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Evaluating Urban Street Space Quality Using Multi-Source Data and Fully Convolutional Neural Networks: A Case Study of Xi'an's Historic Urban Area

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Abstract

Street space quality in historic cities has become a central concern in heritage conservation and urban renewal. Nevertheless, existing evaluation frameworks often overlook the historical dimension and insufficiently address the interaction effects among influencing factors. Taking the historic urban area of Xi'an as a case study, this study constructed a comprehensive assessment framework for street space quality comprising five dimensions: accessibility, comfort, convenience, safety, and historicity. A total of 15 indicators were quantified for 404 street segments across four street typologies—commercial, residential, historic, and mixed-use—using multi-source data and Baidu Street View image analysis based on a fully convolutional neural network. The GeoDetector model was then applied to identify key influencing factors and explore their interaction effects. The results reveal that comfort and convenience are the dominant dimensions affecting street space quality. Among all indicators, street interface permeability and facility density show the strongest explanatory power. Furthermore, all pairs of influencing factors exhibit either bi-factor enhancement or nonlinear enhancement, highlighting the synergistic effects of multiple variables in shaping street quality. Based on these findings, this study proposes differentiated renewal strategies for the four street types and offers a transferable methodological framework for data-driven assessment and targeted intervention in the renewal of historic urban streets.

Keywords: street space quality; multi-source data; fully convolutional neural networks; GeoDetector; Xi'an's historic urban area

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Academic Editor: Haifeng Liao

Received: 12 May 2026
Revised: 17 June 2026
Accepted: 24 June 2026
Published: 27 June 2026

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1. Introduction

Urban development in China has entered a critical transitional stage from incremental expansion to quality enhancement of existing urban stock, with "high-quality development" emerging as a central agenda [1]. Against this backdrop, street space, which functions both as a transport corridor and as a public open space, has become a fundamental unit for assessing urban livability and implementing refined urban governance. This paradigm shift is particularly evident in the built environments of historic cities, where streets not only embody tangible cultural memory but also accommodate contemporary urban functions. On the one hand, streets must meet modern mobility needs and accommodate daily activities; on the other, they must preserve historical character, spatial scale and cultural authenticity. As one of China's four ancient capitals, Xi'an's historic urban area encompasses three national-level historic and cultural districts, 56 heritage conservation sites

and a permanent population of approximately 286,000 within an area of just 13.5 square kilometres. The high degree of overlap between heritage resources and contemporary urban life has created acute contradictions: population loss and declining vitality, spatial disorder caused by mixed functions, and traffic congestion resulting from the separation of work and residence [2]. Despite numerous planning interventions, the actual quality of public space in the historic urban area remains severely at odds with its world-class cultural status. Regulations relating to heritage conservation—such as building height restrictions, demolition limitations, and the preservation of historic street layouts—have precluded the possibility of large-scale demolition and reconstruction. Consequently, the incremental improvement of street spaces has emerged as the most feasible path to revitalization.

The theoretical foundation of street quality research has evolved from perceptual and morphological interpretations of urban space to more systematic and measurable analytical frameworks. Early studies mainly emphasised how people perceive and experience urban environments. Lynch's The Image of the City [3] identified paths, edges, districts, nodes and landmarks as key elements shaping urban spatial cognition, thereby highlighting the legibility of urban space. In contrast, Ashihara's *The Aesthetic Townscape* [4] focused more on the proportional relationship between street width and building height, proposing the D/H ratio as an indicator associated with spatial enclosure and psychological comfort. While Lynch and Ashihara primarily addressed the perceptual and physical dimensions of streetscapes, Jacobs [5] and Jan Gehl [6] shifted attention to the relationship between street form and social activity. Jacobs' concept of "eyes on the street" stressed the importance of mixed uses, short blocks and aged buildings in generating urban vitality, whereas Gehl further foregrounded pedestrian priority and active ground-floor interfaces as essential conditions for human-scale urban environments. Compared with these qualitative and experience-oriented perspectives, the "3Ds" framework proposed by Cervero and Kockelman [7] and the subsequent "5Ds" framework developed by Ewing and Cervero [8] provided a more operational basis for measuring the influence of the built environment on travel behaviour and spatial quality. Together, these studies indicate a gradual shift from descriptive interpretations of street experience to multidimensional and quantifiable evaluations of street quality.

Despite their theoretical contributions, traditional methods for evaluating street quality in historic districts remain limited in terms of objectivity, scale and temporal sensitivity. Questionnaire surveys, field observations and expert assessments [9–11] are valuable for capturing users' perceptions and contextual knowledge, but they are often constrained by subjective judgment, inconsistent evaluation criteria and limited sample sizes [12]. More importantly, these methods are less capable of identifying micro-scale morphological features or dynamically interpreting intangible perceptual elements embedded in everyday street use [9,10]. Spatial syntax partly addressed these limitations by introducing quantitative measures of street network accessibility, integration and centrality [13–15]. However, compared with human-eye-level visual analysis, spatial syntax focuses mainly on topological relationships and is therefore less effective in capturing façade characteristics, greenery, sky visibility, enclosure and other visual components that directly influence pedestrian experience. In recent years, the integration of multi-source big data and artificial intelligence has substantially expanded the methodological scope of street quality research [16–18]. Street-view images from platforms such as Google Street View and Baidu Maps provide large-scale visual data from a pedestrian perspective [19,20], overcoming the limited spatial coverage of conventional field surveys. At the same time, machine learning and deep learning techniques have enabled more efficient extraction and classification of streetscape elements [16,21–23]. Among them, convolutional neural network-based semantic segmentation models, especially encoder–decoder architectures, can classify multi-category pixels

and extract visual features such as greenery, sky, buildings, vehicles and pedestrians with relatively high accuracy and efficiency [24–26]. Compared with earlier machine learning approaches, fully convolutional neural networks and random forest models have shown stronger adaptability to scenes with substantial spatial heterogeneity [27]. As a result, semantic segmentation has been widely used to construct quantitative indicators such as the green view index, sky visibility index, interface enclosure index, public facility accessibility, traffic recognition and mobility levels [28–33]. Empirical studies in Chinese cities, including Shanghai [33,34], Beijing [35], Tianjin [36], Nanjing [37], Guangzhou [38], Hangzhou [39], and Xi'an [40], further demonstrate the applicability of this approach across diverse urban contexts. Nevertheless, most existing studies focus on general urban streets, while relatively limited attention has been paid to historic districts, where street quality is shaped not only by visual composition and accessibility but also by heritage conservation, cultural atmosphere and fine-grained spatial morphology. This gap highlights the need for an integrated analytical framework that combines human-scale visual perception, quantitative spatial indicators and the particular conservation requirements of historic urban areas.

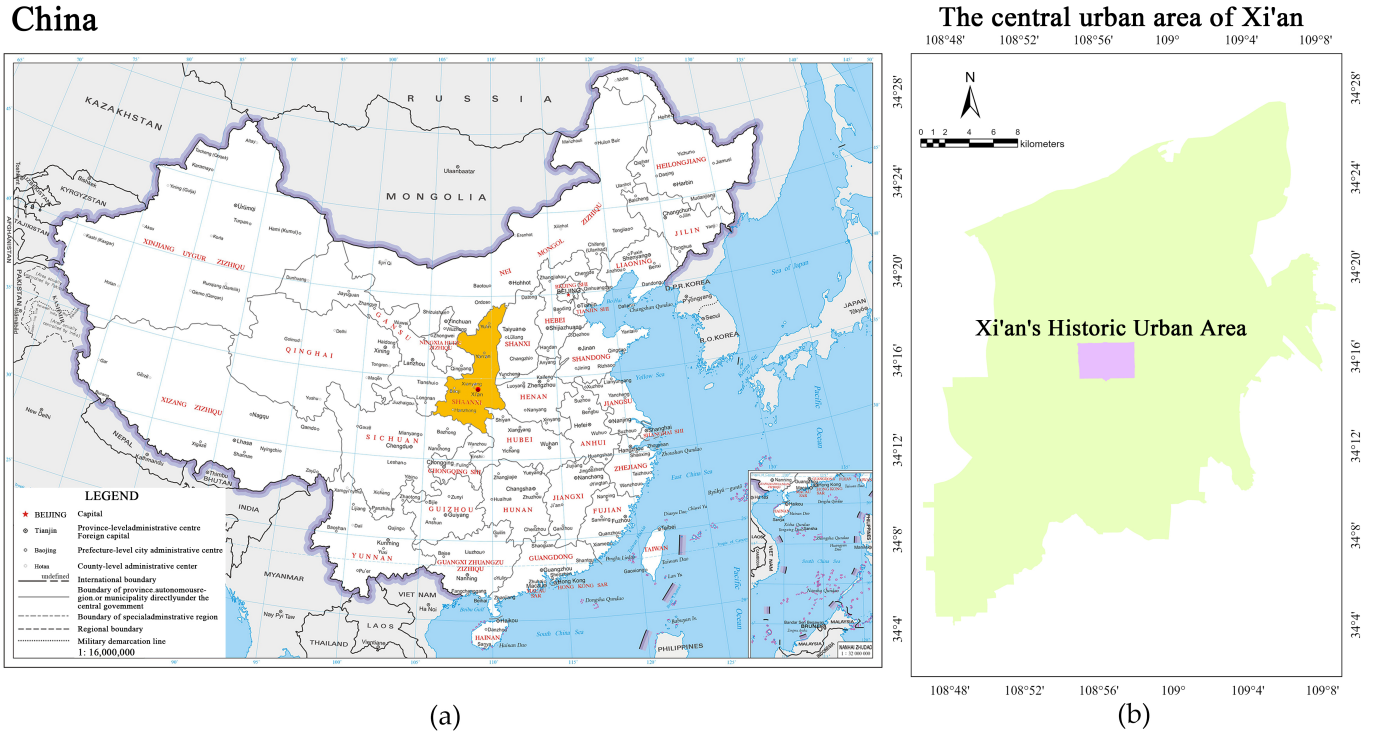
Although previous studies have advanced the measurement of street space quality, several gaps remain when these methods are applied to historic districts. First, most studies focus on general urban contexts, such as commercial streets, residential neighbourhoods or city-wide street networks, and mainly measure physical and visual indicators, including accessibility, greenery, enclosure, sky visibility, facilities and traffic conditions [28–33]. While these studies provide useful references for large-scale quantitative assessment, historic districts involve additional dimensions, such as heritage conservation, historical continuity, cultural atmosphere and traditional spatial morphology. Although historical and cultural values have been discussed in urban regeneration and conservation studies, they are rarely integrated into street quality assessment frameworks [41–43]. Second, existing research often examines individual variables, such as the green view index, sky visibility, enclosure, accessibility or facility distribution [28,33]. These analyses clarify the independent effects of specific factors but insufficiently explain how multiple factors jointly influence street quality. In historic districts, street quality is shaped by interactions among physical form, visual perception, functional mix, traffic conditions and historical-cultural attributes. Therefore, further analysis of multi-factor interactions and explanatory mechanisms is needed. Third, many studies identify spatial patterns and influencing factors of street quality, but fewer translate these findings into differentiated planning strategies. Existing recommendations are often general and do not fully respond to different street functions or conservation requirements. In historic districts, commercial, residential, historic and mixed-use streets require distinct improvement priorities. To address these gaps, this study has three objectives: to construct a street space quality assessment framework for Xi'an's historic districts by integrating historical characteristics with accessibility, comfort, convenience and safety; to identify key influencing factors and their interactions using the Geographical Detector model; and to propose differentiated strategies for commercial, residential, historic and mixed-use streets, thereby linking quantitative diagnosis with targeted regeneration practice.

2. Materials and Methods

2.1. Study Area

The study area comprises the historic urban area of Xi'an, Shaanxi Province, China, specifically the area enclosed by the Xi'an Ming City Wall, bounded by the outer ring road (Figure 1). The area covers approximately 13.5 square kilometres and spans three municipal districts (Beilin, Lianhu and Xincheng) and seven subdistrict offices. According to data from the Seventh National Population Census of 2020, the permanent resident population

within the historic urban area stands at 286,400, with a population density of 25,900 people per square kilometre, which is significantly higher than that of other similar historic urban areas in China. The historic urban area retains the grid-patterned street layout established during the Sui and Tang dynasties and finalised during the Ming and Qing dynasties. The spatial structure is centred on the Bell Tower, with four main thoroughfares (East, West, South and North Avenues) serving as axes, supplemented by a secondary road grid developed during the Republican era. The area encompasses three historic and cultural districts, four historic sites, and 56 cultural heritage sites protected at national, provincial and municipal levels. Through a long history of accumulation, the historic urban area has continuously preserved and innovated the historical and cultural heritage of the ancient city throughout its development. As the urban public centre of Xi'an, the historic urban area currently serves a wide range of functions, including administrative offices, leisure and entertainment, commercial shopping, healthcare and education, tourism services, and residential living.



(a) (b)

Figure 1. Spatial Location Map: (**a**) Map of Shaanxi Province. (**b**) Map of Xi'an's Historic Urban Area.

2.2. Data Sources

This study utilises five types of data: urban road network data, street view imagery, building outline data, POI data for public service facilities, and land use data. All data were collected in August 2025; the specific sources and uses of the data are shown in Table 1. The street view image data features sampling points positioned at 50-m intervals along the road network; for each sampling point, street view images in both forward and reverse directions were extracted via the Baidu Maps API, yielding a total of approximately 4000 images. The public service facility POI data comprises 18 categories, including dining, shopping, accommodation, entertainment and leisure.

Table 1. Data sources and uses.

Data Type	Data Sources	Use of Data
Road network data	Open Street Map	Base map for street segment delineation, followed by spatial syntax analysis
Street View image data	Baidu Maps API *	Calculation of indicators such as green coverage ratio and sky openness
Building outline data	Baidu Maps API *	Calculation of street height-to-width ratio
Public service facility POI data	Baidu Maps API *	Calculation of street facility completeness and density within the accessibility dimension
Land use data	Current Land Survey	Used for the classification of street types

* All Baidu Street View images and POI data were obtained through the official Baidu Maps API under academic use terms https://lbsyun.baidu.com/ (accessed on 30 August 2025). No personal or sensitive information was collected.

2.3. Research Approach and Methods

This study selected 404 street segments in Xi'an's historic district as the research objects and classified them into four types: commercial, residential, historic and mixed-use. Based on the spatial characteristics of the study area, multi-source data were used to construct a hierarchical street space quality measurement framework comprising five dimensions and 15 indicators, together with a system of influencing factors. The indicator system was developed through a systematic literature review and bibliometric analysis of CNKI studies published from 2001 to 2023 using the keywords "street quality" and "street vitality". In total, 253 street quality indicators and 307 street vitality indicators were extracted, followed by keyword co-occurrence and clustering analyses using CiteSpace 6.2.R4. Considering both the bibliometric results and the characteristics and problems of Xi'an's historic district, accessibility, comfort, convenience, safety and historicity were identified as the five core dimensions, and 15 indicators were selected accordingly. The natural breaks classification method was used to discretise the 15 secondary indicators into five grades, with scores ranging from 1 to 5, based on the principle of minimising intra-class variance and maximising inter-class variance. A fully convolutional neural network model was then applied to calculate the spatial quality indicator values of each street segment, while Geodetector was used to examine the non-linear relationships and interaction effects among influencing factors. Finally, differentiated optimisation strategies were proposed for different street types (Figure 2).

2.4. Classification of Street Types and Development of an Evaluation Indicator System

Based on an analysis of street design guidelines for cities such as Shanghai, Beijing and Shenzhen, and taking into account the characteristics of Xi'an's historic urban area, the 404 street sections within the historic urban area have been classified into four types: commercial, residential, historic and mixed-use (Figure 3). Street types were classified through a combination of planning documents, land-use data, and functional verification. First, historic streets were identified based on the Grade I and Grade II historic streets and alleys designated in the Xi'an Historical and Cultural City Protection Plan (2020–2035). For the remaining streets, buffers were generated along the centre lines of existing roads in the central urban area, with buffer radii determined according to road hierarchy. Land-use data for Xi'an were then used to calculate the proportions of commercial land, residential land, and public administration and public service facility land within each buffer. The preliminary classification results were further validated using POI functional points, major urban axes, and functional zoning information. Accordingly, streets with residential land accounting for more than 50% of the buffer area were classified as residential streets, with a total length of 41.53 km, representing 40.05% of the total length of the 404 street segments.

Streets with commercial land accounting for more than 50% of the buffer area were classified as commercial streets, with a total length of 23.19 km, representing 22.36% of the total street length. The identified historic streets had a total length of 16.69 km, representing 16.09% of the total street length. Streets without a clearly dominant land-use function were classified as mixed-use streets, with a total length of 22.29 km, representing 21.49% of the total street length.

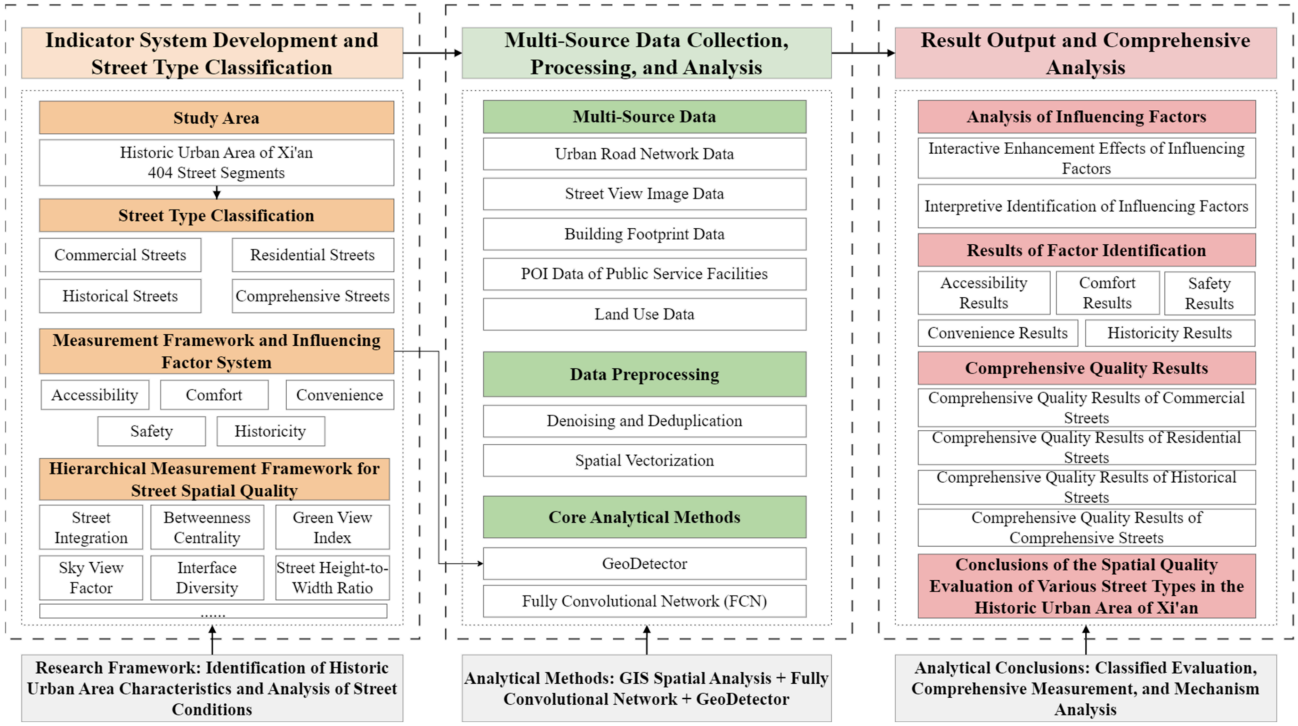


Figure 2. Research framework.

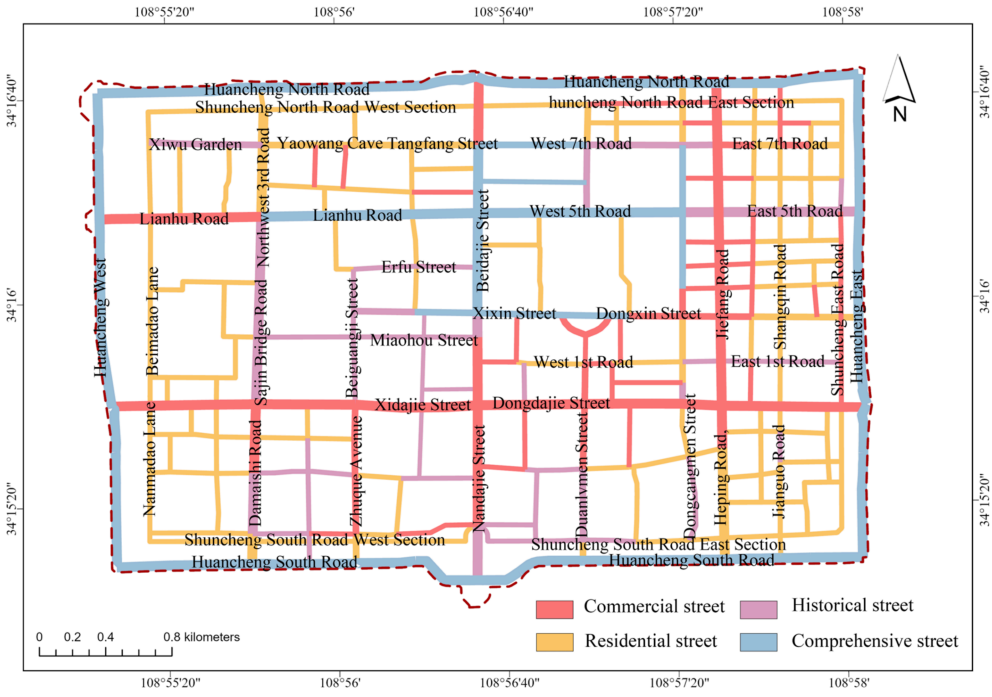


Figure 3. Classification of street types in Xi'an's historic urban area.

Building upon the classification of street types in the historic urban area, a co-occurrence analysis of 253 street quality indicators was conducted using CiteSpace software [34] on relevant papers from China National Knowledge Infrastructure (CNKI) spanning 2001–2023. Combining this with the current spatial characteristics of streets in Xi'an's historic urban area, a hierarchical measurement framework and indicator system for street space quality comprising five dimensions and 15 indicators was ultimately established. The indicator weights were determined using the Analytic Hierarchy Process (AHP) combined with expert scoring. Ten experts in urban planning, urban design, and historic conservation were invited to assess the relative importance of indicators at the same hierarchical level. Following the AHP procedure, a nine-point scale was used to construct pairwise comparison judgment matrices. The values in each row of the matrices were then normalized to calculate the weights of the corresponding indicators. To ensure the reliability of the weighting results, a consistency test was conducted. The results showed that the random consistency index was RI = 0.58, and the consistency ratio was CR = 0.017, which is lower than the acceptable threshold of 0.1. This indicates that the judgment matrices passed the consistency test and that the derived indicator weights were reasonable. The calculation methods and weights for each dimension and indicator are detailed in Table 2.

Table 2. Street space quality indicators and calculation methods for Xi'an's historic urban area.

Indicator Dimensions and Weights	Indicator Name	Calculation Method	Relevance	Secondary Weight
Accessibility (0.10)	Street Integration (SI)	The degree of clustering or dispersion of a given spatial element relative to other elements within the urban road network, calculated using sDNA-V4.2.0 software	Positive correlation	0.70
	Back-to-Back Centrality (BC)	The accessibility of a street to other streets within its search radius, calculated using sDNA software	Positive correlation	0.30
Comfort (0.30)	Green View Index (GVI)	Area of green vegetation pixels in street view images/total pixel area	Positive correlation	0.20
	Sky View Factor (SVF)	Area of sky pixels in street view images/total pixel area	optimal range	0.15
	Interface Diversity (ID)	Number of identified element types in street view images/156	Positive correlation	0.15
	Aspect Ratio (AR)	Average height of buildings on both sides of the street based on building outline data/street width	optimal range	0.15
	Proportion of Pedestrian Space (PSP)	Area of pixels representing pedestrian spaces (including pavements, running tracks, hard-surfaced areas, etc.) in street view images/total pixel area	Positive correlation	0.20
	Interface Permeability (IP)	Pixels representing building facades in street view images/total pixels representing enclosed facades	Positive correlation	0.15
Convenience (0.20)	Facility Completeness (FC)	Number of POI facility types within the 50-m buffer zone on both sides of the street/Total number of POI facility types in the historic urban area	Positive correlation	0.60
	Facility Distribution (FD)	Point density of POI facilities within the 50-m buffer zone on both sides of the street	Positive correlation	0.40

Table 2. *Cont.*

Indicator Dimensions and Weights	Indicator Name	Calculation Method	Relevance	Secondary Weight
Safety (0.25)	Motorised Traffic Impact (MTI)	Area of motorised transport (cars, large vehicles, buses, motorcycles, etc.) pixels in Street View images/Total pixel area	negative correlation	0.70
	Safety Facility Completeness (SFC)	Pixel area of safety facilities (including fences, railings, etc.) in street view images/total pixel area	Positive correlation	0.10
	Road Safety (RSD)	Pixel area of motor vehicle road surfaces in street view images/total pixel area	negative correlation	0.20
Historicity (0.15)	Historical Spatial Authenticity (SA)	Classified into three categories: no change, road widened, and significant changes or adjustments to road length and alignment	Positive correlation	0.30
	Proportion of Heritage Conservation Areas (HSP)	Number of cultural heritage sites within the 50-m buffer zone on either side of the street/total number of cultural heritage sites in the historic urban area	Positive correlation	0.70

'Positive correlation' indicates that higher values of the indicator correspond to better quality; 'negative correlation' indicates that lower values of the indicator correspond to better quality; 'optimal range' indicates that there is an optimal range of values or a directional trend.

2.5. Research Methods

2.5.1. Fully Convolutional Neural Network

Street view images provide a visual data foundation from a human-centred perspective for the quantitative assessment of street-level spatial quality. However, raw street view images contain only pixel colour information and cannot be directly used to extract physical elements of urban design significance, such as greenery, the sky, buildings and pedestrians. Therefore, this study introduces a fully convolutional neural network (FCN) to perform semantic segmentation on street view images, thereby enabling pixel-level scene analysis. The fully convolutional neural network (FCN) is an end-to-end image semantic segmentation framework proposed as an extension of the traditional convolutional neural network (CNN). Unlike CNNs, which use fully connected layers to output classification vectors of fixed length, the FCN replaces all fully connected layers with convolutional layers. Consequently, it can accept input images of any size and produce pixel-level classification results at the same resolution as the input image.

A fully convolutional neural network consists of a series of convolutional and pooling layers stacked alternately. Convolutional layers perform local feature extraction on the input feature maps using learnable convolutional kernels, which can be mathematically expressed as:

$$F_{ij}^{(l)} = f\left(\sum_{m}\sum_{n} W_{mn}^{(l)} \cdot X_{(i+m)(j+n)}^{(l-1)} + b^{(l)}\right) \quad (1)$$

In the equation, $F_{ij}^{(l)}$ denotes the activation value at position (i, j) in the feature map of layer l, $W^{(l)}$ denotes the convolution kernel weight matrix, $X^{(l-1)}$ denotes the input from the previous layer, $b^{(l)}$ denotes the bias term, and $f(\cdot)$ denotes the non-linear activation function (this study employs the ReLU function). The pooling layer performs downsampling on the feature map, reducing the spatial dimension and computational load whilst retaining key feature responses, and simultaneously introducing a degree of translation invariance. As the number of network layers increases, the spatial resolution of the feature

maps gradually decreases, whilst the number of channels gradually increases, forming a process of information abstraction from local details to global semantics.

The study utilised the ADE20K Scene Analysis Dataset, released by the Computer Science and Artificial Intelligence Laboratory at the Massachusetts Institute of Technology, for model training [44,45]. This dataset comprises over 20,000 indoor and outdoor scene images, covering 150 object categories ranging from the sky, vegetation and buildings to street furniture and vehicles, encompassing the vast majority of visual elements required for measuring street-level spatial quality. Training utilised a VGG-16 network pre-trained on the ImageNet dataset as the initialisation weights for the encoder to accelerate convergence and enhance generalisation capabilities for low-frequency categories. The main training hyperparameter settings are shown in Table 3.

Table 3. Training parameters for fully convolutional neural network models.

Parameters Name	Setting	Description
Optimizer	SGD (Stochastic Gradient Descent)	Standard optimizer for momentum
Initial learning rate	0.0004	Employs a polynomial decay strategy
Momentum factor	0.9	Accelerates convergence and suppresses oscillations
Batch size	8	Subject to GPU memory constraints
Number of training iterations	50	Stops once the validation set loss has converged
Loss function	Cross-entropy loss	Standard loss for per-pixel multi-class classification
Input dimensions	768 × 512 pixels	Uniform cropping to a fixed size

Approximately 4000 images of streetscapes in Xi'an's historic district were fed into the model one by one for inference, yielding a pixel-level semantic label map for each image. In the label map, each pixel is assigned a category ID corresponding to one of the 150 object categories defined in the ADE20K dataset, which is used to calculate the values of indicators for factors influencing spatial quality on each street within the historic district.

2.5.2. Analysis of the GeoDetector

Having completed the comprehensive calculation and measurement of street space quality, it is necessary to further examine the extent to which each indicator influences spatial heterogeneity in quality, as well as the mechanisms of interaction between them. Traditional correlation analysis assumes a linear relationship between variables and their independence from one another, whereas the factors influencing street space quality often exhibit non-linear relationships and interactive enhancement effects. Therefore, this study introduces the Geodetector model for analysis. The GeoDetector is a statistical method proposed by Wang Jinfeng and Xu Chengdong [46] for detecting spatial heterogeneity and revealing the underlying driving factors. Its core concept is derived from the notion of spatial hierarchical heterogeneity in medical epidemiology: if a particular independent variable has a significant influence on the dependent variable, then the spatial distribution patterns of the independent and dependent variables should exhibit similarity. This method has been widely applied in the study of urban spatial drivers and influence mechanisms [47,48]. Relevant studies have further adopted the GeoDetector model to identify the determinants of urban street spatial characteristics and to reveal the interactions among

these factors [49,50]. This method calculates the q statistic to measure the explanatory power of each factor in spatial heterogeneity:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2} \quad (2)$$

In the equation, N_h and σ_h^2 represent the sample size and variance within layer h, whilst N and σ^2 denote the population sample size and population variance. $q \in [0, 1]$; a higher value indicates greater explanatory power. The interaction detector assesses whether the combined effect of two factors ($X_1 \cap X_2$) enhances, weakens, or is independent of their respective individual effects. Interaction types are categorised as: non-linear attenuation, single-factor non-linear attenuation, two-factor enhancement, independence, or non-linear enhancement.

3. Results

3.1. Spatial Patterns of Single-Factor Indicators for the Spatial Quality of Streets in Historic Districts

3.1.1. Accessibility

The average score for street connectivity was 4.19, indicating that the historic district possesses a highly connected grid-like street network. High scores were concentrated in the eastern sector (Jiefang Road, Heping Road, Shangde Road), reflecting the crucial role played by the comprehensive grid road network system established during the Republican era in enhancing street accessibility. In the western sector, particularly within and around the Beiyuanmen Historic and Cultural District, street integration is relatively low (scores below 2), primarily due to the disruption of the alleyway layout and the presence of dead-end roads. The average score for centrality is 3.20, with several major urban thoroughfares (Dongda Street, Beida Street, Jiefang Road) achieving the highest scores. This reflects the hierarchical nature of the street network, with main thoroughfares carrying the bulk of through traffic (Figure 4).

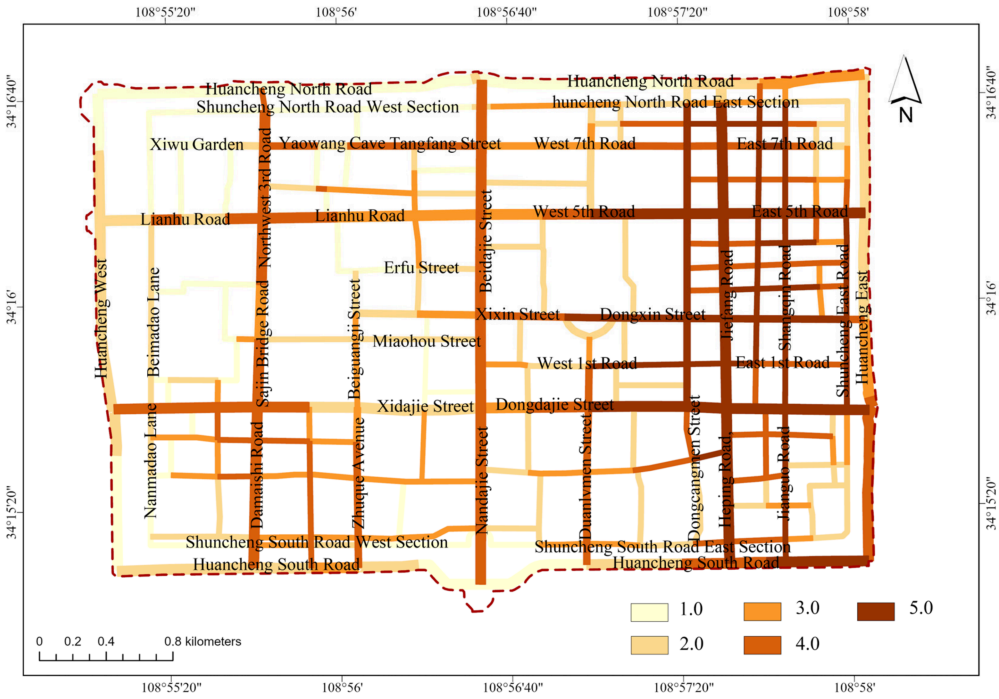


Figure 4. Spatial distribution map of street accessibility scores.

3.1.2. Comfort

The level of street greenery in the historic district is generally low, with an average score of 2.0; only 2% of road sections achieved a score of 5, primarily concentrated on recently refurbished main roads (Lianhu Road, West Fifth Road) and sections of the ring road. In historic and cultural districts and densely populated residential areas, the level of greenery is significantly inadequate due to narrow streets and high building density. The average score for sky openness was 2.6. Due to the impact of tree canopy cover, main roads with good tree shade scored lower, whilst narrow residential alleys with few roadside trees scored higher. The score for façade diversity was relatively high (average 3.8), with peak scores occurring in the Beiyuanmen and Sanxue Street historic districts, indicating that mixed-use shopfronts and diverse building types create a rich visual experience. The street aspect ratio is generally suboptimal: 39% of road sections scored 1 (too wide or too narrow), whilst only 13% fell within the optimal range (scores between 1 and 2). The average score for the proportion of pedestrian space was 3.1, with commercial thoroughfares scoring higher, whilst scores were lower within historic and cultural districts due to narrow alleys and limited pedestrian space. Overall, façade permeability was relatively good (average score of 3.9), reflecting Xi'an's traditional open-block layout; however, permeability was significantly lower in areas adjacent to the city walls or within enclosed residential compounds (Figure 5).

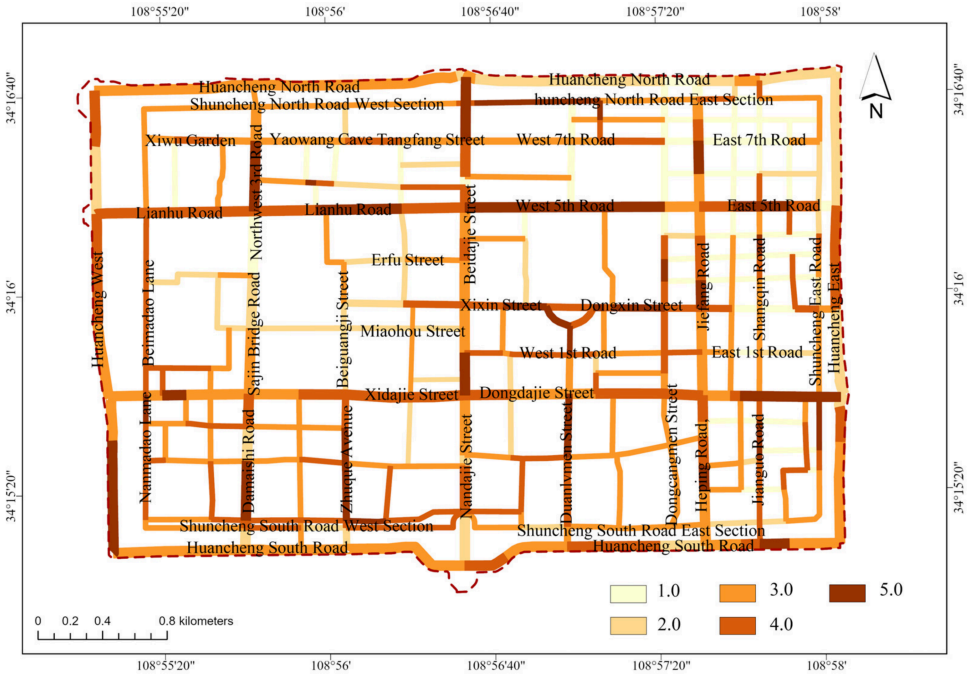


Figure 5. Spatial distribution map of street comfort scores.

3.1.3. Convenience

The average score for the comprehensiveness of facilities was 2.8, with higher-scoring sections located along the city's main commercial corridors (West Street, North Street, Lianhu Road) and the Ring Road. Residential clusters in the north-eastern and south-eastern districts suffer from a marked lack of facilities, particularly in terms of community-level services. The density of facilities (average score of 3.5) shows a strong spatial correlation with the comprehensiveness of facilities, with high-density clusters forming around the Zhonglou commercial hub and major transport interchanges (Figure 6).

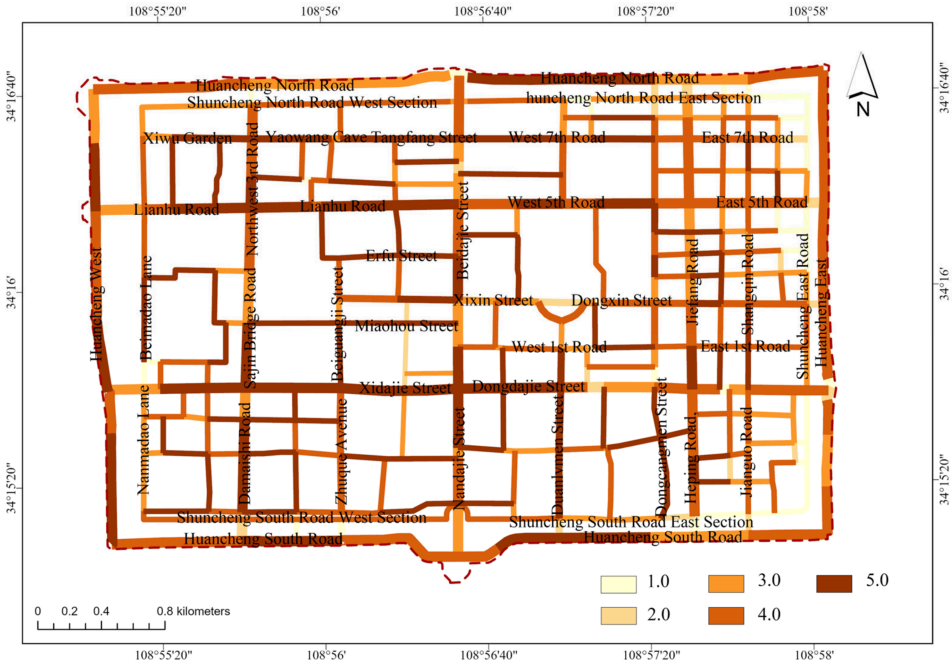


Figure 6. Spatial distribution map of street convenience scores.

3.1.4. Safety

The overall impact of motorised traffic is moderate (average score of 3.6), indicating that the separation of pedestrians and vehicles is acceptable on most streets. Problem areas are concentrated around government offices, hospitals and schools, where on-street parking and drop-off activities create conflict zones. The adequacy of safety facilities is markedly insufficient (average score of 1.6), with 83% of road sections scoring no higher than 2 points. This indicates a general lack of pedestrian safety infrastructure within the Xi'an's historic urban area. Road safety levels (average score of 3.1) exhibit multiple clusters of high values, corresponding to major junctions and transport corridors (Figure 7).

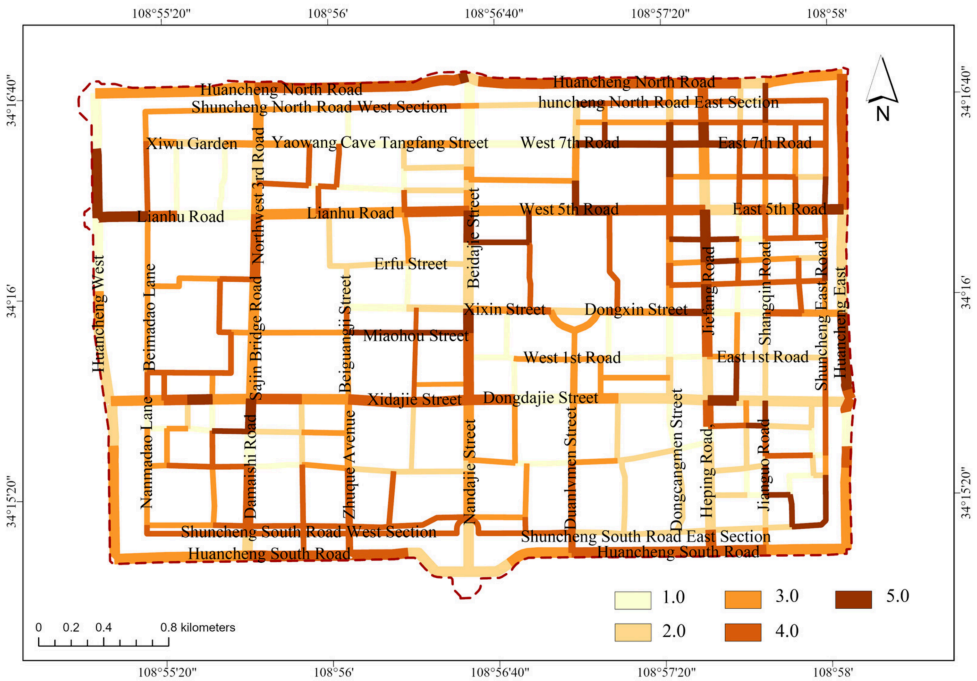


Figure 7. Spatial distribution map of street safety scores.

3.1.5. Historical

The authenticity of the historical space exhibits a clear pattern of differentiation: the streets and alleys within the protected boundaries of the historic and cultural districts have retained a high degree of authenticity, whereas the city's main thoroughfares have undergone significant widening and redevelopment. The density of listed heritage sites is highest in the vicinity of the Bell and Drum Towers and along Shuyuanmen Street. The overall composite score for historicity is relatively low (average score of 1.7), with only 6.68% of road sections scoring above 3 points. This indicates that whilst individual heritage elements have been well preserved, the broader street fabric has undergone significant changes (Figure 8).

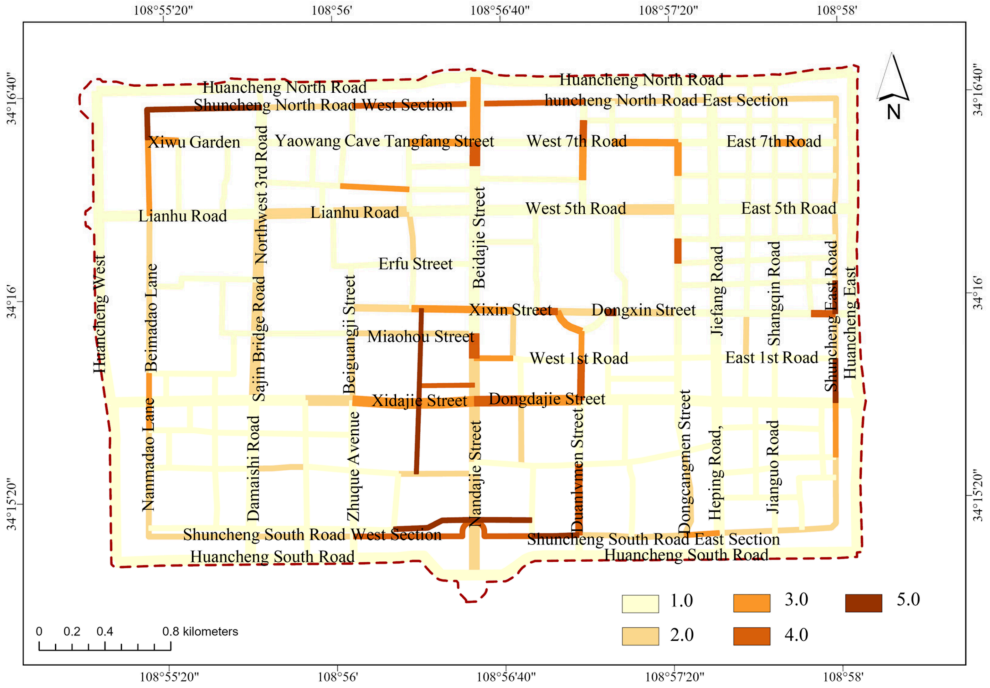


Figure 8. Spatial distribution map of street historical scores.

3.2. Comprehensive Assessment of Street Quality in the Historic District

Using ArcGIS Pro 3.4.3, 15 influencing factors were subjected to comprehensive weighted overlay analysis, yielding a range of comprehensive street quality scores for the historic district of 1.59 to 4.10, with an average of 2.85. The score distribution shows a concentration in the middle range: 58% of the street sections fall within the medium-quality range (scores between 2.5 and 3.5), 38% within the high-quality range (scores greater than 3.5), and only 4% within the low-quality range (scores less than 2.5). In terms of spatial distribution, high-quality streets correspond to the city's main arterial corridors (West Street, Lianhu Road, and the north–south central axes) as well as certain commercial districts that have undergone recent renovation. Low-quality streets are primarily concentrated in older residential areas (East 2nd Road to East 4th Road, Shangjian Road, and West 7th Road), which are characterised by ageing housing stock and inadequate infrastructure. Historic streets achieved the highest overall score (3.14), followed by commercial streets (3.08), mixed-use streets (3.02) and residential streets (2.80). However, the decomposed dimension scores reveal distinct profile characteristics: historical streets hold an absolute advantage in the historical dimension (2.71, compared to 1.41–1.67 for other types) and also perform well in terms of convenience (score of 3.31), but their safety score (3.24) is lower than that of commercial streets (3.40). Lifestyle streets scored lowest across all dimensions (except for historicity) (Figure 9, Table 4).

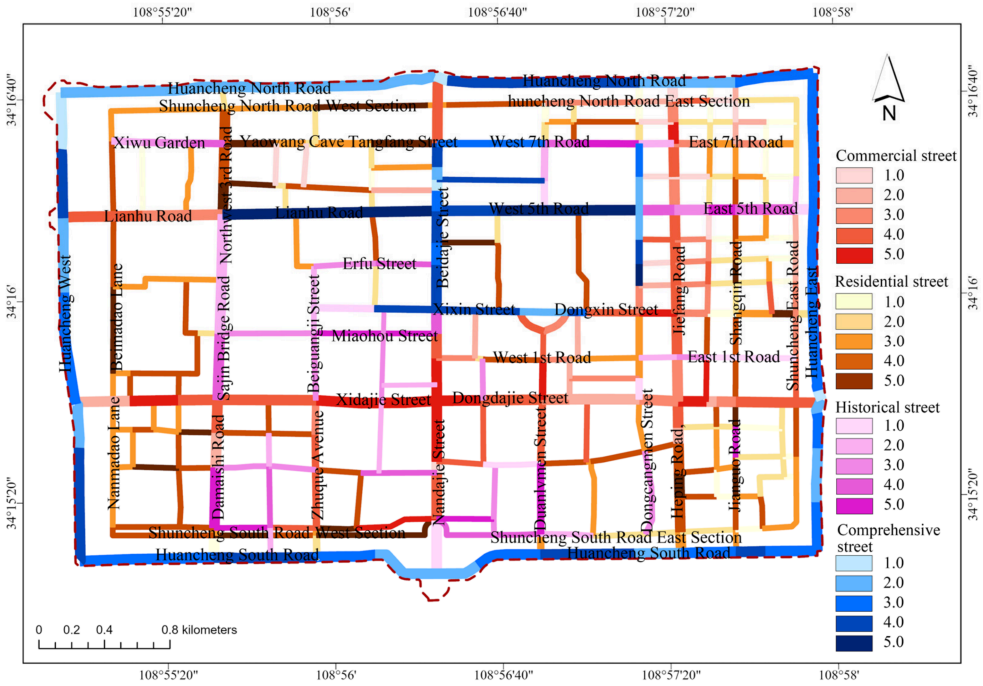


Figure 9. Map of Comprehensive Evaluation Scores for Street Space Quality.

Table 4. Comparison of Dimension Scores across Different Types of Streets.

Type	Commercial Street	Residential Street	Historical Street	Comprehensive Street
Accessibility	4.21	3.77	3.78	3.79
Comfort	3.02	2.75	2.94	3.16
Convenience	3.25	2.90	3.31	3.24
Safety	3.40	3.16	3.24	3.35
Historical	1.67	1.52	2.71	1.41
Overall score	3.08	2.80	3.14	3.02

3.3. Geographical Detection Analysis of Factors Influencing the Spatial Quality of Streets in Historic Urban Areas

3.3.1. Univariate Detection

Similarly, the natural breaks classification method was employed to categorise street space quality into five levels: high, relatively high, moderate, relatively low and low. These categories were then input into the geodetector model as the dependent variable, alongside the scores of the 15 influencing factor indicators. The geodetector revealed the explanatory power (q-value) of each influencing factor indicator on the overall quality of streets in historic districts, as shown in Table 5.

Overall, factors related to comfort dominate the top ten rankings, with interface permeability alone accounting for 41.2% of the variation in street space quality. From an urban form perspective, this confirms the central role of 'permeable interfaces' in historic districts and demonstrates that they capture the spatial attributes that pedestrians perceive first and most consistently when walking along the streets. Convenience factors also demonstrate strong explanatory power (q-values ranging from 0.341 to 0.387). From the perspective of daily life, these reflect the utility-based anchor of street space quality, indicating that residents' and visitors' perceptions of street quality are highly dependent on functional diversity and service accessibility, thereby lowering the barriers to street use. It is worth noting that the standalone effect of the accessibility indicator is relatively weak

(q < 0.10); this may be due to the high overall connectivity and homogeneity of the road network in historic districts, which limits its discriminatory power.

Table 5. Results of single-factor analysis of street-level spatial quality based on the Geodetector (top 10 factors).

Rank	Factor	Dimension	Q-Value	*p*-Value
1	Interface Permeability (IP)	Comfort	0.412	<0.001
2	Facility Distribution (FD)	Convenience	0.387	<0.001
3	Proportion of Pedestrian Space (PSP)	Comfort	0.356	<0.001
4	Facility Completeness (FC)	Convenience	0.341	<0.001
5	Sky View Factor (SVF)	Comfort	0.298	<0.001
6	Interface Diversity (ID)	Comfort	0.267	<0.001
7	Green View Index (GVI)	Comfort	0.245	<0.001
8	Proportion of Heritage Conservation Areas (HSP)	Historical	0.201	<0.01
9	Aspect Ratio (AR)	Comfort	0.178	<0.01
10	Motorised Traffic Impact (MTI)	Safety	0.134	<0.05

3.3.2. Detection of Interactions Between Factors

The interaction detector revealed that all factors influencing street space quality exhibited either two-factor synergy or non-linear synergy effects; that is, the explanatory power when two factors act together is always greater than the sum of their individual effects. The strongest interactions consistently occurred in the combination of the convenience and comfort factors, with the Q-values for all combinations exceeding 0.6 (Figure 10). This result indicates that improving the street-level spatial quality in Xi'an's historic urban area requires multi-dimensional, coordinated interventions rather than isolated optimisation of individual influencing factors.

Index	RI	BC	GVI	SVF	ID	AR	PPS	IP	FC	FDD	MVT	SFC	RS	HAS	PHCS
RI	0.01														
BC	0.13	0.07													
GVI	0.33	0.36	0.3												
SVF	0.33	0.35	0.41	0.29											
ID	0.35	0.39	0.42	0.34	0.31										
AR	0.04	0.12	0.32	0.32	0.33	0									
PPS	0.48	0.48	0.47	0.46	0.47	0.46	0.44								
IP	0.46	0.49	0.48	0.46	0.44	0.44	0.49	0.43							
FC	0.38	0.43	0.57	0.62	0.62	0.35	0.68	0.65	0.33						
FDD	0.39	0.44	0.58	0.61	0.61	0.36	0.68	0.64	0.35	0.34					
MVT	0.17	0.2	0.45	0.47	0.48	0.14	0.6	0.62	0.49	0.5	0.11				
SFC	0.1	0.16	0.35	0.35	0.38	0.08	0.49	0.5	0.4	0.41	0.16	0.06			
RS	0.15	0.17	0.39	0.4	0.42	0.13	0.5	0.53	0.4	0.41	0.23	0.18	0.09		
HAS	0.1	0.17	0.37	0.36	0.38	0.11	0.48	0.46	0.38	0.39	0.23	0.14	0.2	0.08	
PHCS	0.1	0.18	0.36	0.38	0.39	0.11	0.49	0.5	0.43	0.43	0.18	0.17	0.2	0.18	0.08

Figure 10. Results of the analysis of interactions among factors influencing street space quality.

Factor detection by street type further revealed differentiated patterns of factor importance, as shown in Table 6. For commercial streets, the three dominant factors were interface permeability (q = 0.44), pedestrian space proportion (q = 0.42), and interface diversity (q = 0.34). These factors are mainly associated with the comfort dimension, and their q-values were higher than their corresponding values in the overall model, indicating that

the explanatory power of pedestrian space and street environmental quality was further strengthened in commercial street contexts. In contrast, the leading factors for residential streets were interface permeability (q = 0.55), pedestrian space proportion (q = 0.53), and sky openness (q = 0.45). Although the first two factors overlapped with those of commercial streets, the q-value of sky openness was significantly higher than that in the overall model, suggesting the increasing importance of functional integrity in residential street environments. For historical streets, the ranking of factor importance followed a distinctly different logic. Facility distribution density (q = 0.36), facility completeness (q = 0.34), and green view index (q = 0.33) were the dominant factors. By contrast, historical spatial authenticity (q = 0.29) and the proportion of protected cultural heritage units (q = 0.04), which directly represent historical heritage attributes, ranked fifth and thirteenth, respectively. This indicates that, in terms of users' overall experience, the functional quality of street space may be more important than heritage density itself. For mixed-use streets, the top three factors were interface permeability (q = 0.45), facility completeness (q = 0.40), and facility distribution density (q = 0.39). Convenience-related factors occupied two of the top three positions, while interface permeability remained the most influential factor. This reflects the multiple demands carried by such composite urban corridors, which integrate transportation, public services, commercial activities, and residential functions. Therefore, they require not only sufficient pedestrian space but also permeable street interfaces to support visual and behavioral interactions among diverse urban functions.

Table 6. Comparison of Scores for All Indicators across Different Types of Streets.

Factors	Commercial Street	Residential Street	Historical Street	Comprehensive Street
Street Integration (SI)	0.06	0.05	0.03	0.11
Back-to-Back Centrality (BC)	0.09	0.08	0.07	0.08
Green View Index (GVI)	0.19	0.38	0.33	0.34
Sky View Factor (SVF)	0.34	0.45	0.08	0.06
Interface Diversity (ID)	0.34	0.43	0.18	0.05
Aspect Ratio (AR)	0.03	0.05	0.02	0.05
Proportion of Pedestrian Space (PSP)	0.42	0.53	0.30	0.33
Interface Permeability (IP)	0.44	0.55	0.24	0.45
Facility Completeness (FC)	0.25	0.38	0.34	0.4
Facility Distribution (FD)	0.28	0.38	0.36	0.39
Motorised Traffic Impact (MTI)	0.12	0.11	0.16	0.18
Safety Facility Completeness (SFC)	0.11	0.02	0.06	0.10
Road Safety (RSD)	0.06	0.05	0.21	0.06
Historical Spatial Authenticity (SA)	0.06	0.05	0.29	0.21
Proportion of Heritage Conservation Areas (HSP)	0.10	0.04	0.04	0.17

4. Discussion

4.1. Perceived Comfort Plays a Primary Role in Street Quality in Historic Districts

The research findings indicate that comfort-related indicators—particularly visual permeability, the proportion of pedestrian space, and sky openness—are the strongest determinants of street quality. This resonates with Yoshinobu Ashihara's [4] emphasis on the visual experience of street enclosure and Lynch's [3] concept of 'imaginability'. The dominant role of visual perception variables further confirms that, for street users, the immediate sensory environment is more important than abstract network attributes (such as accessibility). The low explanatory power of accessibility indicators (q < 0.10) warrants further discussion, but this does not imply that accessibility is unimportant. On the contrary, within a high-density, well-connected grid road network such as that of Xi'an's

historic urban area (road network density: 7.65 km/km^2), accessibility itself is already at a relatively high and homogeneous level, thereby limiting its discriminatory power. In cities with more fragmented road networks, accessibility is likely to play a greater role. This finding is consistent with previous studies emphasizing the role of human-scale perceptual qualities in shaping walking experience, visual comfort, and perceived urban quality. More importantly, this study extends such evidence to historic districts, suggesting that historic street conservation should not only preserve physical heritage elements but also enhance everyday pedestrian comfort and environmental experience.

4.2. Interaction Effects Between Factors and the Need for Comprehensive Interventions

The widespread amplifying effect observed in the interactions between factors influencing the quality of street space constitutes a significant theoretical contribution of this study. The finding that the explanatory power of any combination of two factors exceeds that of their individual effects challenges the conventional approach of addressing single issues in isolation. For example, simply increasing greenery where pedestrian space is insufficient may yield minimal results; conversely, widening pavements whilst planting more street trees can produce a synergistic enhancement effect. The particularly strong interaction between the convenience and comfort factors (the Q-values for the combinations of facility density and comfort factors all exceed 0.6) indicates that functional completeness and perceived quality are deeply intertwined. A street that is convenient but lacks visual appeal, or vice versa, is unlikely to perform well. This finding supports the 'Complete Streets' concept [51], and the study therefore calls for holistic rather than piecemeal intervention strategies. The observed interaction effects support existing research indicating that street environmental quality is shaped by the combined and often nonlinear influence of multiple built-environment and perceptual attributes, rather than by any single factor alone. In the context of historic streets, these findings further highlight the need for integrated interventions, as improvements in pedestrian space, interface permeability, facility distribution, and visual comfort are likely to be more effective when implemented in coordination.

4.3. Historical Factors and Public Space Improvement Have a Mutually Reinforcing Relationship

The relatively modest influence of historical indicators (the Q-value for the proportion of heritage conservation units was 0.04, ranking 13th) may seem counterintuitive for a study of a historic urban area. However, this finding is consistent with the observation that, although historic streets scored highest in overall quality (3.14), their quality advantage stems more from superior functional and comfort attributes than from heritage characteristics per se. In other words, Xi'an's historic and cultural districts have benefited from concentrated investment in streetscape improvements; whilst this investment has enhanced multiple quality dimensions, it has also indirectly enhanced the historic dimension. This raises an important planning consideration: the preservation of historic character and the provision of high-quality public spaces are not necessarily in conflict. When heritage conservation and public space improvement are considered holistically, the two can reinforce one another, rather than treating conservation as a constraint. This result echoes studies on heritage-led regeneration and living heritage conservation, which argue that the value of historic districts is embedded not only in material heritage but also in public life, everyday spatial practices, and place identity. It further provides quantitative evidence that historical factors and public space quality can reinforce each other when conservation and spatial improvement are balanced, while avoiding potential risks such as homogenization, over-commercialization, and the weakening of local authenticity.

4.4. Differentiated Optimisation Strategies for Different Types of Streets

Based on the findings regarding factors influencing street space quality, this paper proposes the following differentiated optimisation strategies for different types of streets: For commercial streets, the priority targets are façade permeability, the proportion of pedestrian space, and the openness of the sky, transforming the street space from a 'corridor for vehicular traffic' into a 'pedestrian-oriented retail environment'. This includes widening pavements, ensuring the continuity and vibrancy of street-front commercial facades, and installing seating and street furniture in high-traffic areas to encourage longer dwell times, thereby unlocking commercial potential by reducing the space allocated to motor vehicles. For residential streets, the key factors—visibility, proportion of pedestrian space and comprehensiveness of facilities—point to the dual requirements of 'spatial comfort and service coverage'. Strategies should focus on addressing gaps in community-level public services and implementing traffic calming measures, thereby expanding neighbourhood social spaces through the residential street model. Historic streets exhibit a unique pattern dominated by the density of facilities, the comprehensiveness of amenities, and the green view index. Furthermore, the functional quality of the street has a more direct impact on the user experience than the density of heritage sites. Consequently, strategies should not be confined to a 'static, frozen preservation' approach, but should instead adopt a 'cultural corridor' model to comprehensively advance the renovation of street-facing façades, the addition of tourism service facilities, and the refined management of motor vehicle traffic. The structural characteristics of mixed-use streets—including interface permeability, proportion of pedestrian space, and comprehensiveness of facilities—lie between those of commercial and residential streets. This reflects that such composite corridors, which combine transport, public services, commercial activities and residential functions, must achieve a coordination of multiple objectives. Guided by multi-modal integration, strategies should optimise pedestrian safety at intersections and flexibly allocate spatial functions at different times through resilient street design, thereby transforming mixed-use streets from a passive state of coexistence into an active state of coordinated and functionally ordered integration. The differentiated optimisation strategies proposed here are consistent with context-sensitive and typology-based approaches in urban design, as streets with different functional orientations vary in user groups, activity patterns, spatial demands, and perception mechanisms. By linking factor detection results with street-type classification, this study provides a more operational basis for targeted interventions, such as prioritizing pedestrian comfort in commercial streets, openness and service accessibility in residential streets, heritage ambience in historic streets, and both convenience and permeability in mixed-use streets.

5. Conclusions

Taking Xi'an's historic urban area as a case study, this research constructed a comprehensive evaluation framework comprising five dimensions—accessibility, comfort, convenience, safety, and historicity—and 15 indicators. By integrating multi-source urban data, street view imagery, deep learning-based image semantic segmentation, and Geodetector modelling, this study evaluated the spatial quality of streets in historic districts and identified the key influencing factors and their interaction mechanisms. The results show that comfort and convenience are the dominant dimensions shaping street space quality. Interface permeability, facility distribution density, and the proportion of pedestrian space have the strongest explanatory power as single factors. Factor interactions generally show enhancing effects, especially the interaction between comfort and convenience, indicating that street quality improvement requires coordinated multi-dimensional interventions. In addition, different street types show different factor rankings. Residential streets account

for 40% of the total road network length but perform the worst across all dimensions, suggesting that they should be prioritised in future optimisation and regeneration. The main contribution of this study is the construction of a computational system model for street space quality evaluation in historic urban areas. This model integrates multi-source data acquisition, deep learning-based image analysis, multi-dimensional indicator calculation, spatial quality assessment, and Geodetector-based mechanism interpretation into a unified analytical workflow. Compared with traditional field surveys, the proposed framework improves the objectivity, efficiency, and spatial resolution of evaluation. It can also be transferred to other historic districts or urban contexts, providing a replicable tool for evidence-based planning and decision-making.

However, this study has several limitations. First, street view imagery was collected solely in summer, which may affect seasonal indicators such as greenery and sky visibility. Nevertheless, as summer represents the peak period for pedestrian activity in Xi'an's historic area, and our analysis prioritises relative comparisons and factor explanatory power over absolute values, the single-season dataset remains adequate for identifying spatial patterns. Future work should incorporate multi-temporal imagery. Second, the generic FCN categories cannot fully recognise culturally specific heritage elements (e.g., traditional roof forms and decorative details). This is partially mitigated by our operationalisation of historicity via spatial authenticity and heritage-area proportions derived from planning documents, alongside general building proxies from FCN segmentation. Future studies should adopt fine-grained recognition techniques to refine heritage identification. Third, the evaluation mainly relies on measurable physical and visual features, with limited consideration of subjective perceptions, social activities, and behavioural preferences. Fourth, the cross-sectional nature of the data restricts temporal analysis; longitudinal street-view imagery and time-series urban data are needed to examine changes over time. Overall, this study provides a replicable computational framework and empirical evidence for the quantitative assessment and optimisation of street space quality in historic districts, supporting planners and policymakers in balancing heritage conservation with improved contemporary urban liveability.

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

Funding: This research received no external funding.

Data Availability Statement: Data is contained within the article.

Conflicts of Interest: Author Na Liu and Jun Ma were employed by the company Powerchina Northwest Engineering Corporation Limited. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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