual perception of street places. The details and data sources of these indicators are provided in Table 2.

Table 2. Indicators and data sources for measuring the spatial quality of streets.

Dimensions	Indicators	Variables	Description	Data Sources
Physical space elements	Spatial features	Green view index (GVI)	Mean value of pixel ratio of recognizable plants in streetscape images for each streetscape point	(c)
		Sky view index (SVI)	Mean value of pixel ratio of recognizable sky in streetscape images for each streetscape point	
		Street enclosure index (SEI)	Mean value of pixel ratio of recognizable buildings, fences and other elements in streetscape images for each streetscape point	
		Pedestrian safety index (PSI)	Mean value of pixel ratio of recognizable walking paths in streetscape images for each streetscape point	
		Crowd concentration index (CCI)	Mean value of pixel ratio of recognizable pedestrians in streetscape images for each streetscape point	

Table 2. Cont.

Dimensions	Indicators	Variables	Description	Data Sources
Physical space elements	Spatial features	Vehicle interference index (VII)	Mean value of pixel ratio of identifiable motor vehicles in streetscape images for each streetscape point	(c)
		Façade unit index (FUI)	Ratio of the number of identifiable doors and windows to the length of the street in streetscape images for each streetscape point	
		Interface transparency index (ITI)	Mean value of pixel ratios of identifiable glass and other elements in streetscape images for each streetscape point	
		Facility enrichment index (FEI)	Mean value of pixel ratios occupied by recognizable benches, tables and other elements in streetscape images for each streetscape point	
	Convenience	Normalized Angular Choice (NACH)	Number of times each street segment is crossed by the shortest path between any two other street segments within 800 m	(a)
		Integration (INT)	Distance from each street segment to other street segments within 800 m	(b)
		Mixed land use (MLU)	Shannon Diversity Index corresponding to each street attraction	
Cultural space elements	City culture	Percentage of architectural style (PAS)	Ratio of the total length of buildings with distinctive styles in the buffer zone of each streetscape to the length of the street	(d)
		Percentage of historical memory (PHM)	Ratio of the number of old trees, iconic buildings, and sculptural vignettes in the buffer zone of each streetscape to the area of the street	
Human behavioral elements	Behavioral categories	Percentage of passive sociability (PPS)	Ratio of the number of behavioral categories in the buffer zone of each streetscape to the total street area	(e)
		Percentage of fleeting sociability (PFS)		
		Percentage of enduring sociability (PES)		

Note: (a) Road data; (b) POI data; (c) Street view data; (d) Culture data; (e) Behavior data.

3.3.1. Spatial Features

Street spatial features, including nine variables (i.e., GVI, SVI, SEI, etc.), were quantified using street view image data collection and semantic segmentation technology tools. The study measured the street's built environment by collecting street view images through the Baidu map open platform (<https://lbsyun.baidu.com/>, accessed on 9 August 2023). To be more refined to measure the level of residents' perception in the historical block area of Handan Chuancheng Street, the following steps were taken: (1) Street navigation tracks were obtained using Baiducapture_1.2 V, spatially corrected and geographically aligned to simplify them and extract road centerlines; (2) Sampling points were generated with 30–35 m intervals, corresponding to unique latitude and longitude coordinates in ArcGIS 10.5, resulting in 391 points, due to the richness of the streetscape that can be obtained at road intersections, and combined with citizens' behavior; (3) A Python script accessed APIs to acquire street view images with adjusted parameters. To be able to simulate the field of view of pedestrians more accurately, this paper refers to Walker et al.'s findings [61], i.e., a person's field of view, which can be almost 90° to the left and right, can see about 50° upwards and about 75° downwards. And when walking with the head lowered by 10°, one can see 85°. In addition to acquiring images from 4 directions, east, west, south and north, we added two angles (i.e., pitch 45° and pitch −45°) in each direction, twelve

images were captured at each point from four directions (east, west, south, north) and two additional angles (45° and -45° pitch), resulting in 5090 BSVIs, each 1024×512 pixels, due to missing street views at some points. An example of a BSVI is shown in Figure 4, with an acquisition date of July 2023 for the area.

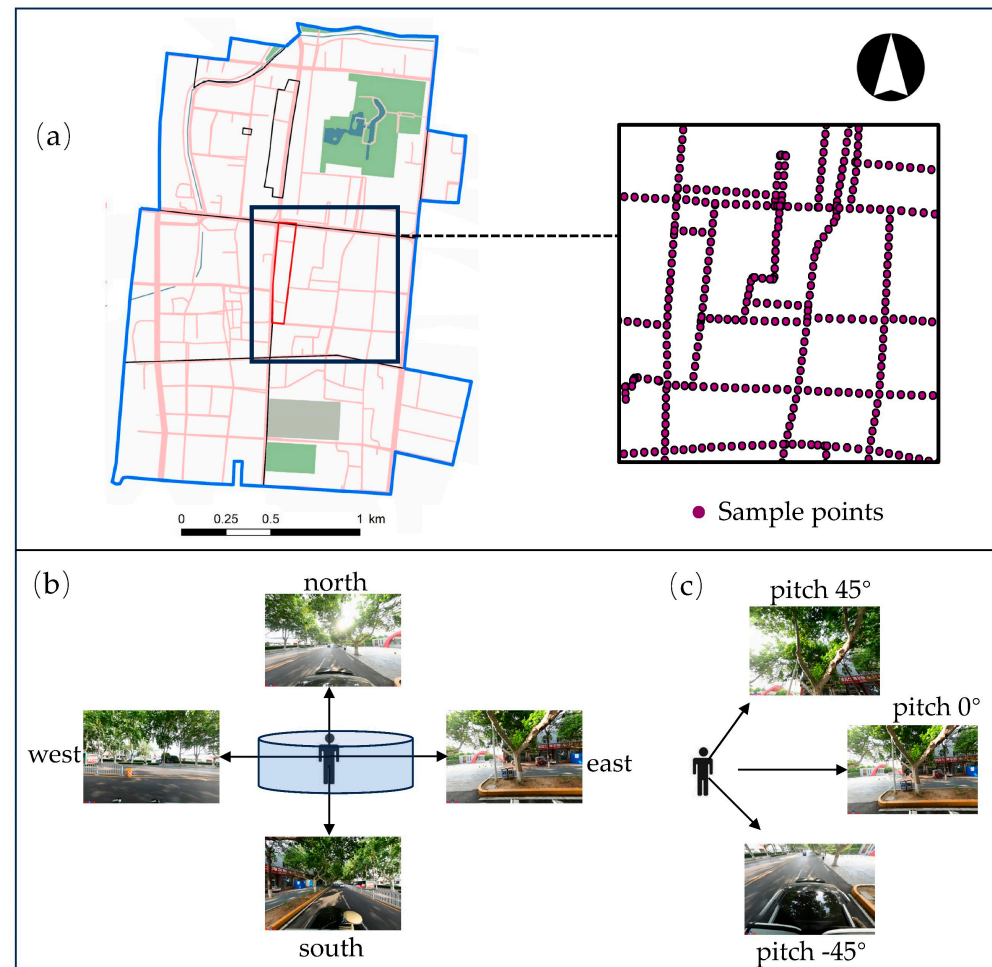


Figure 4. Example of the BSVIs collection process: (a) Road network and sample points in Chuancheng Street area; (b) Horizontal view diagram; (c) Vertical view diagram.

Building a deep learning network for semantic segmentation of street view images involves leveraging datasets like ADE-20K, which offers more categories and data compared to Cityscapes. This extensive data aids in studying the relationship between residential place perception and visual elements [57], enhancing our understanding of urban environment semantics [62]. Despite the emergence of recent architectures, DeepLab-V3 remains a widely used algorithm for semantic segmentation in urban research, delivering reliable performance. DeepLab-V3 employs techniques like null convolution and multi-scale pyramid pooling, incorporating a module for segmenting objects at multiple scales. It also uses serial and parallel null convolution modules with various atrous rates to capture multi-scale content information, enhancing image segmentation accuracy while preserving high resolution. Moreover, DeepLab-V3, based on a robust pre-trained network like ResNet101, excels in adapting to new tasks and datasets through transfer learning [63]. Therefore, we utilized the deep learning toolkit GluonCV (version number is 0.10.5.post0), based on MXNet, with the DeepLab-V3 algorithm, which is trained on the ADE-20K dataset. This semantic segmentation model can accurately identify and segment 150 categories of common objects, such as roads, sky, plants and buildings. Table 3 shows the details of the semantic segmentation framework.

Table 3. The parameter configuration of the DeepLab-V3_ResNet101_ADE-20k framework.

Parameter	Implication	Value
Input Resolution	The size of the image entered into the model	1024 × 512
Batch_Size	The number of samples used in a single gradient update	16
Epochs	The number of complete iterations of the model over the entire training dataset	120
Learning Rate	It determines how much the model parameters are updated in each iteration	0.01
PixAcc	The ratio of the number of correctly predicted pixels to the total number of pixels is used to measure the accuracy of image segmentation	81.1
mIoU	Measures the overlap between the predicted segmentation graph and the true segmentation graph	44.1

3.3.2. Measuring Street Accessibility

Street accessibility is characterized by three indicators: the NACH, INT and MLU. For one thing, we use space syntax segment map modeling, the scope of which includes all streets within Handan's north, south, west and east ring roads. Meanwhile, Baiducapture_1.2 V was utilized to extract the most precise road centerline from Baidu Maps. Finally, the modeling process was finalized through manual adjustments based on streetscape and satellite maps.

For the different parameters, regarding the spatial behavior implied by the algorithm, Integration and Choice reflect the potential of street segments as movement destinations and corridors, respectively. NACH is used to minimize the impact of line segment count on the analysis, facilitating comparisons across spatial systems of varying scales and complexity.

In a typical space syntax analysis, the actual flow data is used to fit the analysis, and the optimal scale is determined by testing various analysis radii. The POI data were dropped onto the road at the appropriate location using ArcGIS10.5, and then the space syntax segment map model was verified. Finally, POI data was homogenized using a combined reachable (distance attenuation) and visible (angle attenuation) approach [64]. This paper employs processed POI data from the Chuancheng Street area as the dependent variable, with Choice, INT, NACH, and Normalized Angular Integration as the independent variables. We tested multiple accessible range radii (400 m, 500 m, 600 m, 800 m, 1000 m, 1200 m, 1500 m, 1600 m, 2400 m, and 3200 m) to identify the best fit. The optimal radii for Integration and NACH were found to be 800 m, with R2 values of 52.3% and 53.4%, respectively.

For another thing, using a Python script, we fetched 7023 latest raw Amap POI data, then filtered out those located away from streets (e.g., neighborhoods, campuses, etc.). POIs were categorized into nine main types: restaurants, shopping, health care services, sports and leisure services, municipal services, educational and cultural services, financial and insurance services, accommodation services, and scenic spots. After categorization, 6690 valid POI data were processed in ArcGIS10.5.

The city's diversity is reflected in the variety of buildings in its blocks, as Jacobs noted [65]. In this paper, MLU is represented by the spatial entropy of POI (i.e., Shannon–Weaver Diversity). A higher entropy value indicates a higher level of street MLU, and this representation does not imply the reverse. The definition of mixed land use is as follows:

$$MixUsed_k = - \frac{(\sum_{i=1}^M p_{ki} \ln p_{ki})}{\ln M} \quad (1)$$

where, $MixUsed_k$ is the mixed land use, p_{ki} refers to the percent of i -th type within unit k of POI or mixed land use, M represents the total number of categories in the current space unit.

3.3.3. Cultural Spatial Cognition

Architectural and historical landmarks enhance local residents' sense of security and promote social identity [66]. Culture is shaped by the interaction between people and

places. How people adapt to and use a particular geographic environment results in particular cultural forms that affect places in a specific environment. And as the geographical environment is regional, culture is bound to take on a local flavor. Geographical variations in climate and resources influence building materials and styles, the architectural style that reflects the regional characteristics becomes the expression of the texture elements of the regional architectural culture [67], these architectural expressions record historical periods and contribute to the continuity of cultural heritage [68]. The city's history and memory are encapsulated in important buildings, sculptures, old trees and urban public spaces [69]; cultural memory in historic cities contributes to a sense of place identity and place [8]. Linking urban cultural memory to place identity fosters a sense of belonging and identity [70].

Therefore, architectural style and historical memory were used to characterize the elements of the cultural space in the Chuancheng Street area. We integrated field observations with relevant data from the Handan Cultural Relics Protection Department. Then, we utilized street and satellite image maps for calibration and spatial recording. Mapping cultural perceptions: first involved establishing a 50 m buffer zone around each sampling point with ArcGIS10.5, then counting the categories and numbers of elements within the buffer, and finally, employing kernel density analysis for visualization.

3.3.4. Street Behavior Observation

Livable streets are characterized by a variety of behavioral activities that foster community bonds and identity among locals [71]. These activities, along with diverse human interactions, contribute to a stronger sense of direction and identity with street places [72,73]. This will promote the public's perception of the spiritual perception of place. The richness of street scenes arises from the presence of people with different habits. The longer a pedestrian travels and stays in a street space, the more nuanced their perception of street quality becomes [74]. Mehta suggests that the characteristics of the street environment, such as land use, physical space, and community management, influence users' perception and willingness to engage in social activities [75–77]. This paper adopts Mehta's typology of social behaviors and a non-participant observation method to record street space behaviors, which are classified into passive and active sociability, with active sociability further divided into fleeting and enduring sociability (Table 4).

Table 4. Typological Classification of Social Behavior in the Streets.

Social Relationships	Passive Sociability	Active Sociability	
		Fleeting Sociability	Enduring Sociability
Definition	Even when there is no desire to socialize actively, people still habitually choose to be alone in public places where other people are present.	People greet their neighbors or interact briefly in public places.	The process of interacting positively with each other between individuals in close relationships (i.e., partners, friends, and community residents) is a frequent and important human contact.
Specific behavior	Eating alone; smoking; contemplating; lounging; carrying goods; watching; cooling off; using a mobile phone; phoning; crafting; fixing things; cleaning up; waiting for the bus.	Brief communication; polite non-verbal communication; brief playfulness of children; commercial behavior.	Lovers, friends, the elderly, children and parents dine in open-air seating and chat on benches or in front of shops. Playing chess and cards (including watchers); street haircuts; rituals; picking up children to and from school; writing large characters; playing Tai Chi; performing.

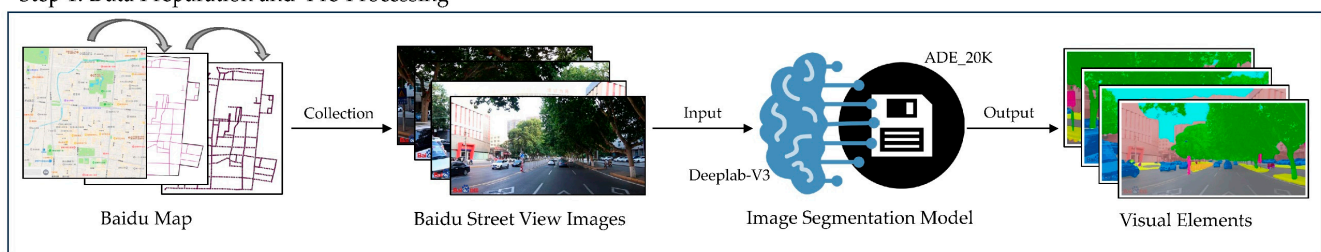
This study used non-participant observation to document social behaviors in the vicinity of a living street. The area was divided into five sections, with team members alternating responsibility for each section. From late June 2023, during clear weather, our team selected four recording days (weekdays and weekends) between 7:00–19:00, with two-hour observation cycles, totaling six cycles. We walked the street, capturing latitude and

longitude with photo software and photographing various behaviors. After eliminating images that did not meet the study criteria, we counted individuals and locations, described behaviors, and compiled 3387 photos.

3.4. Scoring the Spirit of Street Place Using an Interpretable Urban Perception Model

We refer to the human-machine adversarial scoring method to predict perception [78], which is based on street view images, employing deep learning techniques and iterative feedback mechanisms during human-machine interaction scoring, aiming to quickly and efficiently assess urban perception in a given area. This study constructs a deep learning network based on the Deeplab-V3 image semantic segmentation model and the Random Forest model. To identify visual elements in street scene images that impact residents' perception of street places, the Deeplab-V3 is used for semantic segmentation to obtain the proportion of visual elements, which is then integrated into the 150-dimensional feature vector scoring framework of Random Forest for street scene elements. The process is shown in Figure 5.

Step 1. Data Preparation and Pre-Processing



Step 2. Urban Perception Scoring Framework

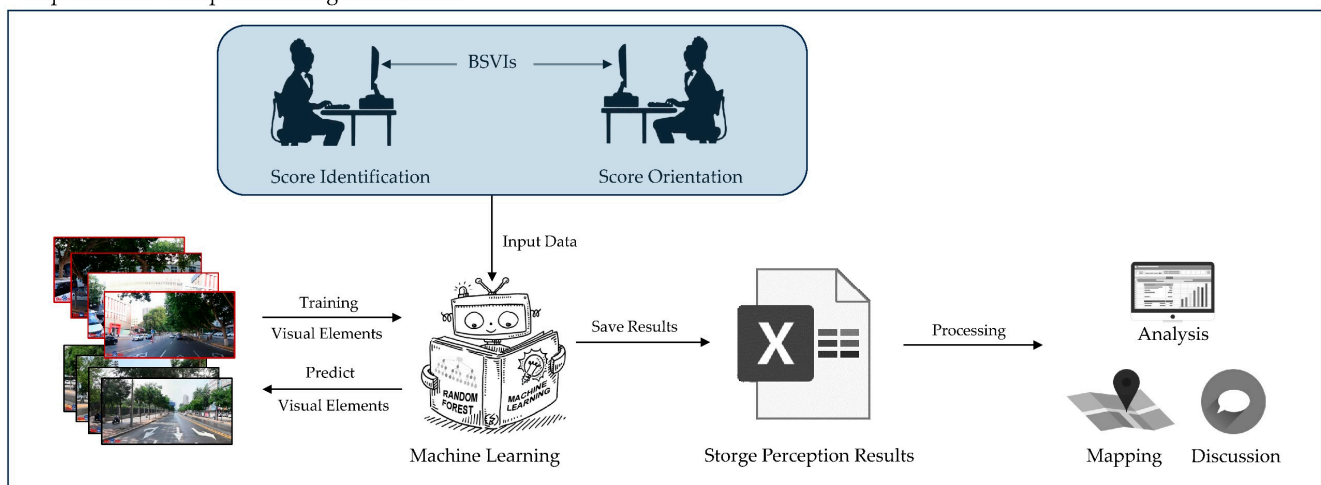


Figure 5. Overview of the spatial perception scoring process for urban streets based on machine learning.

Thirty volunteers, including 10 students (majoring in Urban and Rural Planning subject) and 20 residents with an average age of 39 and a gender ratio of 1:1, were recruited to assess street place perception. Volunteers were first exposed to street view images to form initial perceptions. They then scored the spiritual dimensions of street place perception—identity and orientation—using the scoring model, ranging from 0 to 5, with higher scores indicating stronger perceptions. Each volunteer scored the first 300 street scenes in each dimension subjectively. The Random Forest module then correlated the visual elements of the street scenes with the volunteer scores, and the model automatically provided a

recommended score. These scores were normalized and summed to produce a composite perception score. As follows:

$$P_{total}^i = \frac{1}{2}(P_{identification}^i + P_{orientation}^i) \quad (i = 1, 2, 3, \dots, 5090) \quad (2)$$

where P_{total}^i is the composite perception score for image i , $P_{identification}^i$ refers to perception score for the identity perception dimension of image i , $P_{orientation}^i$ represents perception score for the orientation perception dimension of image i .

3.5. XGBoost Algorithm and Interpretable Machine Learning

XGBoost, an optimized distributed gradient boosting system, is widely used across various domains [79]. It incorporates second-order Taylor expansion for error minimization, and employs L1 and L2 regularization to enhance generalization and prevent overfitting [80]. Its interpretability and accuracy have made it a preferred choice in many studies, and the specific details of its use will not be described here. For this study, we use model-agnostic post-hoc techniques to train XGBoost models and generate predictions, which can then be interpreted through global and local interpretation methods. Global interpretation methods average the relationship across all observations.

SHAP is derived from the Shapley value in game theory, and global interpretability demonstrates whether each feature contributes positively to the model predictions or not, the SHAP method also allows for local analyses that focus on interpreting individual sample predictions [81]. SHAP crystallizes the explanation as [82]:

$$g(z') = \phi_0 + \sum_{i=1}^M \phi_i z'_i \quad (3)$$

where the g is the explanation model, $z'_i \in \{0, 1\}^M$ is the coalition vector, M represents the maximum coalition size, ϕ_0 is the base value, and ϕ_i is the feature attribution for a feature i , Shapley value.

The SHAP value is calculated as follows [82]:

$$\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!(|F| - |S| - 1)!}{|F|!} [f_{S \cup \{i\}}(x_{S \cup \{i\}}) - f_S(x_S)] \quad (4)$$

where f is the prediction/estimation model, F is the set of all features, and S is the set of all features excluding i .

In this study, the interpretable machine learning component consists of three sub-components: multi-class feature importance plots, SHAP summary plots, and SHAP dependence plots. Firstly, the multi-class feature importance plot elucidates model decisions by showing conditional interactions between dependent and independent features across the dataset and ranks the importance of explanatory variables. Secondly, the SHAP summary plot enhances interpretability by visualizing the impact and direction of feature contributions to different perceptions of the spirit of place, with colors representing feature values (red for high, blue for low) and the X-axis showing their effect on perceptions. One-way PDP depicts the marginal effects of input features on model predictions and their interactions (e.g., linear, nonlinear) [54], while two-way SHAP PDP illustrates interaction effects between explanatory variables. PDP explains as follows:

$$\hat{f}_S(x_s) = E_{X_C} = [\hat{f}(x_s, X_C)] \int \hat{f}(x_s, X_C) dP(X_C) \quad (5)$$

where x_s are one or two features, X_C is the remaining features, $\hat{f}$ is the model we utilized in this study.

4. Results

4.1. Perception Scores and Key Dimensional Features

Figure 6 illustrates the eight main dimensional features (i.e., signboard, sky, building, person, sidewalk, road, tree, and car.) obtained through the street place perception scoring process in Section 3.4, following semantic segmentation of five streetscape samples with varying scoring levels. The figure also presents three types of perception scores. There is a connection between the perceptual scores of Baidu Street View images with different features and the semantically segmented dimensional features. The perception scores revealed that 5.62% of the streets had a place spirit perception score of 4 or above, 42.46% scored between 2.5 and 4, and 51.92% scored below 2.5. The average score was 2.623, with a standard deviation of 0.718. These results indicate that the overall place perception of the Chuancheng Street area in Handan City is average.

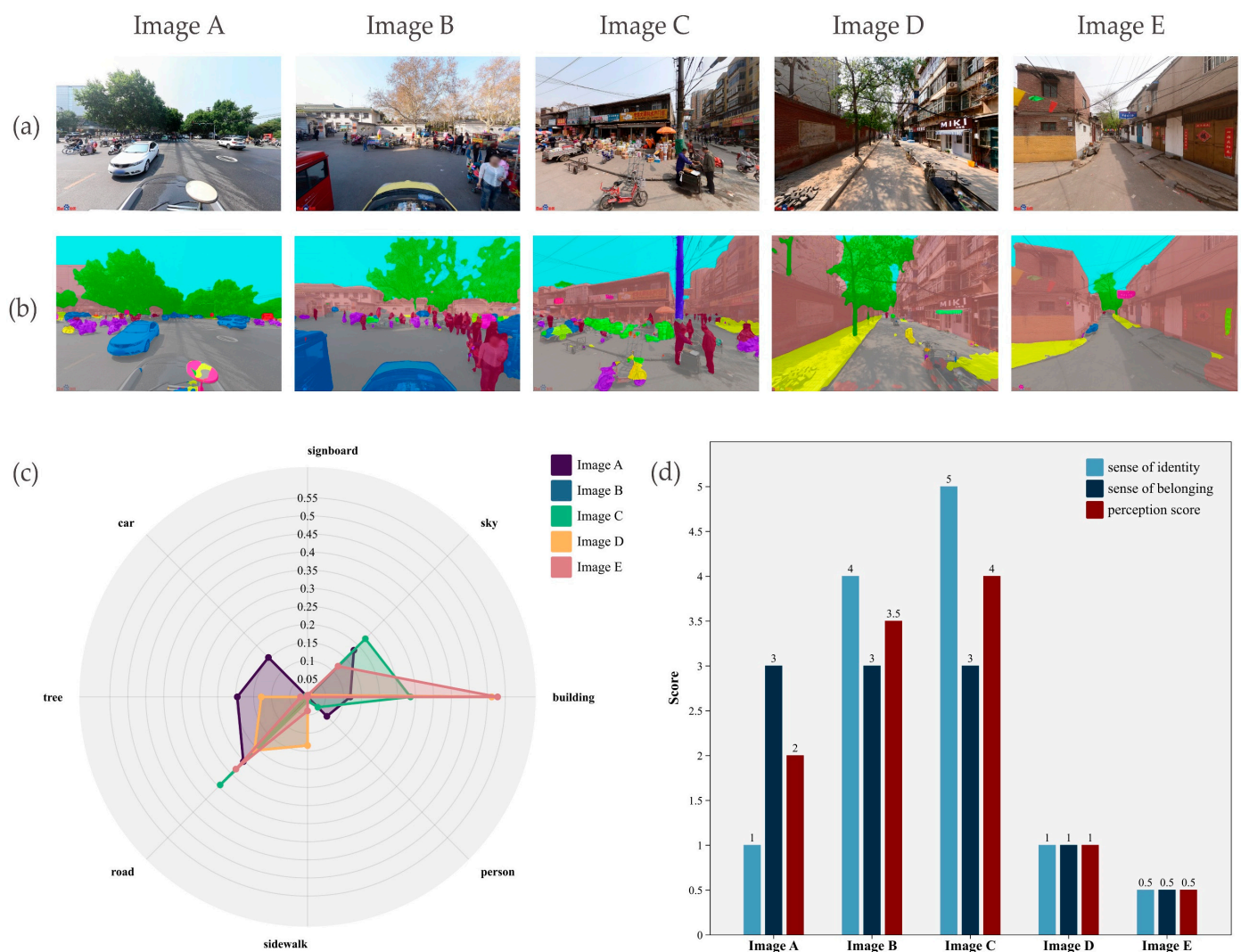


Figure 6. Sample SVIs: (a) Five typical streetscape images; (b) Semantic recognition results of BSVIs; (c) Eight main feature dimensions in the semantic segmentation results; (d) Three perceptual scores for BSVIs.

Image A, positioned at the junction of Congtai Road and North Zhonghua Street beside Congtai Park, receives a low score for place perception. The area features a green setting on either side, enhancing directionality for respondents. However, the high traffic volume diminishes the sense of identity, making it less pedestrian-friendly and inhibiting street-side interactions. Image B, situated at the entrance plaza of the park, achieves a

higher score for place perception. This is attributed to a notable building with a grand and windy design, imbued with a strong humanistic character, which enriches the pedestrian experience. The presence of clear markers contributes to a better sense of direction. Image C, with a lesser amount of greenery, still scores well due to its excellent accessibility and the retention of a vibrant urban atmosphere. The numerous urban elements give the space a strong sense of identity, leading to a high score for spiritual perception of place. Image D, with an underwhelming score for place perception, is perceived as lacking in identity by respondents. Despite having adequate pedestrian space, the area feels less experiential due to the imposing presence of tall buildings and a lack of activity. Image E receives the lowest score, with respondents perceiving it as having a poor orientation and identity. This could be linked to its architectural composition, characterized by numerous monolithic elements, and the absence of human activity, which may be affecting its overall perception.

4.2. Spatial Distribution Patterns of the Street Environment in the Historic District Area

4.2.1. Spatial Distribution Patterns of Street Environment Indicators

In this paper, six important indicators are selected to describe the GVI, SEI, MLU, INT, PAS, and PES, as shown in Figure 7.



Figure 7. Spatial distribution of street environment element characteristics: (a) Spatial distribution of GVI; (b) Spatial distribution of SEI; (c) Spatial distribution of MLU; (d) Spatial distribution of INT; (e) Spatial distribution of PES; (f) Spatial distribution of PAS.

Higher GVI is found on major urban thoroughfares and near waterways, particularly in Congtai Square, North Zhonghua Street and Xuebuqiao Park, while GVI is low on rapid transit routes and residential streets (Figure 7a). SEI values are largely inverse to GVI, with high-intensity development areas having higher SEI scores in core amenity blocks

and Chuancheng Street, while main roads show lower SEI (Figure 7b). Many diverse activity facilities exist in the heart of the city or commercial areas. The high functional mixed degree is reflected near main road intersections and the commercial center in front of Handan Railway Station (Figure 7c). High accessibility to the core area of the Chuancheng Street Block is mainly due to the high density of the built-up and the high density of the road network. Especially reflected in the main development roads of the city as well as in the amenity blocks, the INT tends to be low in internal alleyways (Figure 7d). The remaining cultural relics protection units and historical buildings show the historical style of Handan very well. Hence, the architectural style of these places, such as Chuancheng Street, Huiche Lane, North and South Xie Street and the Exhibition Hall Building Complex, is better. In the area of landscape coordination, the further away from the core area, the weaker the architectural landscape will be (Figure 7e). Recreational and commercial areas tend to attract people, such as streets with a strong sense of life, like Dongfeng Street and Lingyuan Road, and recreational regions, like Congtai Square and Museum Square (Figure 7f). Citizens prefer quieter, traffic-free places where some kind of active interaction is ongoing, such as Xuebuqiao Park, Cultural Palace Square Park, Guyunyuan Park and the night market.

Figure 8 depicts the distribution of civic social behaviors observed at streetscape points in the study area. Enduring sociability is the most prevalent, followed by fleeting sociability, with passive sociability being the least frequent across all ranges. Enduring sociability is consistently observed at almost every point. These interactions foster a sense of inclusion and belonging among individuals when they feel accepted and have positive relationships with group members [83].

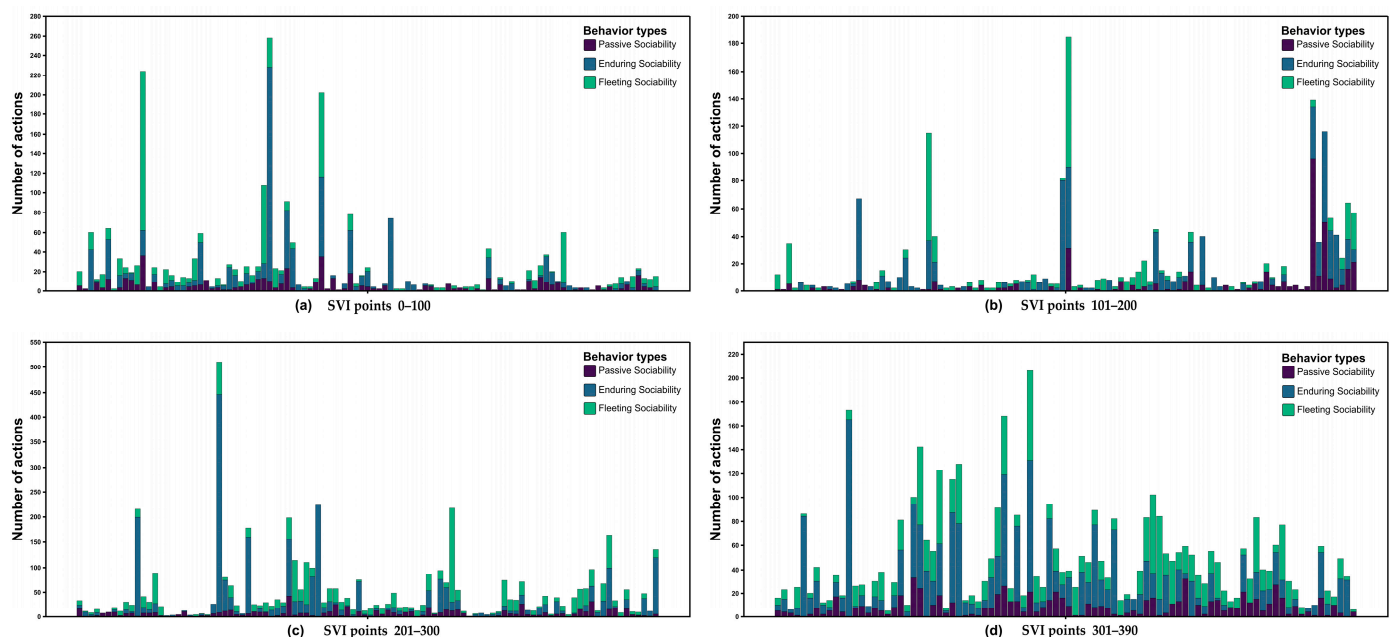


Figure 8. Behavioral characteristics from grouped stacked bar charts: (a) Behavior type results for street spot positions 1–100; (b) Behavior type results for street spot positions 101–200; (c) Behavior type results for street spot positions 201–300; (d) Behavior type results for street spot positions 301–390.

4.2.2. Spatial Distribution Patterns of Block Place Comprehensive Perception

The street points and their perceptual scores were spatially connected to the street by interpolation, then segmented into five intervals using the Natural Breaks to visualize the spatial distribution features on the map, as shown in Figure 9. The Zhonghua Block and Lingyuan Road Block exhibit higher place perception, especially North Zhonghua Street. The West Congtai Block also demonstrates active place perception. In contrast,

the Hepin Block and Huomo Block have lower place perception, mainly because of their proximity to the railway station, with a high transient population and degree of commercialization, leading to a lack of stability in the sense of community and human atmosphere. Inadequate public space and trees contribute to the area's lack of a good living atmosphere. Furthermore, the higher perceived spiritual value of street places is found in street parks, civic squares, City God's Temple, schools, and food markets, where people tend to gather and interact, even in the case of the City God's Temple, which is not solely used for religious purposes.

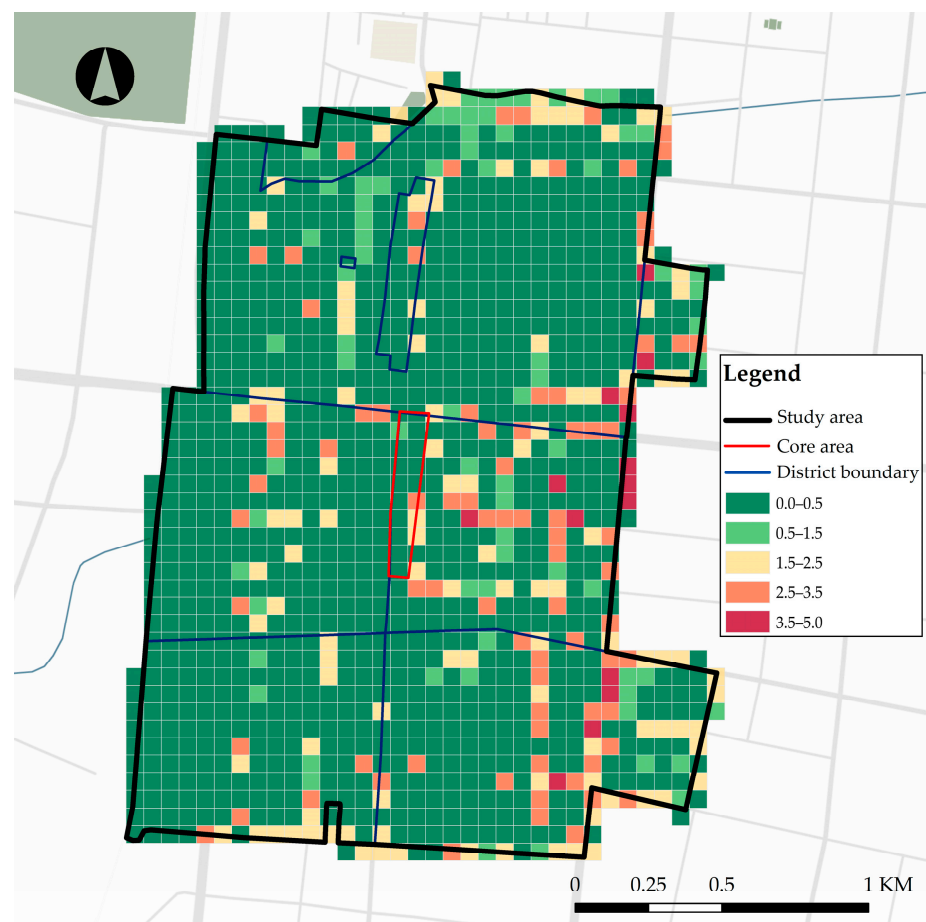


Figure 9. Spatial distribution patterns of block place comprehensive perception.

4.3. Model Effect Analysis

4.3.1. Model Evaluation

Since the rating data is discrete, we transformed it into a three-category problem for ease of analysis. Category 0: poorer spiritual perception of place; Category 1: average spiritual perception of place; and Category 2: better spiritual perception of place. To address data imbalance, we employed the Synthetic Minority Oversampling Technique (SMOTE) oversampling before model fitting. Figure 10 illustrates the model evaluation before and after the tuning. Without adjusting XGBoost model parameters, the prediction accuracy and F1 score using the oversampled test data set are 79.35% and 79.08% respectively. With the Random Search method, the XGBoost model achieved the accuracy and F1 score of 93.70% and 93.58% respectively. Based on the normalized confusion matrix, we can find that the XGBoost model with the Random Search method has the best prediction.

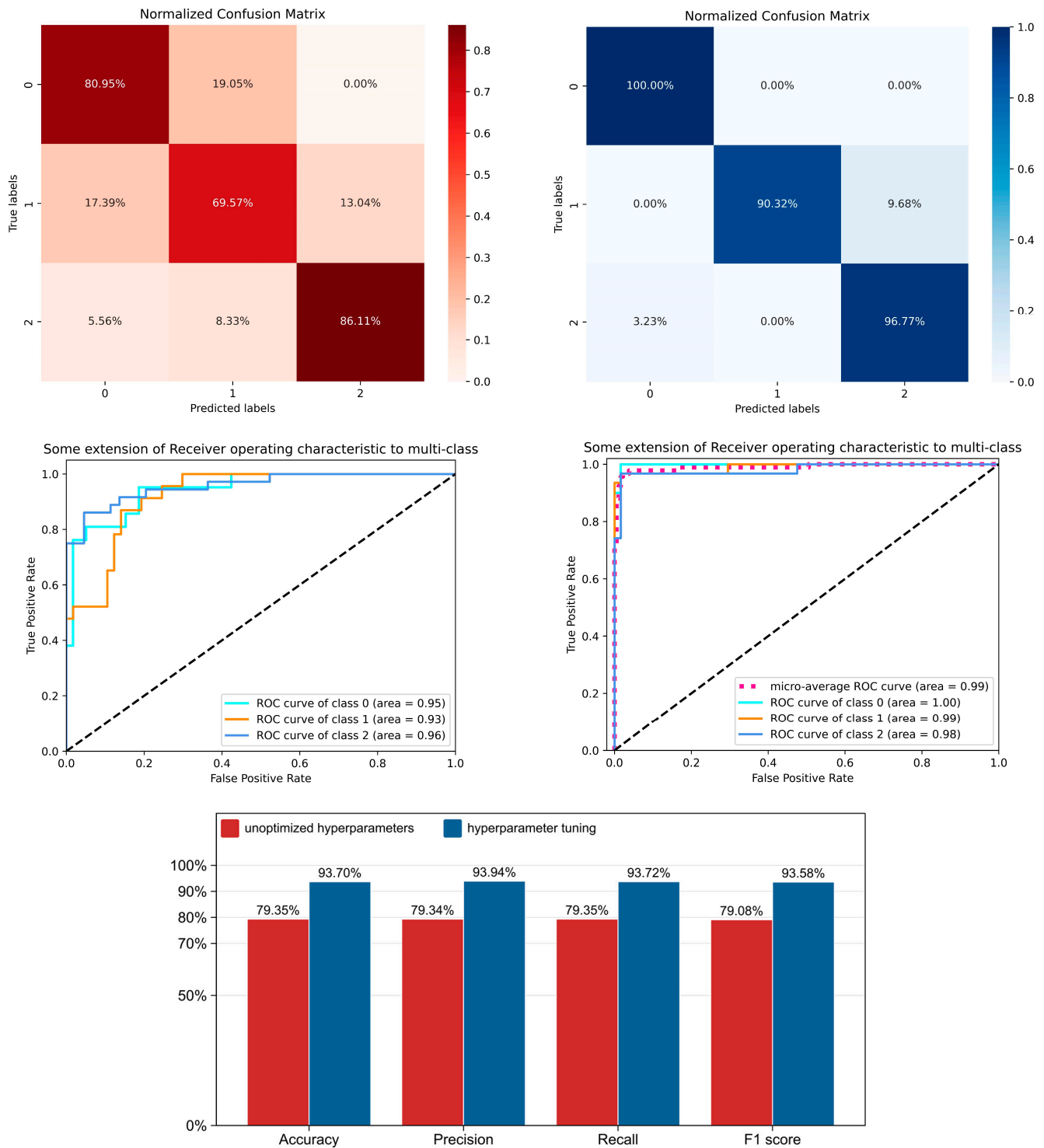


Figure 10. Evaluation effect of XGBoost model.

4.3.2. Feature Importance

Figure 11 shows the characteristic importance of significant variables in the entire sample and their descending ranking in explaining the level of spiritual perception of place. The XGBoost model results were used to calculate the mean absolute SHAP values for each variable, representing the independent variables' contribution to perceived place spirituality. Variables with higher mean SHAP values have a stronger influence. Social behavior types, such as the PES, significantly affect the dependent variable. For street physical space elements such as GVI and SEI—in addition to INT and NACH, which reflect

accessibility to traffic—these largely influence the rating of spiritual perception of places. However, the influence of cultural spatial elements was relatively low.

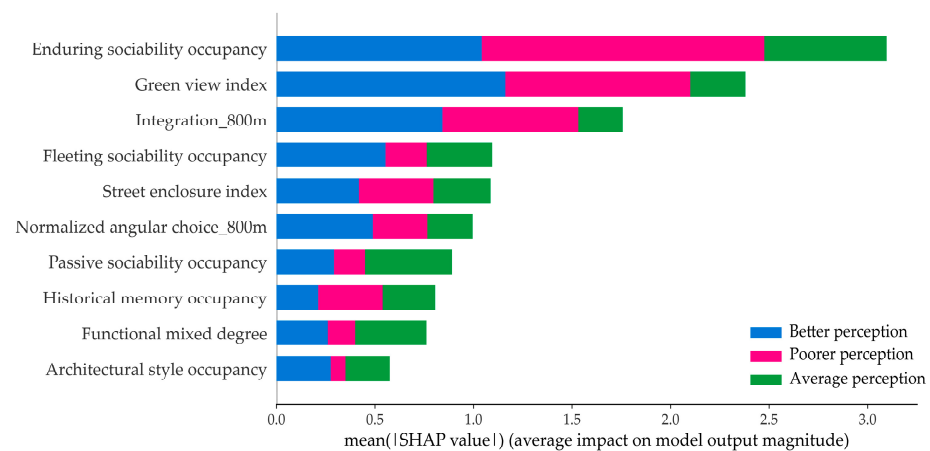


Figure 11. Overall feature importance.

Figure 12 illustrates the ranking of main explanatory variables by their importance in the three levels of spiritual perception of place, with their importance decreasing from top to bottom. The scatterplot displays all training data points, colored from blue to red based on the variable's value, with the horizontal position indicating whether the variable's impact is positively or negatively associated with the prediction. Streets with lower PES, GVI and INT tend to have poorer spiritual perception of place, as shown in Figure 12a. However, there are general indices of the proportion of various social behaviors, GVI, and SEI on the street; lower MLU and AS are associated with a moderate atmosphere of spiritual perception of place (Figure 12b). Similarly, streets with higher GVI and PES in particular, as well as higher INT, SEI and AS, are more likely to have a better spiritual perception of place (Figure 12c).

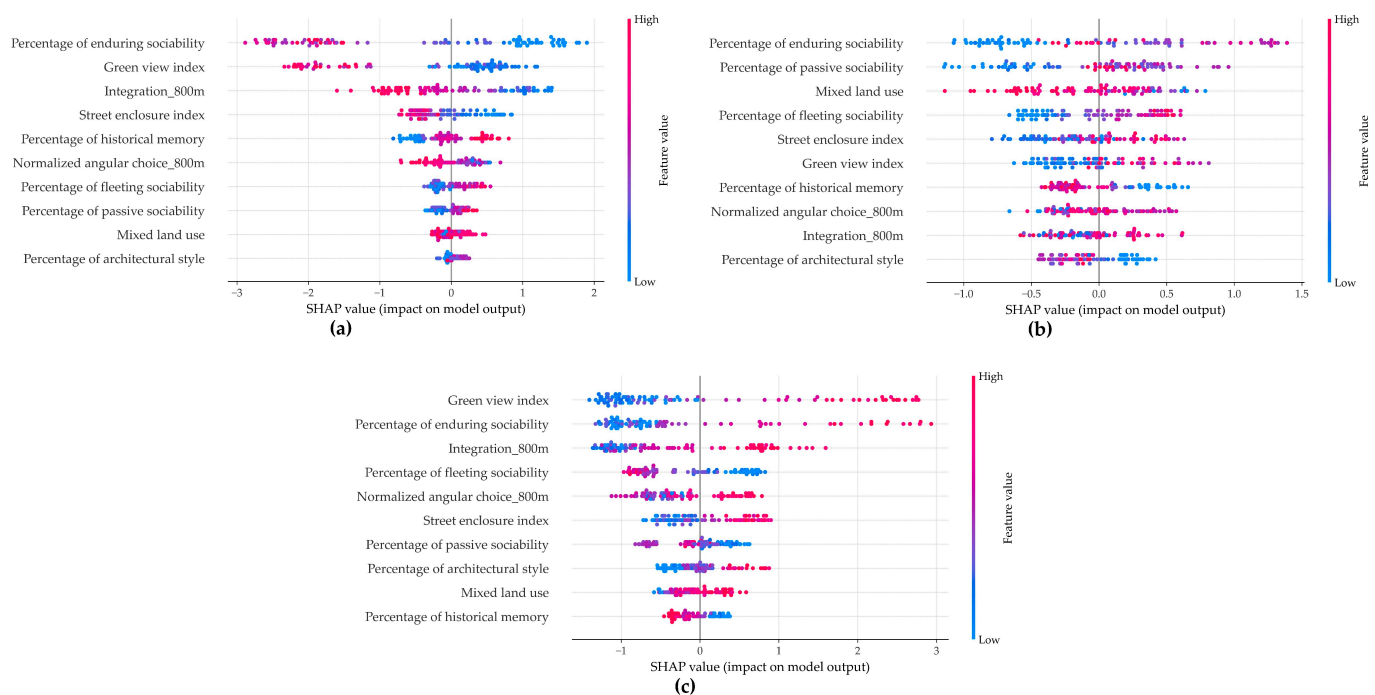


Figure 12. Feature importance of variables for each level: (a) Feature importance of variables for poorer spiritual perception of place; (b) Feature importance of variables for average spiritual perception of place; (c) Feature importance of variables for better spiritual perception of place.

4.3.3. Interaction Effects between Explanatory Variables

Here, we analyzed SHAP PDP to investigate the interaction among several key variables in the XGBoost model predictions, namely the PES, GVI, SEI and AS (Figure 13). The scatter plots with red and blue points show the variations in the variable and the SHAP values of the variable.

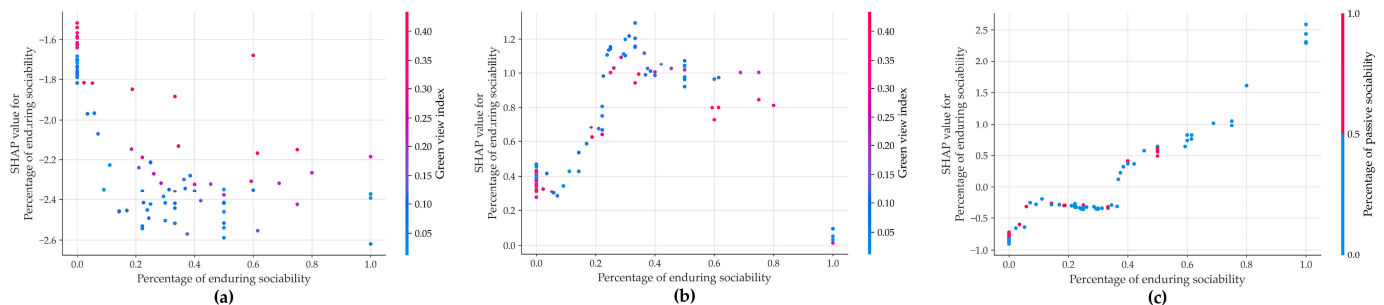


Figure 13. Interaction of the PES: (a) Interaction of the PES for poorer spiritual perception of place; (b) Interaction of the PES for average spiritual perception of place; (c) Interaction of the PES for better spiritual perception of place.

Figure 13 shows that as the PES on the street increases, it becomes more conducive to enhancing the spiritual perception of place. At the same time, we can also observe that PES interacts with GVI and PSB in shaping the spiritual perception of street places, respectively. For example, on streets with lower spiritual perception of place, there was a significant change in the trend for PES of 35%, with a higher uniformity in SHAP values above 35% compared to below it. This suggests that above 35%, the impact on spiritual perception increases with SHAP value, while below this threshold, lower SHAP values indicate a reduced contribution to the spiritual atmosphere, with GVI exerting a greater influence on the model.

Figure 14 demonstrates that GVI contributes to the level of spiritual perception of place. We observed that GVI interacted with PHM, MLU, and PES on the levels of spiritual perception of street places, respectively. For example, in areas with poor spiritual perception, the SHAP value of GVI increases in the opposite direction to GVI itself, with an interaction PHM that decreases as it approaches red, and the SHAP value of GVI decreases. In areas with average spiritual perception, GVI is in the 10–25% range, and the SHAP value of GVI decreases as MLU increases, contributing to the spiritual perception rating.

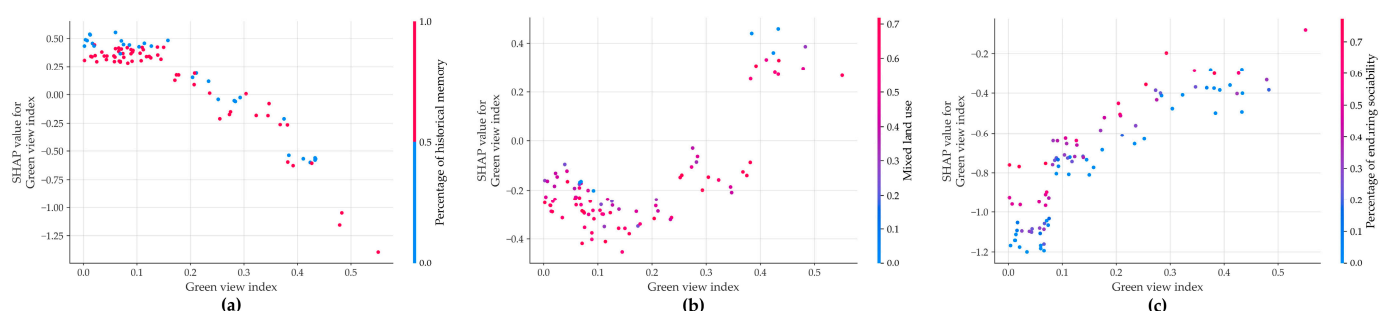


Figure 14. Interaction of GVI: (a) Interaction of GVI for poorer spiritual perception of place; (b) Interaction of GVI for average spiritual perception of place; (c) Interaction of GVI for better spiritual perception of place.

Figure 15 illustrates that a higher SEI is more conducive to the ratings of spiritual perception of place. For example, the SEI and SEI SHAP values exhibit a notable variation of around 40%, with a higher spiritual perception of place at this threshold. From the graph, it can be concluded that the SHAP value is relatively high at 40% and tends to flatten

out and remain constant as the index rises. We can infer that, below 40%, increasing SEI significantly enhances model predictions, while above this threshold, the contribution of SEI diminishes, and the interaction with GVI becomes more influential. Figure 16 shows that the trend shifts significantly around 50% for PAS. Below 50%, as MLU increases, the PAS SHAP value decreases, indicating a reduced impact on the model. Above 50%, the PAS SHAP value increases significantly with increasing MLU, closer to red.

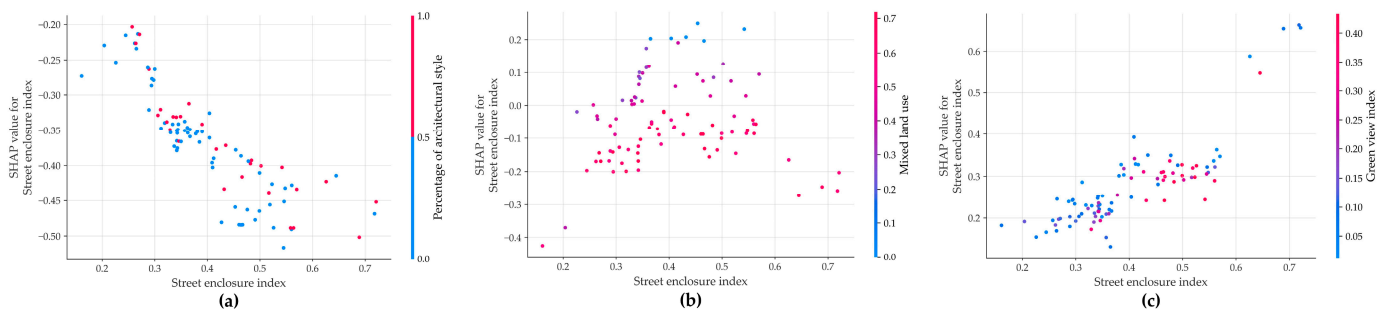


Figure 15. Interaction of SEI: (a) Interaction of SEI for poorer spiritual perception of place; (b) Interaction of SEI for average spiritual perception of place; (c) Interaction of SEI for better spiritual perception of place.

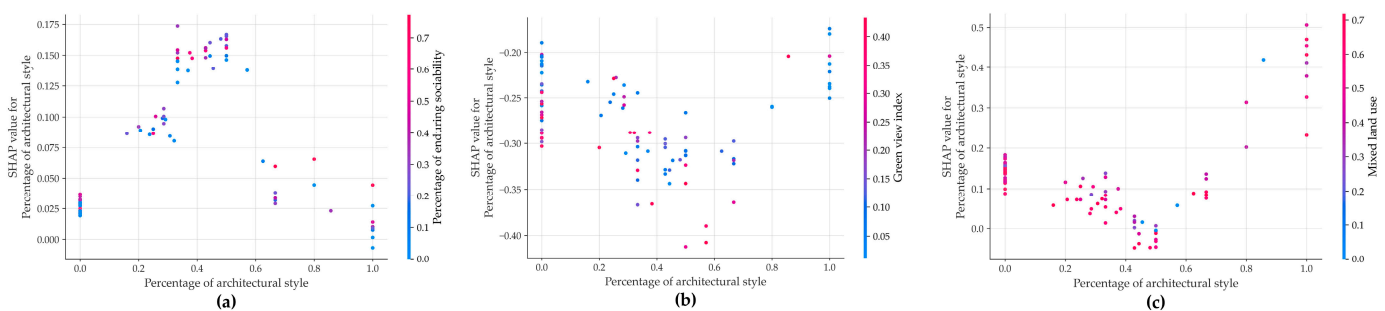


Figure 16. Interaction of PAS: (a) Interaction of PAS for poorer spiritual perception of place; (b) Interaction of PAS for average spiritual perception of place; (c) Interaction of PAS for better spiritual perception of place.

4.3.4. Threshold Effects of Explanatory Variables

Based on the results of the relative importance of the independent variables and the interactions above, four explanatory variables (i.e., PES, GVI, INT, and MLU) were selected to investigate threshold effects, all of which exhibit significant non-linear relationships in predicting the ranking of spiritual perception of place. Figure 17 presents the PDP of four critical explanatory variables, illustrating their nonlinear effects on the excellent rating of spiritual perception with XGBoost. These four one-way partial dependence plots demonstrate the marginal impact of each feature on the model's predictions, with all other features held constant.

Figure 17a illustrates a positive correlation between PES and spiritual perception of place, with an optimal range of 38–65% where the impact is significant. This range is the threshold, significantly influencing model predictions. Above 80%, the impact continues to increase, possibly due to enhanced social interactions in historical and cultural areas, emphasizing the importance of public spaces in cultural district revitalization for improved experiences.

Figure 17b indicates that GVI's threshold for enhancing spiritual perception is 15–34%, after which its impact tends to plateau. Increased GVI has been associated with a positive perception of the environment, reduced stress and improved mood. Higher GVI has been linked to positive environmental perception, reduced stress, improved mood and enhanced social interaction and community cohesion [83–86]. However, the figure suggests that

the contribution of GVI to enhanced spiritual perception is lower in the 34–40% range, indicating that further increases may lead to diminishing returns.

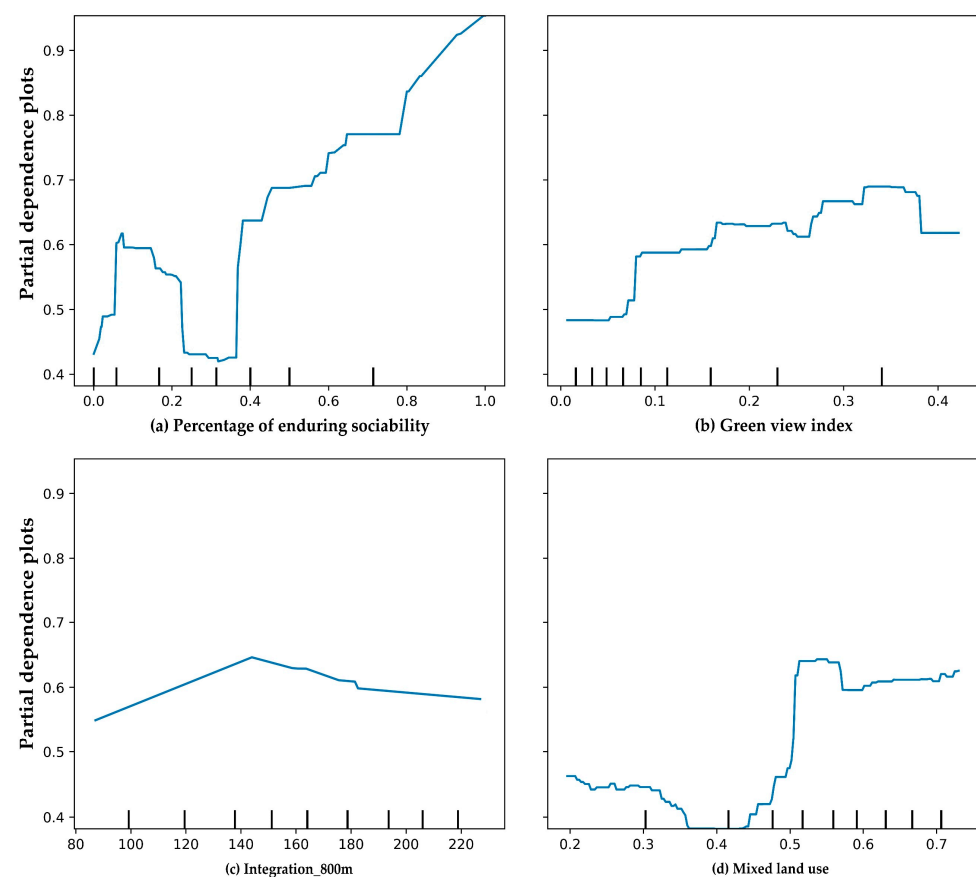


Figure 17. Obvious nonlinear effects of explanatory variables on the spiritual perception of place.

Figure 17c indicates that INT's threshold for enhancing spiritual perception of place is 140–180, with its impact on place perception remaining constant beyond 180. This aligns with Manzo et al.'s study [87]: even if we do not express ourselves similarly, we can learn from it. This suggests that community accessibility affects community cohesion and identity to some extent. Better traffic mobility conditions promote social cohesion [88], and this ease and accessibility increase positive feelings about the place and enhance the experience and satisfaction of being there. However, excessive traffic can impede travel, especially as road integration increases.

Figure 17d indicates that MLU's threshold for enhancing spiritual perception is around 40–52%, with a stable impact on better spiritual perception of place above 65%. It is easy to notice from this figure that the probability of the model prediction plummets around 60% of the functional mix. This may be because highly mixed blocks attract different types of people to communicate and interact [89], creating a unique community culture. However, excessive mixed land use can lead to traffic and noise issues, which can detract from the place's spirit in historic and cultural districts. Carrying the local humanistic colors is more important for historic and cultural districts. The weaker traffic carrying capacity and the intrusion of foreign functional elements have caused the living space of residents to be compressed, which will negatively impact the place's spirit.

5. Discussion

5.1. Impact of Street Environment Indicators on the Spiritual Perception of Place

Based on the threshold effect elaborated in Section 4.3.4, we further discuss the influence of four notable explanatory variables (i.e., PES, MLU, SEI, and PAS) on the better rating of spiritual perception of place.

We have established that PES is a primary factor shaping the spiritual perception of street places, aligning with Abusaada et al.'s findings [43]. Enduring participation exhibits complex and varied behaviors that will enhance placemaking, fulfill individual identity and expressive needs and contribute to developing citizens' sense of attachment to their local communities [90,91].

From Figure 11, we observe that MLU has a minimal impact on the rating predicting spiritual perception of street places. This suggests that enhancing MLU may not directly influence spiritual perception, but does so indirectly through mediating factors, aligning with Fang et al.'s findings. MLU influences spiritual perception through functional attractiveness, traffic accessibility and social group tolerance [88], promoting social interaction and cohesion [92,93] and increasing the potential for interaction with others. Communication is an essential way of generating place identity. As Goffman's interactionism theory suggests, individuals can make social connections, share common values and identities, and gain a sense of identity and belonging to a particular place through social interaction [94].

SEI demonstrates a weak positive correlation on better rating of the spiritual perception of street places, with a non-linear effect as observed in Figure 18a. This is not quite in line with the findings of Alain Jacobs et al., who concluded that intimate environments create spaces with high interface enclosure that enable people to stay, and low enclosure in open spaces that make people feel comfortable [95]. However, the study area's historical and cultural nature, along with Congtai Park's large area and the wall surrounding it, hinder social interaction and spiritual perception. Gehl's work suggests that ground-floor facades have a significant emotional impact, with open and attractive ones encouraging engagement [96]. Gorgul et al. also noted that streets with more shop windows and openings facilitate social interaction [97]. Therefore, moderate enclosures can create a warm and intimate street atmosphere in historical and cultural blocks, enhancing people's sense of security and belonging. However, the ground floor of buildings in street facades is pivotal for public engagement and social interaction [98,99].

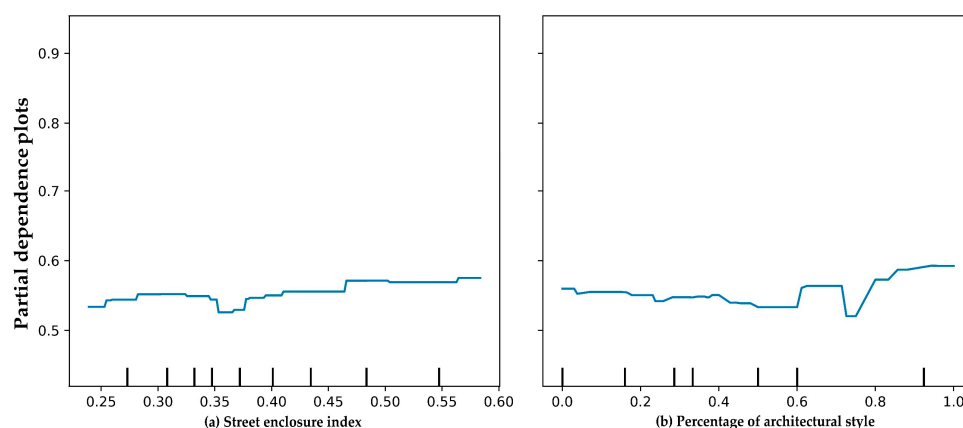


Figure 18. Nonlinear effects of SEI&PAS on the spiritual perception of place.

In this paper, PAS poorly predicts the spiritual perception of street places in the better grade, with an ambiguous threshold effect seen in Figure 18b. Which is not consistent with the present findings. Public spaces in historical and cultural blocks are complex, merging material and immaterial needs [100], and historic districts carry the spatial characteristics of the spirit of place due to historical evolution and human activities [101]. Because places with historical and cultural factors contribute to local identity formation [66,102], places

with a sense of age tend to evoke place attachment [103]. However, the cultural heritage in Chuancheng Street, such as municipal cultural protection units and Ming and Qing Dynasty buildings, has not been well-preserved; despite efforts to maintain their original style, their cultural heritage has yet to be completely recovered. The embodiment of the spirit of place should be dynamic, relating not only to the architectural value of the local landscape but also to the time of interaction and exchange between residents [104,105]. This underscores the importance of deeply exploring the unique historical and cultural spirit to enhance people's sense of identity with historical district places [8].

5.2. Impact of Cultural Heritage Authenticity on the Spiritual Perception of Place

We further integrated perception scores with street administrative divisions, averaged them and mapped them to the map to obtain the comprehensive perception situation of the eight street administrative divisions, as shown in Figure 19a. Here, we categorized the perception scores into five levels for a detailed evaluation. The East Congtai Block stands out with an excellent comprehensive perception evaluation, while Sijiqing, Zhonghua, and Lingyuan Road Blocks have average scores. West Lianfang and Huomo Blocks fare poorly, and West Congtai and Heping Blocks are the worst. This indicates a generally poor spiritual perception of place in the Chuancheng Street area, with high-scoring spaces primarily along Zhonghua Avenue and Renmin Road.

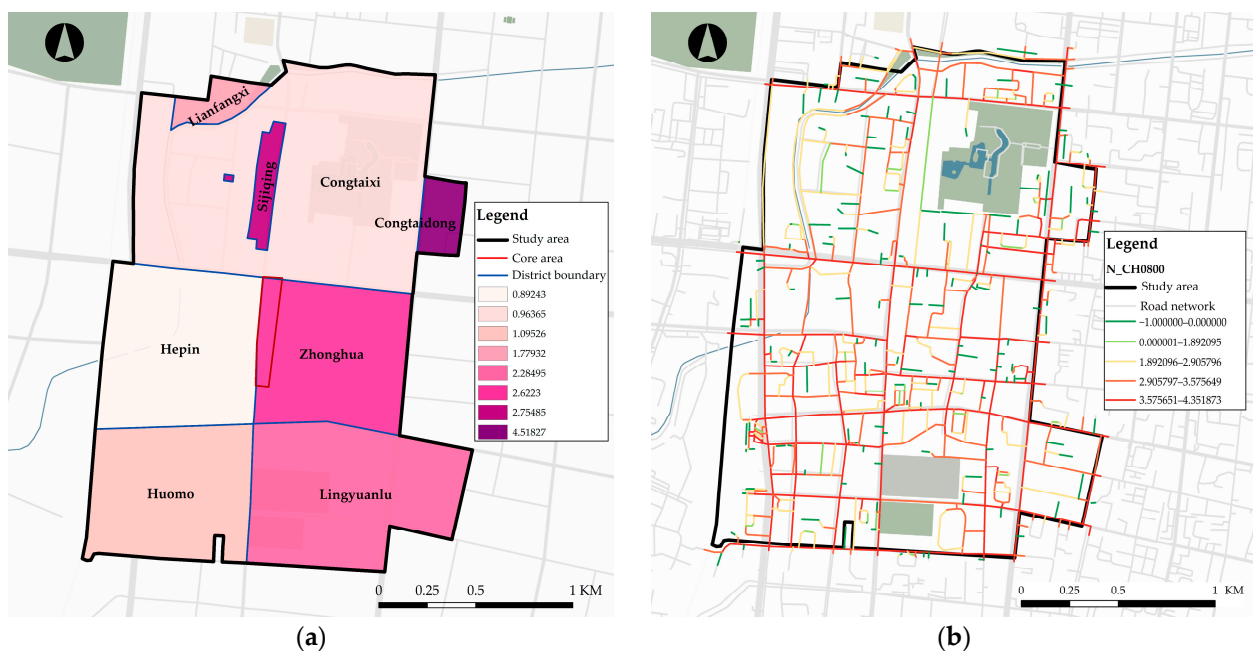


Figure 19. Impact of cultural heritage authenticity on the spiritual perception of place: (a) Comprehensive perception scores of street administrative divisions; (b) Spatial distribution of NACH_800 m.

Figure 19a presents the comprehensive place spirit perception score of 2.62 for the core area of Chuancheng Street in the Zhonghua Block. Figure 19b indicates that the core area generally has a high NACH. The direction to Renmin Road and Zhonghua Avenue has good traffic movement potential, especially the surrounding lanes, which also have good traffic potential. At this point, despite the high Integration in the core area (Figure 7d) the surrounding lanes are relatively low, and there is no strong potential to attract people without a specific purpose. The East Congtai and Zhonghua Blocks, situated near Renmin Road and Zhonghua Avenue, benefit from superior traffic conditions, business districts, and heritage conservation units. The East Congtai Block has a significantly higher perception score of 4.52 compared to the Zhonghua Block.

Investigating the reason behind the high perception score in the East Congtai Block reveals that its cultural relics protection units are well-preserved and actively open to the public, maintaining their original functions. These heritage sites provide an excellent spiritual medium between the past and present. The museum complex has slowly transformed into a cultural space that precipitates and inherits local culture and lifestyle customs in urban historical changes, which contains historical value and local significance related to time, space and events. In addition, the area's large squares and green spaces also cater to public leisure and recreation. The authenticity of local humanities promotes the formation of local attachment and sense of place [106–108]. In contrast, the loss of cultural heritage authenticity in the core area of Chuancheng Street negatively impacts residents' cultural cognition and social activities [109]. The atmosphere of urban blocks is shaped by prioritizing activities and functions over form [70], which is crucial for preserving historical memory and enhancing residents' identity and direction. All in all, what is more important here is whether the spiritual medium provided by the place is compelling enough for citizens, and whether the cultural space preserves the memory of the city community through historical changes. This aligns with previous research findings [110–112]. These also explain precisely why cultural space elements are not easily perceived by people in the first place.

5.3. The Research Limitations

Although this study has explored the factors and nonlinear effects of the spiritual perception of street places in historic districts, we must acknowledge that there are still some shortcomings. This study has developed a three-dimensional indicator assessment system for physical, cultural and behavioral spaces, based on the spiritual perception of street places. However, it is limited by the lack of research data types for diverse social groups and the inefficiency of technical research methods. First, the study's selection of physical space indicators requires revision due to their complexity, and future research should incorporate additional data such as architectural colors. Second, location-tagged Internet comment data contain the subject's emotional perception of place, and a more comprehensive perception of place could be achieved by introducing semantic text analysis in subsequent studies [24]. Third, the acquisition of crowd behavior data is subject to human error, and future research may consider using OpenCV and YOLO5 algorithms to build behavioral recognition models, enhancing efficiency and accuracy. Lastly, given the existence of semantic segmentation models with better performance, we intend to incorporate the DeepLab-V3 plus_Cityscapes architecture into our future research to process street view imagery.

6. Conclusions

This study constructs a method for assessing the spiritual perception of places in historic district streets, based on human–place relationship theory and artificial intelligence technology, with place taken as a cognitive perspective. The highlights of our research include: (1) The integration of social behavior and local culture as explanatory variables. (2) The use of deep learning and ML to quantify the spiritual perception of place. (3) Interpretable ML technique to explore the potential for urban street space spatial renewal remodeling and cultural revitalization.

Our investigation has concluded that citizen behavior significantly contributes to the spiritual atmosphere of places in historical and cultural blocks. In addition, the authenticity of cultural heritage is pivotal in shaping the spiritual perception of place and fostering sustainable development of the urban context. The methodology used in this study can effectively assess the spiritual perception of places in historic neighborhoods, offering guidance for enhancing street perceptions. The spiritual perception of street places of historical and cultural blocks and the three-dimensional indicators proposed in this paper can be applied in contemporary urban spatial remodeling and cultural regeneration, providing valuable references for people's urban development. Furthermore, with the availability of

multi-source data, the methodology can be extended to assess place perception in various urban historic districts.

Future work aims to utilize multi-source data from different social groups to conduct large-scale urban research. Further deepening the connotation of place perception data in historic districts, we intend to understand the characteristics of places from spatial interactions and attempt to delineate the scope of places. Last but not least, we should consider applying traditional methods of evaluating cultural, architectural and social values in urban spaces in further research to conduct comparative studies and assess the consistency of the conclusions drawn from traditional analyses versus numerical and digital methods.

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