

Article

Exploring Heterogeneous and Non-Linear Effects of the Built Environment on Street Quality: A Computational Approach Towards Precise Regeneration

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Abstract

As a key strategy for broader sustainability, effective street regeneration requires a precise understanding of the built environment's influence mechanisms. However, existing approaches often overlook the functional heterogeneity of streets and the non-linearity of their influence mechanisms. Addressing this gap, we developed an approach to analyze these mechanisms of the built environment, differentiated by street function. Integrating multi-source urban data, street quality was measured across three dimensions (visual quality, vibrancy, and functionality), and specialized weights for streets were determined according to their dominant functions. Applying this approach in Shanghai, we explained the non-linear effects of the built environment for each street function type through separate GBDT models and SHAP analysis. The results reveal that the influence mechanisms of built environment factors vary significantly across dominant street functions. Specifically, the heterogeneity of critical activation thresholds and saturation points provides direct evidence for more targeted regeneration strategies. Key findings highlight that a strong sense of enclosure is a priority for the quality of residential street, as measured by a low Sky View Factor. In contrast, vertical development intensity is a priority for commercial streets, as Floor Area Ratio requires a high activation threshold to exert a positive influence. In short, this research provides a computational approach that enables precise and data-driven interventions, which contribute to sustainable urban development.

Keywords: urban design; street quality; urban regeneration; built environment; non-linear effect



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1. Introduction

With 68% of the world's population projected to reside in urban areas by 2050, enhancing the quality of public space has become a vital mission for promoting residents' well-being and quality of life. Streets are a dominant component among the public spaces [1], serving as not only the primary space for urban mobility but also the fundamental venues for daily social interaction, economic activity, and cultural life [2–5]. Consequently, improving street quality has emerged as an important theme in contemporary urban planning. This focus is also evidenced by policy initiatives worldwide, such as London's "Better Streets" program and the "Urban Street Design Guide" in the United States. This trend is

especially pronounced in China, where accelerated urbanization has produced vast areas of low-quality urban space [6]. As a result, Chinese cities are focusing on improving the quality of existing urban space. Regeneration of streets has become a primary strategy to promote sustainable urban development. Therefore, major cities like Shanghai [7] and Beijing [8] have developed detailed design guidelines for the precise regeneration of the streetscapes. This type of precise regeneration employs targeted design to achieve a spatial improvement with a minimal investment, demanding a nuanced understanding of street quality and its mechanisms [7,9].

Despite its recognized importance, a systematic measurement of street quality and a deep understanding of its mechanisms have long been challenging. This is due to the functional heterogeneity of streets [10] and the built environment's complex influence mechanisms that shape quality [11–13]. Existing research has explored different dimensions of street quality, but still lacks a comprehensive measurement to account for different functions, leading to an incomplete understanding [14]. This knowledge gap has hindered the formulation of effective regeneration strategies, which may cause a waste of design resources. In recent years, the emergence of multi-source urban big data [15,16] and the analytical techniques, such as machine learning, have created unprecedented opportunities to overcome these limitations [17,18]. Consequently, leveraging these new capabilities to quantify the complex influence mechanisms of the built environment has emerged as a key research frontier [11,19,20].

To address this research frontier, this study employs machine learning and multi-source urban data to quantify the complex influence mechanisms of the built environment on street quality. Specifically, we hypothesize that these mechanisms are both non-linear and functionally heterogeneous. This research contributes to sustainable urban development by enabling regeneration with targeted, cost-effective interventions, making them both economically efficient and socially beneficial.

2. Literature Review

2.1. Measuring Street Quality: Towards a Multi-Dimensional Framework

The quality of street space has long been a central topic in urban studies. Methodologies have evolved from early theoretical inquiries [21,22] and small-scale surveys [23] to the large-scale, data-driven quantitative analyses [24]. As a multifaceted concept, street quality encompasses not only the physical comfort of the environment [25] but also the perceptual experiences and use patterns [26] of its inhabitants. Among its numerous dimensions, three have consistently emerged as central to the discussion: visual quality, functional support, and vibrancy.

Visual quality represents the comfort and pleasantness of the visual environment. The emergence of Street View Imagery (SVI) and advances in computer vision have enabled large-scale measurement of visual quality. Numerous data-driven studies have focused on objectively quantifying physical elements from SVIs to calculate metrics such as the Green View Index (GVI) [27,28], the Sky View Factor (SVF) [29], building style [30], and interface transparency [31]. Subsequent research began to integrate subjective human perception [32,33]. For instance, the MIT Place Pulse project crowdsourced public evaluation of perceived street qualities such as “beautiful,” “lively,” and “boring” [34].

Providing functional support is a crucial dimension of street quality, as high-quality streets are defined not just by their transportation efficiency but by their capacity to support various daily activities [35,36]. Jane Jacobs noted that a fine-grained mix of functions is the foundation for creating vibrant and safe streets [26]. Similarly, Allan Jacobs' research concluded that great streets are consistently characterized by diverse land uses and numerous active commercial entrances [35]. In recent years, the rise in urban big data, such

as Points of Interest (POIs), has enabled the quantitative validation of these theories [37]. A large body of empirical research demonstrates that functional attributes such as the density, diversity, and accessibility of different functions are significant determinants of street quality [38,39].

Street vibrancy is also a crucial component of street quality. Conceptually, it encompasses the dynamic interplay of social, economic, and recreational activities that constitute a lively public life [23,40,41]. While this rich interplay is abstract and difficult to quantify directly, research on this topic has operationalized vibrancy by focusing on people as its core producers [42]. The presence and activity of people on the street serve as a key proxy for its vibrancy. Streets that are populated at various times of the day are often considered safe and prosperous [26]. Early research on street vibrancy typically relied on manual counting and questionnaire surveys to conduct small-scale investigations of street activity [23,43]. While these techniques can provide nuanced insights, their high costs and small scale limit their generalizability. The emergence of geo-tagged data, such as Location-Based Services (LBS) data, has enabled the large-scale and fine-grained measurement of human vibrancy [44–47]. These datasets are sampled continuously over time and effectively capture the spatial clustering of populations, offering a dynamic and detailed view of public life.

As methodologies for measuring the individual dimensions of street quality have matured, a new trend has emerged toward more comprehensive and integrated assessments. Recent studies have started to combine multi-source data and multi-dimensional indicators to achieve a more comprehensive evaluation of street quality [14,15].

2.2. *The Complex Influence Mechanisms of the Built Environment*

Understanding the influence of the built environment is crucial for advancing both urban theory and fine-grained design practice. Within this broad field, the street has remained a central focus for both research and design, as it serves as the fundamental carrier of public life. In the 1960s, Jane Jacobs emphasized that features like mixed-use development and small blocks are essential for creating vibrant and safe streets [26]. Similarly, Ewing and Handy [48] identified five qualities of built environments that influence walkability. These foundational theories have laid the conceptual foundation for street research on the mechanisms of the built environment at the street level.

The emergence of new technologies and large-scale data has enabled researchers to empirically test and refine classical urban theories, revealing a multi-faceted complexity in the built environment's influence. One dimension of this complexity is the heterogeneity of influence. Methods like multiple linear regression have quantified the relative importance of different built environment factors, showing that their contributions are not uniform. For instance, studies indicate that functional attributes are more strongly correlated with urban vitality than human-scale design elements [47], while features like blank street walls are significantly linked to negative perceptions [49]. Another dimension is spatial heterogeneity, where the effects of the built environment are not geographically constant [50,51]. Geographically Weighted Regression (GWR) models have demonstrated that the influence of factors like functional diversity and proximity to the city center on residential satisfaction can vary in both magnitude and even direction across a city [52]. Furthermore, data-driven methods have uncovered the non-linear and interactive nature of these mechanisms [19]. Research suggests that due to carrying capacity limits and crowding effects, variables often exhibit “threshold effects” in their relationship with outcomes like street vitality and cycling [53,54]. Moreover, these factors do not act in isolation but engage in complex interactions. Density serves as a prime example. Although it is widely established that high density is beneficial for vibrancy [55], research indicates that its effect is non-linear, exhibiting diminishing returns [56]. Furthermore, studies reveal the synergistic effects of

density with other factors like commercial facilities [57]. These findings indicate the complexity of the built environment's influence, highlighting the need for more fine-grained investigations to effectively to improve street quality.

2.3. The Paradigm Shift Towards Precise Urban Regeneration

A key challenge for large-scale urban analytics is to reconcile the quest for generalizable patterns with the need for context-sensitive insights [58]. Early empirical studies of streets often adopted this uniform perspective, treating all streets as homogenous units to evaluate their universal qualities and analyze the effects of the built environments [19,33].

However, in the era of precise urban regeneration, effective interventions demand a more fine-grained understanding of spatial characteristics [59]. Driven by the availability of more granular data, urban research has also been moving towards a more precise perspective. A growing body of work seeks to quantify and analyze the unique characteristics of different street types, the results of which can inform precise regeneration. For instance, some studies focus on color palettes, indicating that a street's physical form is intrinsically linked to its functional and cultural identity [60]. Other studies focus on specific typologies, such as historical streets [38], commercial corridors [61], or scenic routes [62], yielding type-specific conclusions. These tailored analyses emphasize the importance of a meticulous consideration of unique built environment characteristics for achieving precise regeneration. Therefore, an important direction for future research is to develop analytical methods that are both scalable and precise, retaining the advantage of large-scale data measurement while incorporating a more nuanced understanding of street characteristics [63].

2.4. Research Gap and Our Study

Despite extensive research on street space quality, two key gaps remain.

First, a systematic framework for evaluating street quality that accounts for diverse street functions is still lacking. As discussed, most studies apply a uniform framework to assess all streets or focus on a specific street type.

Second, there is a limited understanding of the heterogeneous and non-linear mechanisms through which the built environment influences street quality. While recent research has begun to explore non-linear effects using machine learning, these studies often target single performance indicators such as vibrancy or travel behavior. Furthermore, a crucial gap remains in understanding how the non-linear influence of the built environment on comprehensive street quality varies across different street functions.

To address these gaps, this study employs machine learning to investigate these complex mechanisms, developing a function-based computational framework that explicitly answers two questions: (1) How does the influence of the built environment on multi-dimensional street quality vary across different street functions? (2) What are the non-linear characteristics of these heterogeneous effects?

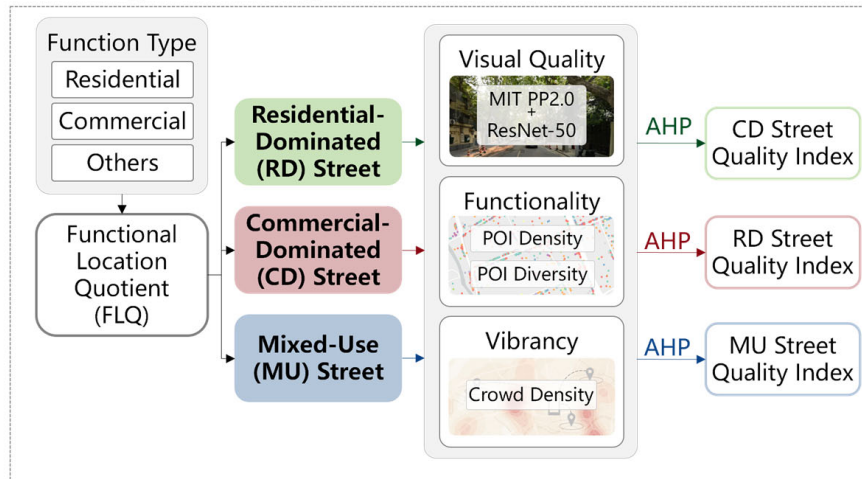
3. Materials and Methods

3.1. Research Framework

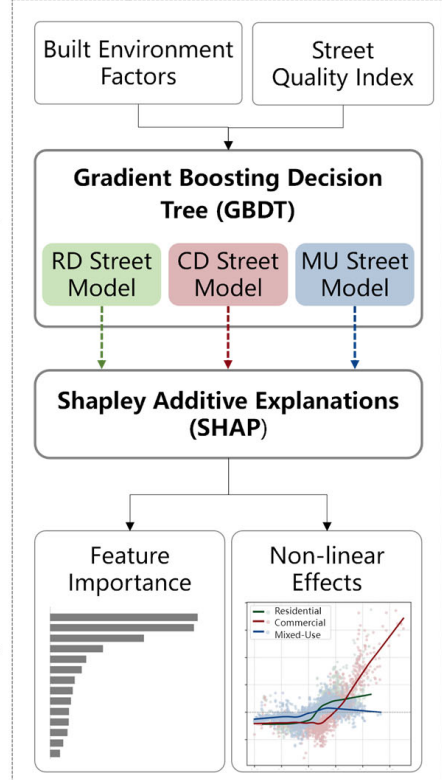
We proposed a machine learning framework to evaluate street quality according to the dominant function and examine the non-linear effects of built environment factors (Figure 1). First, streets were classified by their dominant function (Residential-Dominated, Commercial-Dominated, and Mixed-Use) via Location Quotient (LQ). A specialized quality index was then calculated for each type by weighting its visual quality, vibrancy, and functionality using separate weights from the Analytic Hierarchy Process (AHP). Second, we measured built environment factors across three dimensions using multimodal urban big data. Finally, we modeled the relationship between the built environment factors and

street quality. The Gradient Boosting Decision Tree (GBDT) model was developed for each street type, and Shapley Additive Explanations (SHAP) were used to interpret feature importance and non-linear effects.

Measuring Street Quality



Modeling Non-linear Effects



Measuring Built Environment Factors

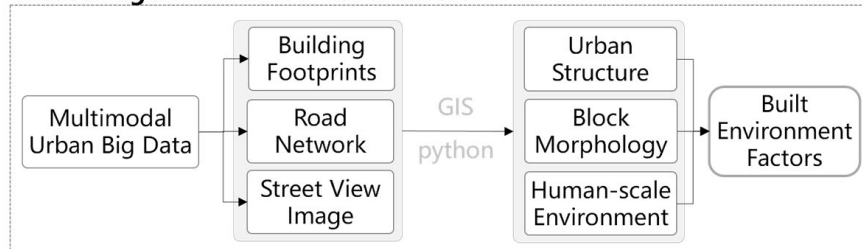


Figure 1. Research Framework.

3.2. Study Area

The study focused on the 431 km² area within Shanghai's Middle Ring Road (See Figure 2). This area is characterized by its diverse built environment and relevant policy context, making it suitable for this research. On the one hand, the built environment of central Shanghai is exceptionally heterogeneous, shaped by the diverse urban planning from different historical eras. This diversity provides various empirical examples, which are ideal for an analysis of heterogeneity. On the other hand, Shanghai is at the forefront of exploring urban regeneration as a key strategy for sustainable revitalization, a move that aligns with China's broader developmental shift from quantitative expansion to qualitative improvement. Therefore, the findings of this research can offer targeted design guidance for ongoing regeneration projects.

We extracted road centerlines from the OpenStreetMap (OSM) platform. To align with our focus on streets as public spaces rather than purely transport corridors, we excluded centerlines corresponding to expressways, tunnels, and flyovers. Additionally, road segments that were either too short (<50 m) or lacked necessary data were excluded. Finally, the analysis comprised 12,335 streets within the study area.

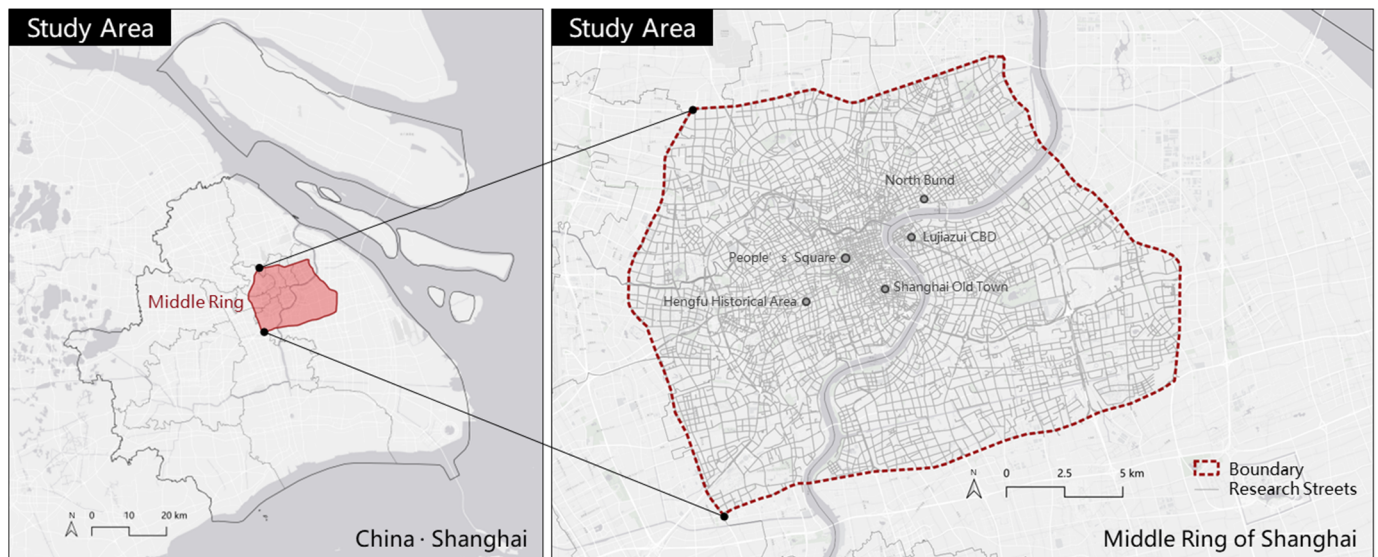


Figure 2. Study area and analysis units.

3.3. Measuring Street Quality

3.3.1. Street Classification Based on Dominant Functions

This study classified streets from a functional perspective to enable specialized quality measurement that incorporates function-specific weighting systems. Our approach, informed by the classification in *Shanghai Street Design Guidelines*, classified the streets into three categories: Residential-Dominated (RD), Commercial-Dominated (CD), and Mixed-Use (MU). Residential-Dominated (RD) streets primarily serve the daily lives of local inhabitants, with their core function being to provide a safe and comfortable living environment. Commercial-Dominated (CD) streets serve as the city's primary business and retail corridors, facilitating economic activity for commuters and shoppers. Mixed-Use (MU) streets serve as vibrant community hubs, featuring a fine-grained integration of commercial and residential activities that attract a diverse range of users. The dominant function of each street was determined by the dominant type of Points of Interest (POIs) within a 50 m buffer of its centerline. Simple proportional analysis of POIs proved inadequate, as commercial POIs significantly outnumber other types, obscuring the dominant function. To overcome this challenge, we employed the Location Quotient (LQ) method, an index widely used in urban economics to measure the relative concentration and specialization of an industry within a region. To apply this method, we specifically identified POIs associated with residential and commercial activities. Separate LQ scores were then calculated for each of these two functions for every street. A street was defined as Residential-Dominated or Commercial-Dominated if its residential or commercial LQ value exceeded a threshold of 1.1. Streets that met neither criterion were categorized as Mixed-Use streets.

The resulting classification shown in Figure 3 demonstrated a high degree of accuracy, showing strong alignment with Shanghai's well-known functional zones. For instance, most streets within major CBDs, such as Lujiazui and People's Square, were correctly identified as Commercial-Dominated streets. Conversely, streets in residential neighborhoods like the Hengfu Historical Area and the Shanghai Old Town, as well as those in newly developed communities such as the North Bund, were identified as Residential-Dominated streets.

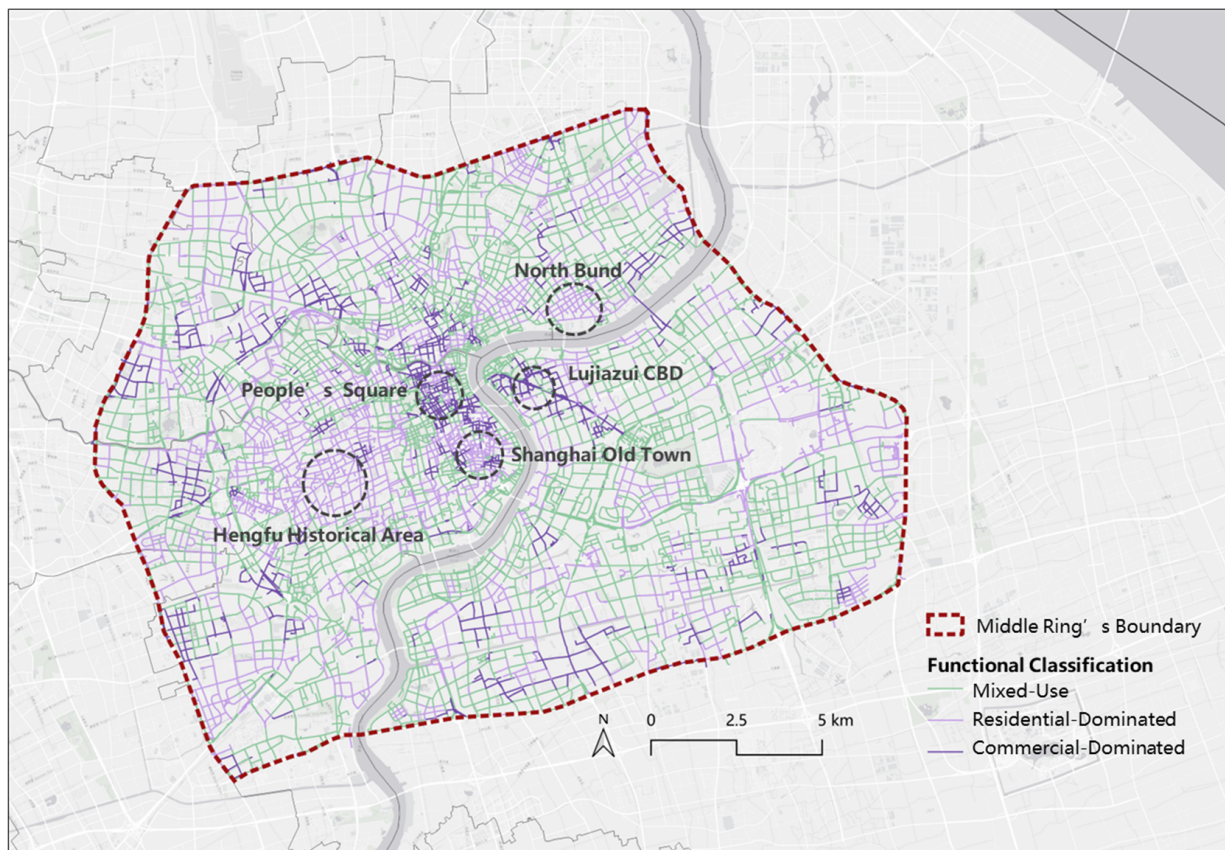


Figure 3. Classification of Streets within the Middle Ring of Shanghai.

3.3.2. Measuring the Dimensions of Street Quality

This section details the measurement of street quality across three dimensions: visual, functional, and vibrancy.

Visual quality was measured by applying a deep learning model to score Street View Images (SVIs). First, we collected SVIs from the Baidu Map platform via API (<https://lbsyun.baidu.com>, accessed on 25 July 2025). Sampling points were generated along street centerlines at 100 m intervals, from which images in four cardinal directions (left, right, front, back) were collected. For the scoring model, we developed a Siamese Neural Network with a ResNet-50 backbone [64], and utilized the dataset for the “beautiful” label from the MIT Place Pulse 2.0 project for training. As this dataset is based on pairwise comparisons, the Siamese architecture was ideally suited to learn the scoring preference. The network uses two weight-sharing ResNet-50 backbones to output a comparative probability of relative aesthetic quality for pairwise input images (Figure 4). To generate an absolute score for a single SVI from this comparative model, we introduced a black image as a uniform reference baseline. Each SVI was scored against a blank image in two reversed forward passes to generate two comparative probabilities. The final visual quality score was then defined as the difference between these two probabilities. The model was trained on this binary classification task using the Adam optimizer and a binary cross-entropy loss function, achieving a 68% accuracy on the validation set. Subsequently, the trained model was used to score our collected SVIs, generating the visual quality scores for each SVI. The mean score of all sampled images for each street was calculated as its final visual quality score.

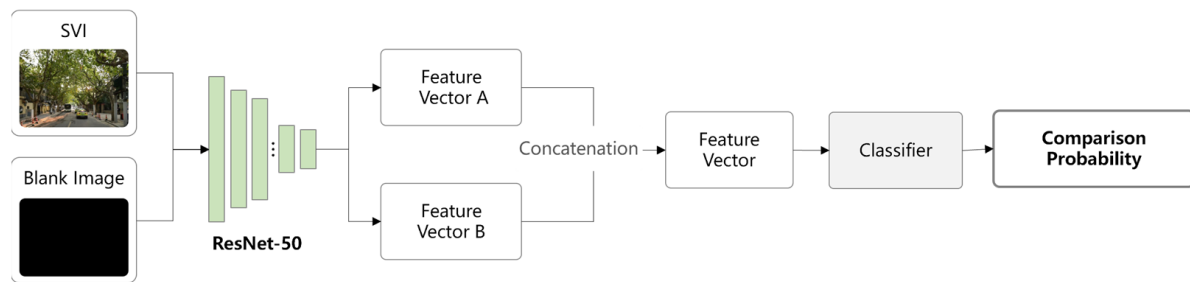


Figure 4. Architecture of the Visual Quality Scoring Model.

The functionality was defined as a composite of functional density and functional diversity, with each component given equal weight. Functional density was calculated for each street by creating a 50 m buffer and then computing the ratio of the total number of POIs to the buffer area, using data obtained from the Baidu Map platform via API (<https://lbsyun.baidu.com>, accessed on 11 April 2021). Functional diversity was measured using the Shannon Index applied to the primary categories within the buffer. The calculation is as follows:

$$\text{Functional Diversity} = - \sum_{i=1}^n p_i \ln p_i \quad (1)$$

In this formula, n represents the total number of primary POI categories, and p_i represents the proportion of the total number of POIs belonging to the category i within the buffer zone of the street. The index value increases as both the richness and evenness of functions increase, thus reflecting a higher degree of functional diversity.

Vibrancy was measured by crowd density derived from Location Based Service (LBS) data. Through a collaboration with Baidu Huiyan (Beijing, China), we obtained anonymized user count data for Shanghai at a 100 m grid resolution for a typical weekday (13 May 2021). The vibrancy score for each street was then calculated as the average user count from all grids that intersect a 50 m buffer of its centerline.

3.3.3. AHP-Based Weighting for Comprehensive Quality

To establish functionally dependent weights for the visual quality, vibrancy, and functionality dimensions, we conducted a separate Analytic Hierarchy Process (AHP) for each of the three street types. The expert panel consisted of fifteen participants holding bachelor's or master's professional degrees in architecture and urban planning. To ensure deep contextual knowledge, all selected experts had lived in Shanghai for over two years. The experts were tasked with completing a questionnaire designed for pairwise comparisons of the relative importance of quality dimensions for each street type (the full questionnaire is provided in Appendix A). This procedure generated three sets of weights (see Table 1), all of which passed the consistency tests. The quality indices of Residential-Dominated, Commercial-Dominated, and Mixed-Use streets were then calculated using corresponding weights.

Table 1. Quality Dimension Weights by Street Type.

Street Type	Visual Quality	Functionality	Vibrancy
RD	0.1663	0.5262	0.3075
CD	0.1398	0.3562	0.5041
MU	0.1861	0.3835	0.4303

3.4. Measuring Built Environment Factors

To explain the effects of the built environment on street quality, we first quantified a comprehensive set of built environment factors across three hierarchical scales: urban structure, block morphology, and human-scale environment (Table 2).

Table 2. Built Environment Factors and the Calculation method.

Dimension	Factor	Description	Calculation Method/ Formulation	Symbolic Meaning
Urban Structure	Accessibility	The potential for through-movement determined by the spatial topology of the street network	sDNA plug-in for ArcMap 10.8, used to calculate Betweenness Centrality with an 800 m network radius (Cardiff University, https://sdna.cardiff.ac.uk , accessed on 20 June 2025). $Betweenness(v) = \sum \frac{\sigma_{st}(v)}{\sigma_{st}}$	σ_{st} is the total number of shortest paths between nodes s and t , $\sigma_{st}(v)$ is the number of such paths that passes through node v .
	Road density	Concentration of road network	$RD = \frac{\sum L_{street}}{A_b^*}$	L_{street} is the length of street in the buffer zone
	Intersection density	Concentration of intersections	$ID = \frac{N_{intersection}}{A_b^*}$	$N_{intersection}$ is the number of intersections in the buffer zone
Block Morphology	Block area	Average block area	$BA = \frac{\sum A_{block}}{A_b^*}$	A_{block} is the area of block in the buffer zone
	Building density	Mean building density of urban blocks	$BD = \frac{\sum A_{footprint}}{\sum A_{block}}$	$A_{footprint}$ is the area of buildings in the buffer zone, A_{block} is the area of block in the buffer zone
	Floor area ratio (FAR)	Mean FAR of urban blocks	$FAR = \frac{\sum A_{GFA}}{\sum A_{block}}$	A_{GFA} is the Gross Floor Area (total floor area of all stories) of a single building, A_{block} is the area of block in the buffer zone
Human-scale Environment	Alignment ratio	Ratio of the parallel building facade length to the street length	$AR = \frac{\sum L_{street\ wall}}{\sum L_{street}}$	$L_{street\ wall}$ is the length of building facade parallel to the street, L_{street} is the length of the street
	Green View Index (GVI)	Proportion of vegetation in street view	$P_i = \frac{n_i}{N}$	i represents a specific visual element (e.g., vegetation, sky, sidewalk)., n_i is the number of pixel points of element i , N is the number of pixel points in the entire street view image
	Sky View Factor (SVF)	Proportion of sky in street view		
	Sidewalk Ratio	Proportion of sidewalk in street view		
	Road ratio	Proportion of road surface in street view		
	Building façade ratio	Proportion of building facades in street view		

* A_b represents the area of the buffer zone (in km²).

The urban structure dimension captures the position attributes within a broader urban spatial network. This dimension comprises road density and intersection density, which were calculated within a 500 m buffer around each street, as well as network accessibility. Accessibility was measured using Betweenness Centrality calculated in sDNA

software (Version 4.1.1), which represents the potential of through-movement on a given street [65]. For this network analysis, we set a search radius of 800 m, a threshold widely recognized in previous research as a proxy for pedestrian-scale accessibility and walkable neighborhoods [66].

The block morphology dimension reflects the development intensity of the street's immediate surroundings, including block area, building density, and floor area ratio. Research has shown the importance of block morphology to urban vibrancy [55].

The human-scale environment dimension encompasses characteristics of the street as perceived by a pedestrian, including its spatial scale and the composition of its visual elements. We measured the street's sense of enclosure using the building alignment ratio, which has been shown in behavioral psychology to be strongly related to human spatial perception [67]. To quantify the composition of visible spatial elements (e.g., vegetation, sidewalks, road surfaces), we utilized the Street View Images (SVIs) described in Section 3.3.2. We employed DeepLabv3 to perform semantic segmentation on these images. It is a deep convolutional neural network (DCNN) capable of assigning a class label (e.g., sky, road, building) to every pixel in an image. The final indicator for each element was derived by calculating its average proportion across all SVIs sampled along a given street.

3.5. Modeling and Interpreting the Non-Linear Effects

3.5.1. GBDT Modeling

To investigate the heterogeneous and non-linear relationships between the built environment and street quality, we developed three separate Gradient Boosting Decision Tree (GBDT) models, one for each of the three functional street types. This machine learning approach was chosen over traditional linear models due to its superior ability to capture the complex, non-linear, and threshold effects inherent in the built environment's influence on urban phenomena [19]. The GBDT model operates on the principle of boosting, sequentially adding decision trees to form a final additive model represented by the following formulation:

$$F_m(x) = F_0(x) + \sum_{m=1}^M v \cdot h_m(x) \quad (2)$$

where $F_m(x)$ is the final model after M boosting iterations; $F_0(x)$ is the initial base model, typically the mean of the target variable; M is the total number of sequentially added decision trees; v represents the learning rate, which controls the contribution of each tree; and $h_m(x)$ is the decision tree fit to the residual errors at iteration m .

Before model training, we conducted a multicollinearity analysis to ensure the reliability of the feature importance interpretation. Specifically, we calculated the Pearson correlation coefficients for all built environment factors and removed variables that exceeded a correlation of 0.7 [68,69]. The detailed correlation matrices for the variables in each of the three models are presented in Appendix B Figure A1. In each model, the quantified built environment factors served as the independent variables, and the Quality Index was the dependent variable. To optimize the predictive performance, we employed the Optuna library in Python (Version 3.11.5) to conduct an automated hyperparameter search for each model. The final set of hyperparameters and the corresponding model performance are summarized in Table 3.

Table 3. Hyperparameters and Model Performance.

Category	Parameter/ Metric	Model Type		
		RD Model	CD Model	MU Model
Hyperparameter	learning rate	0.033	0.031	0.042
	n estimators	393	371	307
	max depth	7	9	9
	Subsample	0.6364	0.5989	0.8531
	min samples leaf	3	4	6
	min samples split	5	4	4
Performance	R-squared	0.7229	0.7789	0.6649

3.5.2. SHAP Interpretation

To interpret the results of the GBDT models, we employed Shapley Additive Explanations (SHAP), a game theory-based method that accurately quantifies each feature's contribution to the prediction. The SHAP value (φ_j) for a feature is the average contribution to the prediction across all possible feature combinations, as defined in the classic Shapley value formulation:

$$\varphi_j(x) = \sum_{S \subseteq P \setminus \{j\}} \frac{|S|!(|P| - |S| - 1)!}{|P|!} [f(S \cup \{j\}) - f(S)] \quad (3)$$

where $\varphi_j(x)$ is the SHAP value of feature j ; S is a subset of all features in the model; and $[f(S \cup \{j\}) - f(S)]$ represents the marginal contribution of adding feature j .

The SHAP analysis was used to generate two primary outputs: relative feature importance in each model and SHAP dependence plots to interpret the non-linear relationships of each model. To facilitate a direct comparison of how the influence of built environment factors varies across different functions, we overlaid the SHAP dependence plots for each variable from all three models onto a single chart. This comparative visualization allows for an intuitive analysis of heterogeneous and non-linear mechanisms and threshold effects, thereby providing data-driven insights for urban design theory and practice.

4. Results

4.1. Measurement Results of Street Quality

4.1.1. A Core-Periphery Pattern of Comprehensive Street Quality

The results of the comprehensive street quality assessment for central Shanghai are presented in Figure 5. Overall, the spatial distribution of street quality exhibits a distinct core-periphery pattern, with higher scores concentrated in the city center and decreasing towards the outskirts. A clear disparity is also evident between the two sides of the Huangpu River, with the quality in Puxi (west of the Huangpu River) being generally higher than in Pudong (east of the Huangpu River). The high-quality streets are predominantly located in Puxi, the historic core of Shanghai, which is characterized by a long history of urban development and a dense, fine-grained urban fabric. In contrast, Pudong is a modern district developed primarily over the last four decades. Its high-quality streets are largely confined to the corridor along Century Avenue. This finding suggests that despite its modern image, a significant portion of streets in Pudong still faces the challenge of low quality often associated with rapid, large-scale urbanization.

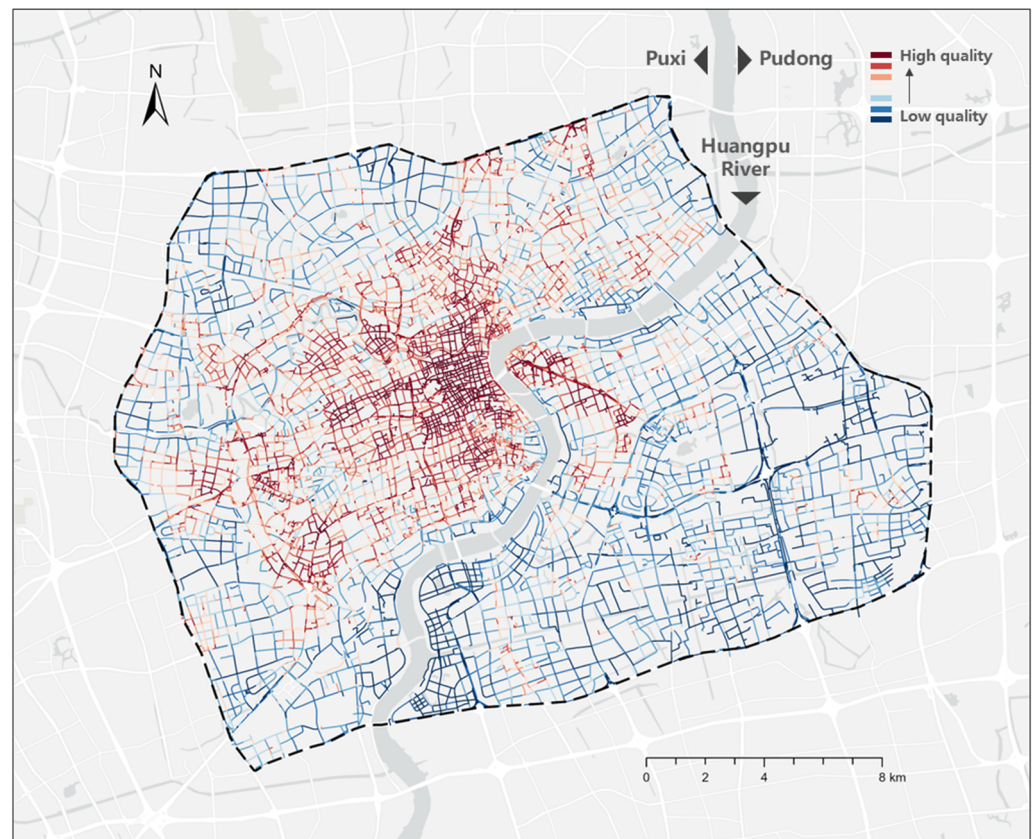


Figure 5. Measurement Results of Comprehensive Quality.

4.1.2. Distinct Spatial Patterns Across Quality Dimensions

As shown in Figure 6, the analysis of visual quality reveals significant spatial heterogeneity.

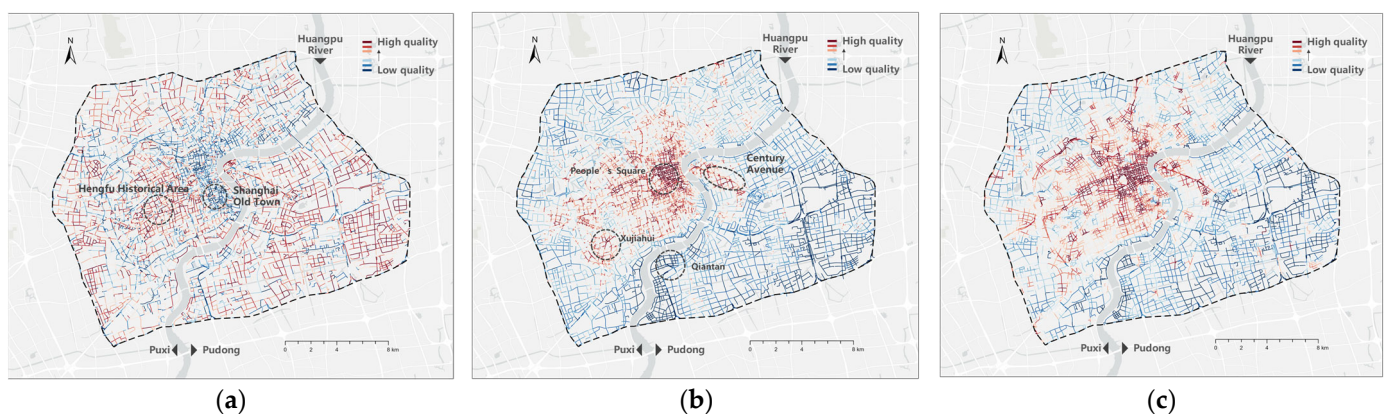


Figure 6. Measurement Results of Individual Quality Dimension: (a) visual quality, (b) functional quality, (c) vibrancy quality.

High-quality visual streets are predominantly found in newly constructed areas of Pudong and near the Hengfu historical area. Conversely, while the Shanghai Old Town possesses high cultural and historical value, it exhibits low measured visual quality. The low scores in the “beautiful” assessment for this core area can be attributed to aging infrastructure and deteriorating road surfaces. This finding offers a clear explanation for the concentration of Shanghai’s urban renewal initiatives in these specific areas. The

renewal initiatives aim to enhance the visual environment of this geographically central yet aesthetically deficient area, addressing a key aspect of its overall quality.

The measurement of functional quality clearly illustrates Shanghai's planned "one primary, multiple sub-centers" spatial structure. Streets with high functional sufficiency and diversity are clustered in the primary metropolitan center around People's Square, with other functional hubs emerging in the Century Avenue CBD and the Xujiahui sub-center. In contrast, the Qiantan area exhibits significantly lower functional quality. Given the concentration of large-scale residential communities in this area, this finding highlights a potential insufficiency in functional amenities.

The spatial patterns of vibrancy quality are largely similar to those of functional quality, with high-vibrancy areas concentrated in the center of Shanghai. This strong correlation indicates that streets with abundant and diverse functions attract more residents and visitors, ultimately shaping a more vibrant streetscape. However, while the macro-patterns overlap, the vibrancy scores reveal a more complex pattern at the micro-level. Notably, several localized centers of high vibrancy emerge in the outer areas of the study region, indicating that the sources of street vibrancy are diverse and not limited to primary commercial and functional hubs.

4.1.3. Distinct Spatial Patterns Across Street Function Types

The spatial distribution of quality varies significantly across the three street types, revealing distinct, function-dependent patterns (Figure 7). High-quality Residential-Dominated streets are primarily clustered in the historic areas of Puxi, such as the Hengfu historical area and the Bund, which benefit from historical accumulation and a fine-grained community environment. In contrast, lower-quality Residential-Dominated streets are often found in newly developed, large-scale residential compounds in Pudong, suggesting a potential neglect of the public street environment in modern, developer-led projects. Commercial-Dominated streets, meanwhile, exhibit a clear core-periphery pattern, following a logic of capital-driven agglomeration. Quality peaks in the central business districts of the Bund and Lujiazui, while peripheral office and industrial parks, such as Zhangjiang Hi-Tech Park and Caohejing, tend to have lower quality. The emergence of high-quality Mixed-Use streets is more flexible and complex. They often appear in areas characterized by the synergistic co-existence of multiple functions, such as in the Hongkou and Yangpu districts of northern Puxi.

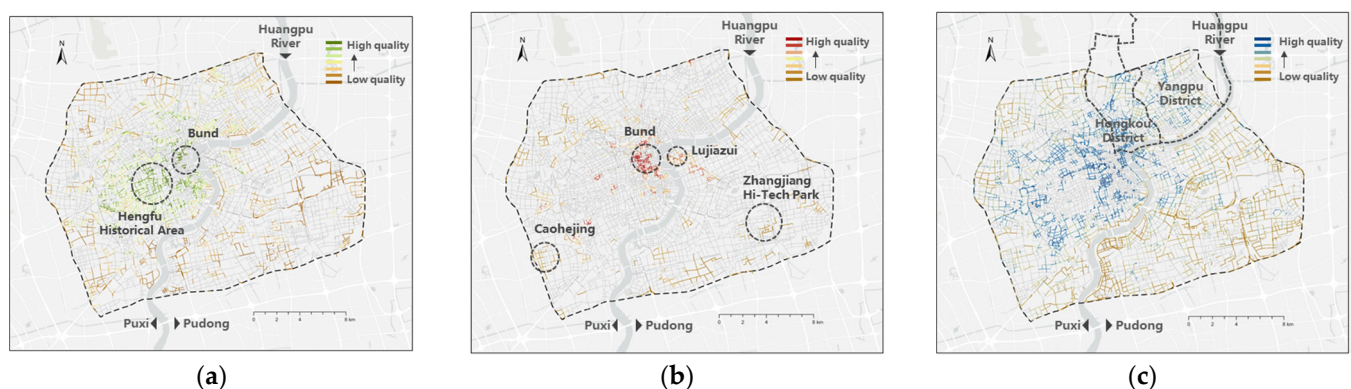


Figure 7. Measurement Results of Individual Quality Dimensions: (a) residential-dominated (RD) streets, (b) commercial-dominated (CD) streets, (c) mixed-use (MU) streets.

These distinct patterns demonstrate that there is no universal template for a high-quality street. The mechanisms of quality formation are intrinsically linked to a street's function, necessitating differentiated assessment and improvement strategies.

4.2. Heterogeneous Importance of Built Environment Factors

As shown in the feature importance charts derived from SHAP values (Figure 8), a consistent macro-level pattern emerges across the three models. Block morphology is consistently the most influential dimension in predicting street quality for all three street types (RD: 49.4%, CD: 54.6%, MU: 47.4%). These morphological factors can be considered foundational determinants, as they address a street's primary requirements, such as its accessibility and functional capacity. The relatively weak importance of the human-scale dimension in this study is consistent with prior research in high-density Chinese cities [19]. This primary finding suggests that in a functionally complex megacity like Shanghai, perception of street quality is still predominantly shaped by these foundational factors over more fine-grained aesthetic elements.

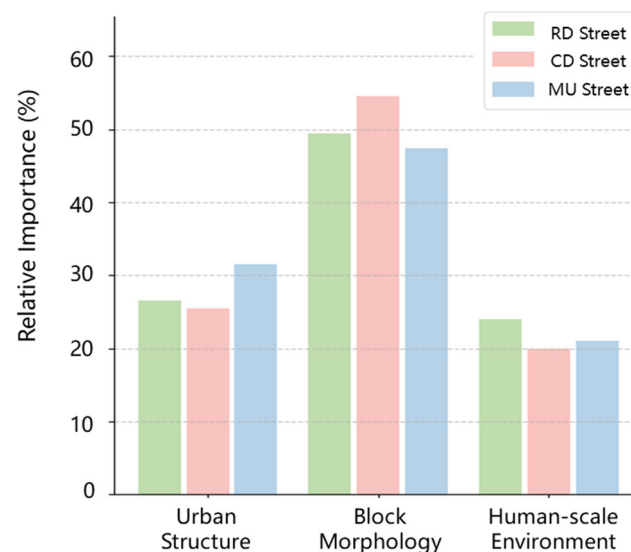


Figure 8. Relative Importance of Built Environment Dimensions.

Beyond this general trend, significant variations in dimensional importance reveal the heterogeneous effects of the built environment. Urban structure shows its greatest influence on Mixed-Use streets, suggesting that location and connectivity are more critical for this street type. Finally, the human-scale environment, while the least important overall, shows its highest relative importance for Residential-Dominated streets, reflecting the heightened significance of fine-grained design in neighborhood environments.

A more granular analysis at the individual indicator level reveals both universal design principles and highly function-specific patterns.

First, the results provide quantitative validation for classic urban design theories. For instance, block area consistently exhibits a negative relationship with quality across all three street types, while intersection density shows a positive one. This finding empirically supports the “small blocks, dense network” principle of urban design.

Second, the analysis uncovers profound heterogeneity in the key drivers of quality for each street function (Figure 9; see Appendix C for the corresponding violin plots). For both Residential-Dominated and Commercial-Dominated streets, the block area is the most important factor. However, for Mixed-Use streets, FAR becomes the primary driver (27.9%). This suggests that the vertical intensity of development becomes more critical in shaping a high-quality environment when the street is highly mixed-use. Similarly, while a lower Sky View Factor, representing a greater sense of enclosure, is universally associated with higher quality, its importance is significantly more pronounced for Residential-Dominated streets (9.1%), where it surpasses even the Green View Index. This indicates that the sense

of place and security afforded by spatial enclosure is a crucial component of high-quality residential environments.

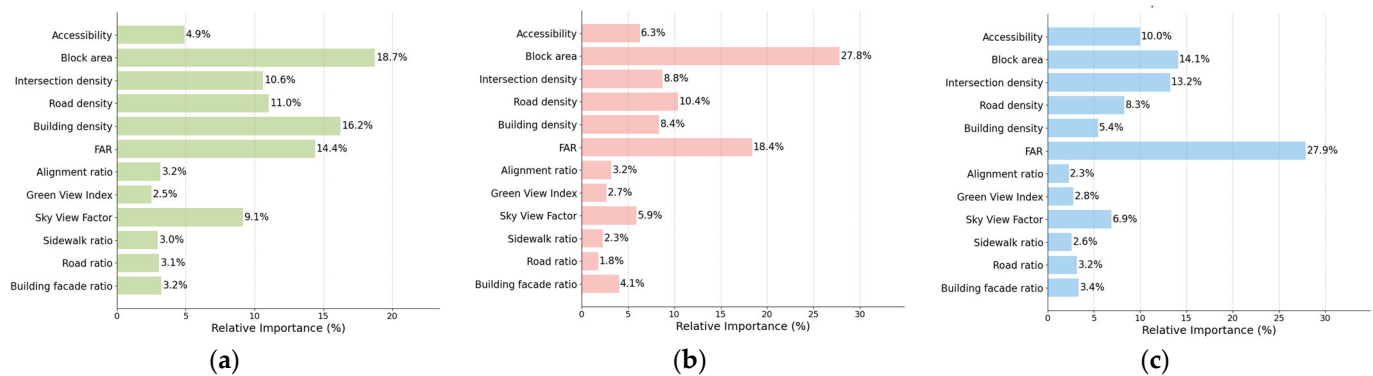


Figure 9. Relative Importance of Built Environment Factors: (a) residential-dominated (RD) streets, (b) commercial-dominated (CD) streets, (c) mixed-use (MU) streets.

4.3. Non-Linear Effect of Built Environment Factors

In this section, we analyze the SHAP dependence plots overlaid with trend curves (see Figure 10), which provide a granular understanding of the non-linear relationships and impact thresholds of built environment factors across the different street types. The specific activation points, saturation points, and overall trends for each built environment factor across the three types of streets are summarized in Table 4. We define the activation point as the value at which the trend curve intersects the $y = 0$ axis, representing the threshold where the factor's influence shifts between negative and positive. For factors with a positive trend, it is advisable in regeneration strategies to maintain their values above this activation point to ensure a positive impact, and vice versa. Furthermore, saturation points were identified where the slope of the trend curve flattens, indicating diminishing marginal returns. The presence of a saturation point suggests that when design resources are limited, maintaining a factor's value near this point is a cost-effective strategy to maximize its positive influence and minimize its negative influence. For factors with U-shaped trends, a more detailed interpretation is required to balance these effects. This analysis provides direct, quantitative guidance for precise regeneration in Shanghai.

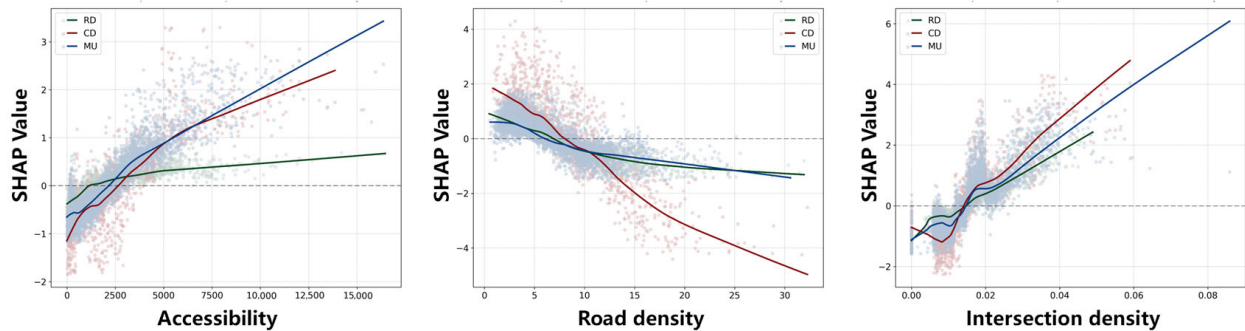
First, the analysis reveals that the activation points for positive effects are highly function-dependent and heterogeneous, particularly for factors related to development intensity. While Floor Area Ratio (FAR) generally has a positive impact, its effective threshold varies. For Commercial-Dominated streets, a significant positive effect on quality only emerges after the FAR exceeds 2.5. Similarly, the activation threshold for building density differs by function. For Residential-Dominated and Mixed-Use streets, quality begins to improve once density surpasses approximately 0.24, whereas Commercial-Dominated streets require a higher threshold of around 0.30. This may reflect the need for greater building continuity to foster a commercial atmosphere.

Furthermore, the non-linear analysis identifies clear saturation points and instances of diminishing marginal returns for several built environment factors. For example, while the impact of accessibility on Residential-Dominated streets turns positive at a very low level, further increases yield minimal additional benefits compared to its sustained positive effect on Commercial-Dominated and Mixed-Use streets. Similarly, for Commercial-Dominated streets, the marginal benefit of increasing FAR plateaus beyond a value of 4.0, defining an optimal range for development intensity in commercial districts.

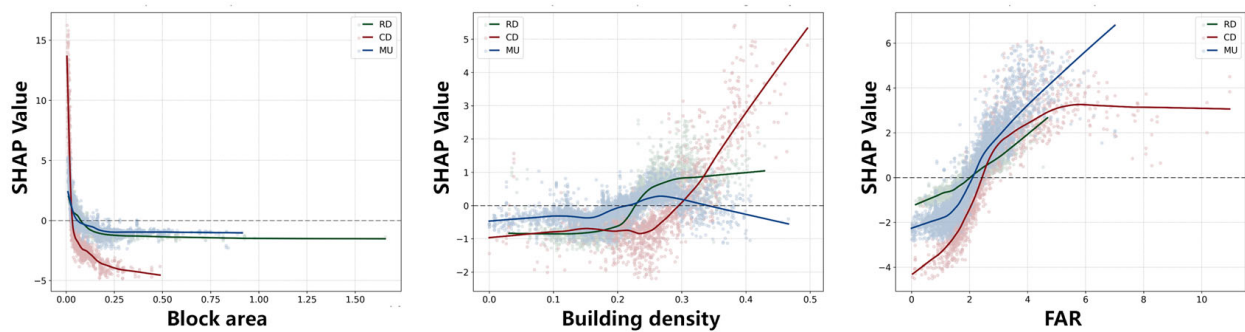
Finally, the analysis reveals that the influence mechanism of a built environment factor can be fundamentally different, or even opposite, across different functions. The most striking example is the road ratio. Both Residential-Dominated and Mixed-Use streets

show a low tolerance for wide roads, with a negative impact on quality emerging once the ratio exceeds 0.30, reflecting a preference for pedestrian-oriented spaces. In contrast, Commercial-Dominated streets exhibit a more complex, inverted U-shaped relationship. They are negatively affected by very narrow roads (ratio < 0.28), suggesting that a moderate width is necessary to create a bustling commercial atmosphere, though the positive effect diminishes again if the road becomes excessively wide.

■ Urban Structure



■ Block Morphology



■ Human-scale Environment

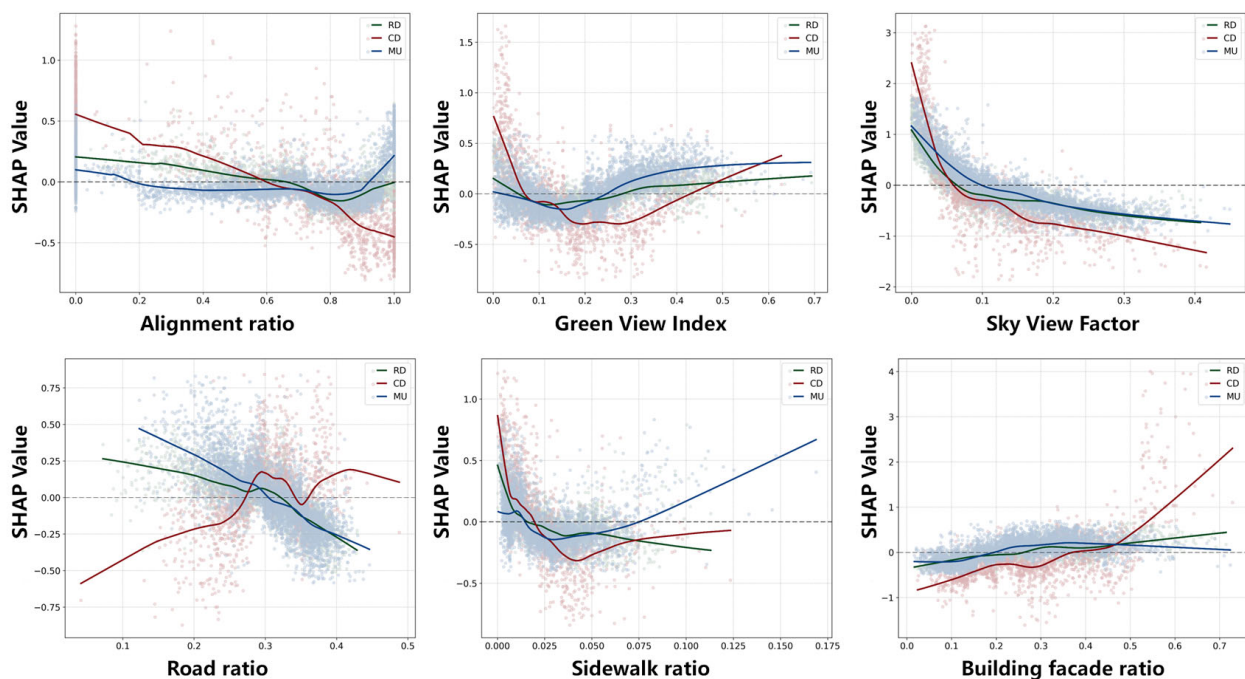


Figure 10. SHAP value plots of Built Environment Factors.

Table 4. Quantitative Analysis of the Non-linear Effects of Built Environment Factors.

	Factor	Residential-Dominant (RD)			Commercial-Dominant (CD)			Mixed-Use (MU)		
		Activation Point	Saturation Point	Trend	Activation Point	Saturation Point	Trend	Activation Point	Saturation Point	Trend
Urban structure	Accessibility	1147.03	1506.63	positive	2651.51	-	positive	2162.86	-	positive
	Road density	6.87	10.63	negative	8.01	-	negative	6.02	8.33	negative
	Intersection density	0.015	-	positive	0.014	0.01	positive	0.014	-	positive
Block morphology	Block area	0.08	0.13	negative	0.03	-	negative	0.06	0.19	negative
	Building density	0.23	0.25	positive	0.30	0.26	positive	0.24	0.28	negative
	Floor area ratio (FAR)	2.02	-	positive	2.50	4.0	positive	2.11	-	positive
Human-scale environment	Alignment ratio	0.66	0.86	U-shaped	0.60	-	negative	0.18	0.87	U-shaped
	Green View Index (GVI)	0.28	0.24	U-shaped	0.42	0.23	U-shaped	0.24	0.34	U-shaped
	Sky View Factor (SVF)	0.06	0.09	negative	0.05	0.16	negative	0.09	0.20	negative
	Sidewalk Ratio	0.015	0.031	U-shaped	0.020	0.033	U-shaped	0.075	0.029	U-shaped
	Road ratio	0.30	-	negative	0.28	0.31	U-shaped	0.30	-	negative
	Building façade ratio	0.26	-	positive	0.37	0.42	positive	0.20	-	positive

5. Discussion

5.1. Measuring Comprehensive Street Quality Toward Better Public Space

A primary contribution of this study is the development of a comprehensive framework for street quality assessment, which addresses the limitations of prevalent single-dimensional approaches. Previous studies often conducted single-dimensional assessments, failing to fully align with the multi-objective optimization principles essential for effective urban development and regeneration [14,70,71]. This research integrates three crucial dimensions identified in previous research. The measurement results reveal distinct spatial differentiations across these three qualities. This mismatch among quality dimensions may stem from the varying priorities and limitations of Shanghai's different historical development periods, which underscores the importance of targeted interventions. Driven by the rapid advancements in big data and analytical technologies, urban studies have an unprecedented capacity to describe urban forms and spaces from multifaceted perspectives. Compared to single-dimensional quantification, comprehensive quality provides a more holistic understanding of a street's aesthetic appeal, its functional adequacy, and the utilization of its space by residents. This comprehensive understanding aligns more closely with the complex and integrated human perception of urban environments. In the context of global urbanization reaching a relative state of maturity, urban research must increasingly focus on the comprehensive optimization of public space. Our study responds to this evolving demand in sustainable urban development by quantifying the comprehensive street quality.

5.2. Function-Sensitive Analysis Informing Precise Street Regeneration

Furthermore, this research makes a crucial contribution by constructing and validating a function-sensitive analytical framework. Existing methods often apply the same metrics to all streets, often producing homogenized evaluations and erasing the crucial context of the built environment. This is particularly problematic for urban regeneration, which requires a deep understanding of the unique characteristics of existing spaces. Our study addresses this by treating a street's primary function as a key contextual lens, thereby advocating for a more human-centric analysis in urban science. By systematically incorporating functional

context into both the quality measurement and the effect analysis, our framework reveals the heterogeneous effects of the built environment. Revealing these function-dependent mechanisms, this research provides urban designers and planners with a data-driven basis to move beyond uniform standards and formulate the precise, context-sensitive optimization strategies that maturing cities require.

5.3. Limitations and Future Research

This study has several limitations that should be acknowledged, which also suggest directions for future research.

First, the definition of context in this study is based on three primary functional types. Future research could develop a more nuanced contextualization by incorporating multi-source data, such as the demographic characteristics and cultural context, to achieve a more precise understanding to guide urban regeneration. Second, we acknowledge that a broader conceptualization of street quality should include important aspects such as environmental comfort, safety, and residents' health and perception. While these are beyond the scope of this study, integrating these dimensions represents a valuable and necessary next step for future research in this area. Third, the measurement of vibrancy in this study relies on Baidu Huiyan LBS data, which limits the direct replicability in other regions. Future research could explore the use of more widely available datasets to represent street vibrancy. Finally, the study was conducted in Shanghai, and its findings may not be directly generalizable to other cities. However, the paradigm and research framework can be adapted to different urban contexts through a process of local adaptation. First, it would necessitate refining the dimensions of quality and their weights through collaboration with local planners and designers to reflect the city's unique regeneration goals and cultural values. Second, the data sources would need to be adapted to the local conditions. For instance, this adaptation would involve both expanding the input features to include unique local characteristics, such as coastlines or mountains, and utilizing alternative local datasets, such as social media check-ins or public transportation data.

6. Conclusions

By integrating classic urban design theories with multi-source urban data and machine learning methods, this research explored the non-linear and context-dependent effects of the built environment on street quality. This study has made three primary findings. First, our empirical results demonstrate that in Shanghai, meso-scale factors related to block morphology are most critical for street quality. Second, the research reveals a functional heterogeneity in the importance of built environment factors, with residential streets prioritizing a sense of enclosure while commercial streets prioritize vertical development intensity. Third, the research reveals that the non-linear effects of built environment factors are functionally heterogeneous, characterized by distinct activation thresholds and saturation points that vary across different street types.

The findings advance the theoretical understanding of the built environment's heterogeneous and non-linear mechanisms, which can support more fine-grained, effective strategies for street regeneration. For urban planners and designers, this study provides a data-driven method to move beyond intuition and uniform design strategies. The identified activation and saturation points can directly inform more precise street design for different types of streets. For policymakers, it underscores the need for differentiated design guidelines responsive to specific street functions, fostering a more nuanced urban governance.

Furthermore, this research offers a transferable paradigm for future urban studies. While transferring this paradigm requires local adaptation of the measurement framework

and dataset, the process intrinsically offers valuable insights into a city's unique context. The paradigm advocates a more nuanced analysis differentiated by function, which is critical in the current era of urban regeneration. Ultimately, this shift from uniform standards to context-sensitive and precise solutions fosters a more socially and economically sustainable regeneration, leading to the creation of high-quality public spaces.

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Institutional Review Board Statement: This study is waived for ethical review as 1. The study is a minimal-risk social science research project. 2. It does not involve any personally identifiable or sensitive data, and all data were fully anonymized prior to analysis. 3. Informed consent was duly obtained from all participants after they were fully apprised of the study's purpose, procedures, and their right to withdraw at any time. 4. The research design and plan are deemed scientifically reasonable, fair, and impartial. by Institution Committee.

Informed Consent Statement: Informed consent for participation was obtained from all subjects involved in the study.

Data Availability Statement: The data that support the findings of this study are available from the corresponding author upon reasonable request, with the exception of the LBS data. The LBS data from Baidu Huiyan are not publicly available due to a confidentiality agreement and restrictions imposed by the data provider.

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Abbreviations

The following abbreviations are used in this manuscript:

sDNA	Spatial Design Network Analysis
GBDT	Gradient Boosting Decision Tree
LBS	Location-Based Services
RD	Residential-Dominated
CD	Commercial-Dominated
MU	Mixed-Use

Appendix A

This appendix shows a sample of our Analytic Hierarchy Process (AHP) Expert Questionnaire, mainly consisting of an introduction and instructions, definitions of key concepts, and the pairwise comparison matrices.

Appendix A.1. Introduction and Instructions

Thank you for participating in this important study. In the context of urban regeneration, a comprehensive evaluation of street quality is essential. This research aims to determine the relative importance weights of three key dimensions of street quality (Visual Quality, Functional Quality, and Vibrancy Quality) for different types of streets. Your expert judgment is crucial for establishing these weights.

In the following sections, you will be asked to perform pairwise comparisons for three different street types. For each comparison, please use the 1–9 scale provided below to indicate which of the two dimensions you believe is more important for the overall quality of that specific street type, and by how much.

The following matrices require a pairwise comparison of the relative importance of the row criterion against the column criterion. Please refer to the table below for instructions on how to assign a value based on your judgment.

Judgment of Comparison	Assigned Value
Row is Extremely more important than Column	9
Row is Very strongly more important than Column	7
Row is Strongly more important than Column	5
Row is Moderately more important than Column	3
Row is Equally important as Column	1
Row is Moderately less important than Column	1/3
Row is Strongly less important than Column	1/5
Row is Very strongly less important than Column	1/7
Row is Extremely less important than Column	1/9

Appendix A.2. Definitions of Key Concept

(a) Quality Dimensions

Visual Quality: Refers to the aesthetic appeal, pleasantness, and harmony provided by the street space and its various elements, creating a positive visual experience for people.

Functional Quality: Refers to the diversity and richness of urban functions (e.g., commercial, restaurants, offices, public facilities) in the street’s immediate vicinity.

Vibrancy Quality: Reflected by the level of human activity and liveliness present on the street.

(b) Street Functional Types

Residential-Dominant Streets: These streets are primarily located within or provide access to residential neighborhoods. Their main function is to support daily life, providing a safe and comfortable environment for residents. Dominant users are local inhabitants.

Commercial-Dominant Streets: These streets serve as the city’s primary business and retail corridors. Their core function is to facilitate economic activity and high-volume transportation. Dominant users typically include commuters, shoppers, and office workers.

Mixed-Use Streets: These streets feature a fine-grained integration of commercial (e.g., shops, restaurants) and residential functions. They serve as hubs for a variety of activities. This functional mix attracts a diverse range of users—including local residents, visitors, and customers.

Appendix A.3. Pairwise Comparison Matrices

Matrix 1: Judgments for Residential-Dominant Streets

For the matrix below, please compare the dimension in the row to the dimension in the column.

Residential-Dominant	Visual Quality	Functional Quality	Vibrancy Quality
Visual Quality	1	[Your judgment here]	[Your judgment here]
Functional Quality	-	1	[Your judgment here]
Vibrancy Quality	-	-	1

Matrix 2: Judgments for Commercial-Dominant Streets

For the matrix below, please compare the dimension in the row to the dimension in the column.

Commercial-Dominant	Visual Quality	Functional Quality	Vibrancy Quality
Visual Quality	1	[Your judgment here]	[Your judgment here]
Functional Quality	-	1	[Your judgment here]
Vibrancy Quality	-	-	1

Matrix 3: Judgments for Mixed-Use Streets

For the matrix below, please compare the dimension in the row to the dimension in the column.

Mixed-Use	Visual Quality	Functional Quality	Vibrancy Quality
Visual Quality	1	[Your judgment here]	[Your judgment here]
Functional Quality	-	1	[Your judgment here]
Vibrancy Quality	-	-	1

Appendix B

This appendix presents the results of the bivariate correlation analysis performed to check for multicollinearity before GBDT modeling. As visualized in Figure A1, all correlation coefficients were below 0.5, indicating that there was no significant collinearity issue among the selected variables.

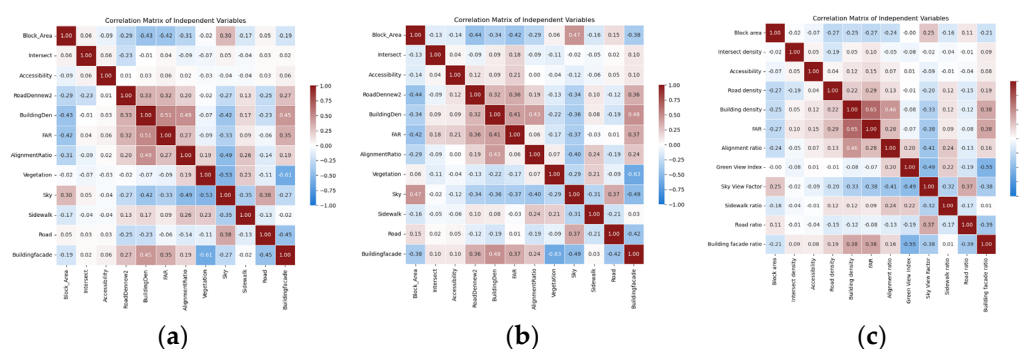


Figure A1. Correlation matrices of independent variables for different street types. The heatmaps display the bivariate correlations (Pearson's r) for variables used in the GBDT models. The analysis is presented separately for three street types: (a) residential-dominated streets, (b) commercial-dominated streets, and (c) mixed-use streets.

Appendix C

This appendix presents the violin plots of the SHAP values for each feature. This plots supplement the mean feature importance results represented in the main text by visualizing the full distribution of impacts for each variable.

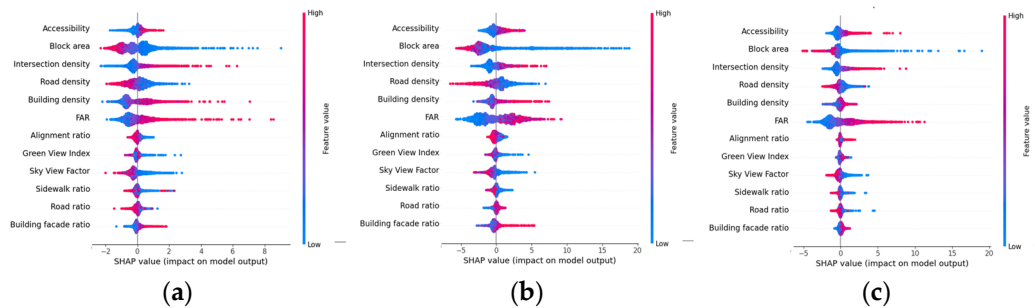


Figure A2. SHAP violin plots of feature importance for different street types: (a) residential-dominated streets, (b) commercial-dominated streets, and (c) mixed-use streets.

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