Research Paper

Research on Urban Renewal Strategies from the Perspective of Safety

A Case Study of Jinan

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Abstract

In the context of urban regeneration, the construction of a safe urban environment has emerged as a critical and widely discussed issue. Previous theoretical research has established that the occurrence of crime is intricately linked to social, economic, and environmental factors. Quantitatively analyzing the mechanisms behind urban crime and connecting them to key indicators across different levels of urban planning is of significant importance for implementing the concept of safe cities. This study aims to reveal the relationship between spatial design and urban safety through a combination of statistical analysis and public participation. Using both planning and urban management strategies, it proposes spatial interventions to optimize problematic areas. Drawing on publicly available crime data from the central urban area of Jinan, the study employs Geographic Information Systems and spatial autocorrelation methods to examine the spatial clustering of crime incidents. The results show a distinct west–east gradient, with a higher concentration of incidents in the western part of the study area. High-crime hotspots are primarily located in the northern section of the central city, exhibiting a pattern of pronounced spatial concentration. By integrating social, economic, and spatial datasets, the study conducts constructs a geographically weighted regression (GWR) model to identify the key factors influencing crime distribution in high-incidence areas. Findings suggest that development intensity and land-use function are the most influential variables associated with crime occurrence. In contrast to conventional urban crime research, this study introduces an interactive urban regeneration module that enables participatory updates of spaces perceived as unsafe by local residents. To support this interaction, a participatory spatial update framework based on Bayesian network technology is developed, significantly enhancing the efficiency of spatial design and urban management. This approach serves as a valuable addition to current smart city design paradigms. Finally, the study proposes strategic recommendations for spatial optimization aimed at enhancing urban safety in Jinan and advancing the broader goal of building sustainable and safe cities.

Keywords

Urban renewal, Crime distribution, Spatial characteristics, Crime prevention, Urban safety analysis

1. Introduction

Creating a safe urban environment has become a central objective of contemporary urban renewal. The New Urban Agenda emphasizes the development of inclusive, safe, and sustainable cities, highlighting the need for public spaces free from crime and violence [1]. In China, recent national policies have further reinforced the importance of integrated public security systems and risk-monitoring mechanisms in promoting high-quality urban development [2][3]. Within this policy context, enhancing urban safety through spatial governance has become a key concern in planning practice[4].

Various researches in different fields of study have proven the existence of temporal and spatial patterns in crime rather than being randomly committed [5]. Existing studies have demonstrated that crime is jointly shaped by social structure and the built environment. Theories such as social disorganization emphasize the role of demographic composition and socio-economic conditions, while Crime Prevention Through Environmental Design (CPTED) highlights the influence of environmental design and spatial configuration on crime occurrence[6][7]. Empirical research further shows that factors such as land-use intensity, commercial density, and urban form are significantly associated with crime distribution, and that micro-scale environmental features—including lighting conditions and visual quality—also affect crime risk[8].

Despite these advances, existing research often lacks fine-grained quantitative analysis, and public participation in crime-related urban renewal remains limited [9]. To explore the spatial distribution of crime, the influencing factors of crime distribution, and the influencing factors for perceivedcrime safety on the one hand, for the other, the research uses crime data from 2021 to 2023 in the main downtown region of Jinan in Shandong Province. According to the research results, the research constructs top-down and bottom-up perspectives towards crime-related urban renovation strategies to limit the scale of crime increase.

2. Extraction of Indicators Influencing Crime in Jinan

2.1. Study Area

As the capital of Shandong Province, Jinan exhibits a diverse urban structure and a population scale that provide a representative context for examining the relationship between crime distribution and spatial characteristics[10].Guided by Shandong's Implementation Opinions on Promoting New Urban Infrastructure and Building Resilient Cities, Jinan has adopted satellite remote sensing, AI large-model analysis, and IoT-based sensing technologies for incident monitoring and prevention. These advancements enable high-resolution data acquisition and technical feasibility for this study, making Jinan an ideal research case. The study focuses on the central urban area of Jinan, encompassing five districts and 71 subdistricts. To ensure analysis complexity is reduced for the research work's precision analysis of the region's attributes for crime distribution mapped in 150 m x 150 m resolution according to block-level resolution. Thus producing 36,254 samples for analysis in the study.

2.2. Data Sources and Processing

2.2.1 Independent Variables

Crime density per grid cell is the response variable. Based on a review of publications from 2019–2025 using CiteSpace, keyword co-occurrence analysis informed the selection of explanatory variables (Figure 1).

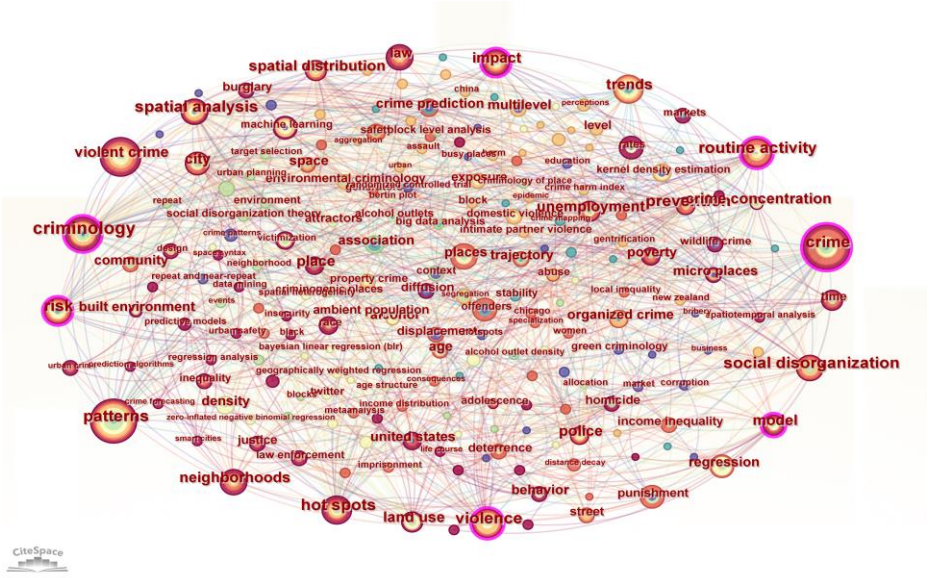


Figure 1. Keyword co-occurrence map. Source: Authors.

Social-environmental parameters were chosen for their ability to represent social control, economic condition, demographic composition, including: children, women; proportion of migrant population and GDP per capita [11–13]. Spatial-environment variables reflect built-form characteristics known to influence crime distribution [14–16]. Urban morphology parameters are measured through the extraction of Baidu Street View images by means of the Convolutional Neural Network model for image segmentation [17][18] (Table 1).

Table 1. Descriptive Statistics of Variables

	Variable	Source
Social Environmental Factors	GDP	Jinan Statistical Yearbook
	Proportion of children	Seventh National Census
	Proportion of females	Seventh National Census
	Proportion of migrants	Seventh National Census
Spatial Environmental Factors	Building density	Gaode Map building attributes
	Distance to police station	Baidu POI data
	Density of commercial facilities	Baidu POI data
	Density of entertainment facilities	Baidu POI data
	Green view index	Baidu Street View data
	Spatial openness	Baidu Street View data

	Interface enclosure	Baidu Street View data

Variance inflation factor (VIF) tests showed values between 1.3 and 4.0, all below the threshold of 5, indicating no significant multicollinearity and confirming suitability for further analysis [19].

2.2.2 Dependent Variable: Crime Data

Data on crime records was collected from the Shandong Public Security Law Enforcement and Case Handling Open Platform available sources to ensure the data was accurate (Figure 2).

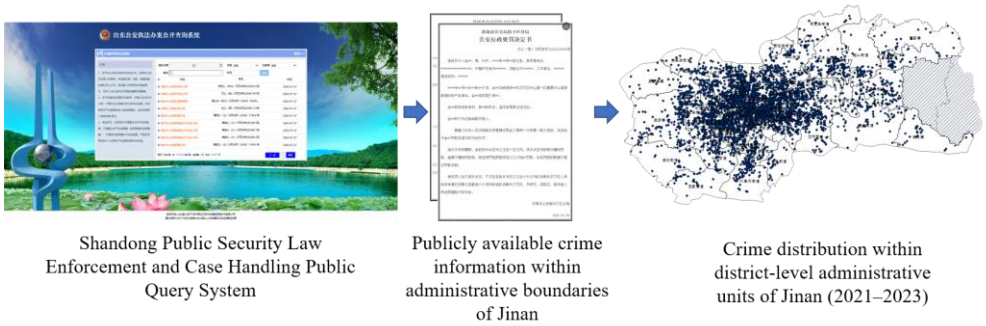


Figure 2. Schematic diagram of crime data collection. Source: Authors.

A total of 14,027 crime records from 2021–2023 were collected for the central urban area, covering incident type, location, and time. Through natural-language processing, incident locations were extracted and geocoded using Baidu Map coordinate tools. Records with incomplete descriptions or inaccurate geolocation were removed. After data cleaning, 12,759 valid crime events remained. These were imported into ArcGIS 10.2, spatially registered to the study area's administrative boundaries, and mapped as crime-incident points (Figure 3).

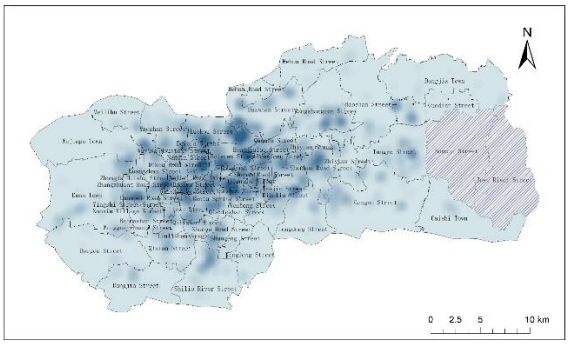


Figure 3. Kernel Density of Crime Events in Jinan's Central Urban Area. Source: Authors.

3. Methodology

3.1. Multivariate Factor Overlap and Coupling Analysis

Traditional methods such as Ordinary Least Squares (OLS) and Poisson regression often ignore spatial heterogeneity, leading to biased estimates that fail to reflect actual spatial variation [19]. To overcome these limitations, this study employs the Geographically Weighted Regression (GWR) model [20]. The model is expressed as:

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i) \cdot x_{ik} + \varepsilon_i$$

3.2. Public-Participation–Based Bayesian Network (BN) Model for Diagnosing Perceived Safety

To better understand the determinants of perceived safety within urban spaces, a Bayesian Network (BN) was developed based on public perceptions. This bottom-up approach supports targeted interventions for improving public-space safety. Probabilities are updated using Bayes' theorem:

$$P(H \mid E) = \frac{P(E \mid H)P(H)}{P(E)}$$

4. Spatial Distribution and Clustering of Crime

4.1. Spatial Patterns of Crime Distribution

Local hotspot analysis shows that crime hotspots cluster predominantly in the northern part of the central urban area, forming highly concentrated high-value zones that extend into surrounding areas (Figure 4). Land-use characteristics indicate that four types of spaces exhibit particularly high crime densities and require prioritized control: (1) logistics and commercial-trade clusters, (2) residential clusters with dense commercial and entertainment uses, (3) old residential clusters adjacent to major transport hubs, and (4) resettlement communities near wholesale trade markets.

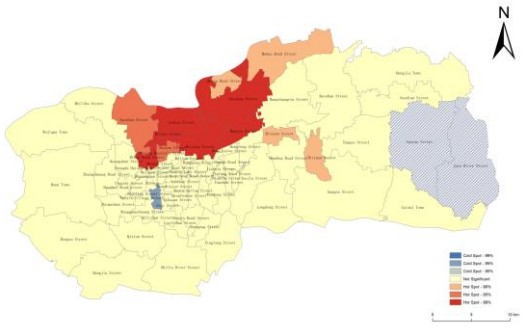


Figure 4. Spatial distribution characteristics of crime in Jinan. Source: Authors.

4.2. Results of the Multivariate Coupling Analysis

A random sample of 5,440 grid cells was selected for the GWR analysis. For each explanatory variable, only samples with p-values $\leqslant 0.05$ were retained to examine their effects on crime distribution. The results show that GDP and enclosure ratio are not statistically significant. Among all variables, the density of entertainment POIs, building density, and commercial-facility POI density exert the strongest influence on crime distribution. These are followed by the proportion of children, distance to the nearest police station, and migrant population ratio. Green-view index and spatial openness show the weakest effects. Generally,

the influence of development intensity and land use-related aspects appears paramount on crime incidence.

GWR results were analyzed for each area type to understand how spatial and social factors influence crime in different contexts. Combined with local spatial characteristics, the mechanisms behind crime concentration were identified (Figure 5).

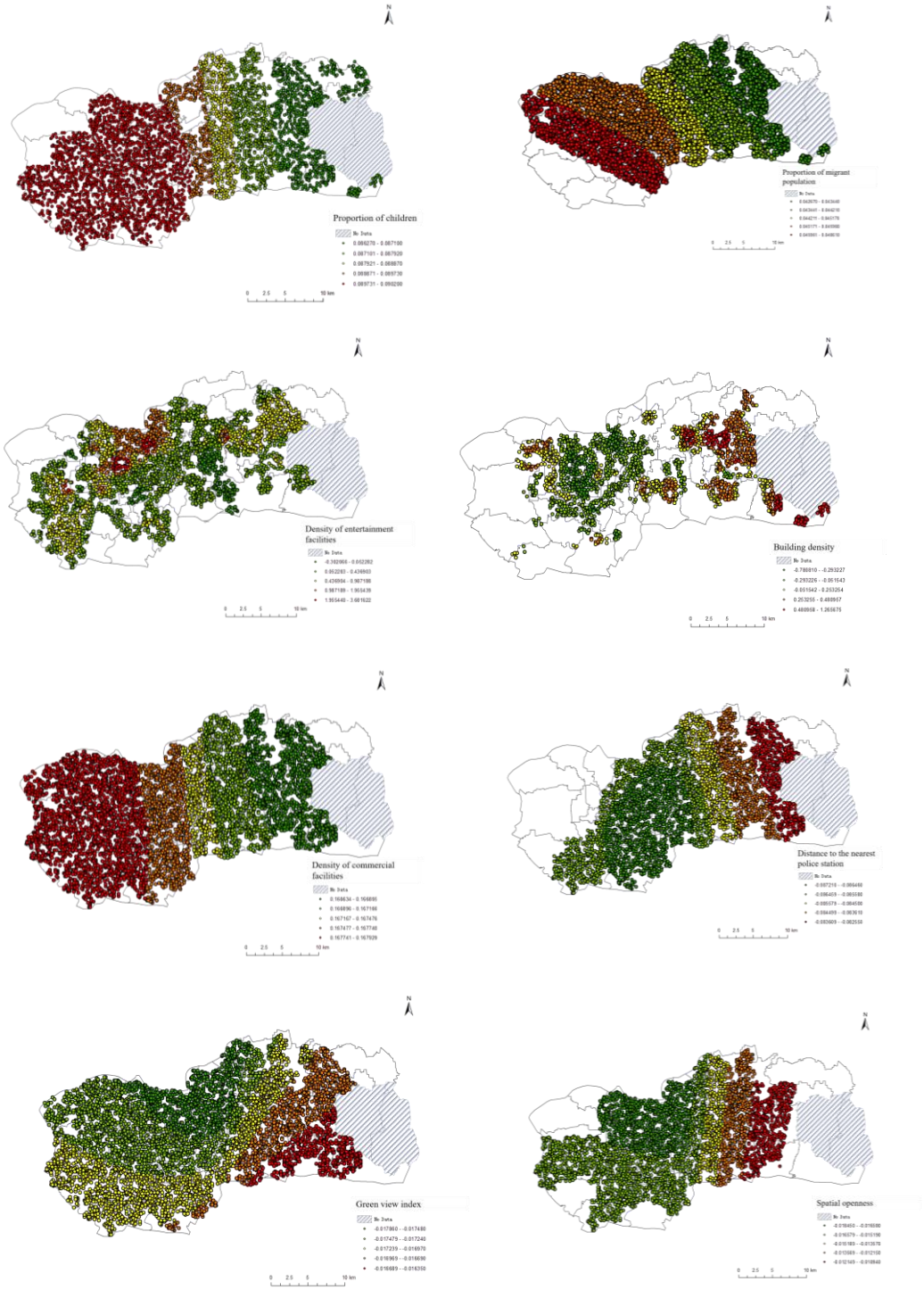


Figure 5. Spatial patterns of GWR coefficients in high-crime zones. Source: Authors.

Consideration of the built environment parameters in the logistics and commercial-trade clusters indicates that the entertainment POI density parameter and the building density parameter influence the most. Among social-environment factors, the proportion of children has the largest effect. Large parcels of logistics land typically have limited pedestrian activity, reducing natural surveillance and providing concealment opportunities for criminal behavior.

In residential clusters with dense commercial and entertainment uses, entertainment POI density and building density again exert the strongest influence. Among the social environment factors, the proportion of migrants is the most influential in the urban village. This is because the higher the concentration of migrants in the area where social services are low, the more difficult it becomes to keep public order. Mixing land use improves the vitality of the place but also leads to environmental complexity.

In old residential clusters adjacent to transport hubs, entertainment POI density has the strongest impact. Field surveys show that these spaces are often poorly maintained. Elevated roads ensure the easiest access for entering and exiting the territory. Ease of evading witnesses also promotes crime commission.

In resettlement communities near wholesale trade markets, entertainment POI density again exerts the greatest influence among built-environment factors. Among social factors, the proportions of children have notable impacts. These areas often lack overall vitality, and some suffer from incomplete infrastructure and low-quality public spaces. Unoccupied business areas contribute to the lack of natural surveillance.

5. Bayesian-Network–Based Diagnosis of Perceived Spatial Safety

5.1. Construction of the Perceived-Safety Evaluation Model

Alongside the GWR analysis, a Bayesian Network (BN) was developed to diagnose perceived spatial safety from the perspective of public cognition. Public semantic data were obtained from an open-ended survey in which respondents freely described their subjective impressions of safety; a total of 36,974 text tokens were collected. Topic extraction and word-frequency statistics produced multi-level probability distributions. After expert review, prior probabilities were derived, and a three-layer Bayesian Network was constructed using the GeNIe platform (Table 2).

Table2 Prior probability table

Fuzzy natural semantics	Prior probability	Refined natural semantics	Conditional probability*	Semantic attributes	Influencing factors
noisy	0.09	Lots of conflicts, messy storefronts…	0.91	Development intensity	Density of entertainment facilities
		Noisy, crowded, chaotic…	0.91	Development intensity	Density of commercial facilities
		Chaotic, loud, packed…	0.83	Environmental perception	Pedestrian flow

		Confusing, bad vibes…	0.83	Environmental perception	Lighting ambience
lawless	0.06	No gate, no control…	0.87	Spatial controllability	Access-control mechanisms
		A security blind spot with poor patrols	0.87	Spatial controllability	Police station
		Too many outsiders, mixed tenants…	0.87	Spatial controllability	Social capital
desolate	0.11	Run-down, empty…	0.83	Spatial orderliness	Infrastructure
		Bare, barren…	0.83	Environmental perception	Green view index
		Desolate, lifeless…	0.83	Environmental perception	Pedestrian flow
open	0.08	Windy, wide-open, desolate…	0.92	Spatial morphology	Enclosure ratio
		Too open, out of scale…	0.92	Spatial morphology	D/H
run-down	0.13	Broken, run-down…	0.83	Spatial orderliness	Infrastructure
		Old, dark, damaged…	0.83	Environmental perception	Lighting facilities
		Worn-out, not working…	0.87	Spatial controllability	Access-control mechanisms
crowded	0.05	Drunk troublemakers, mixed crowds…	0.91	Development intensity	Density of entertainment facilities
		Too dense and packed…	0.91	Development intensity	Density of commercial facilities
		Crowded and hectic…	0.83	Environmental perception	Pedestrian flow
creepy	0.08	Too quiet and unsettling...	0.83	Environmental perception	Pedestrian flow
		Creepy, dim…	0.83	Environmental perception	Green view index

		Dark, eerie…	0.83	Environmental perception	Lighting facilities
uneasy	0.07	Hard to navigate with no guidance…	0.83	Spatial orderliness	Infrastructure
		Feels unsafe, unreliable…	0.87	Spatial controllability	Police station
dirty	0.09	Dirty, run-down, trash-filled…	0.83	Spatial orderliness	Street cleanliness
exposed	0.08	Uncontrolled, wide open…	0.87	Spatial controllability	Access-control mechanisms
		Empty…	0.92	Spatial morphology	D/H
		Open, spacious…	0.92	Spatial morphology	Enclosure ratio
cramped	0.08	Blocked views, oppressive…	0.92	Spatial morphology	Enclosure ratio
		Narrow, cramped…	0.92	Spatial morphology	D/H
chaotic	0.08	Heavy, mixed foot traffic…	0.83	Environmental perception	Pedestrian flow
		Too many strangers and poor supervision	0.87	Spatial controllability	Access-control mechanisms
		Messy tenants and group rentals…	0.87	Spatial controllability	Social capital

* The conditional probabilities listed represent example values calculated under the condition that all parent nodes are in their positive state, reflecting the highest-association scenario for each node.

5.2. Application of the Perceived-Safety Diagnostic Model

Among the whole business network in Quancheng Road, the low vitality area on Xigengdao Street stands out. Despite being near very active business areas, the low vitality on Xigengdao Street is of concern for the community. The area was selected to be the diagnostic case, the relevant public assessment data was used in the BN model, assigning prior probabilities.

The results indicate that D/H, lighting conditions, and street cleanliness are the most critical factors affecting perceived safety (Figure 6). D/H shows the highest probability among all influencing factors, suggesting that visual openness strongly shapes public perception. Parts of the street are narrow, reducing visual permeability; high enclosure can trigger negative emotions and weaken perceived safety. Poorly maintained infrastructure is also identified as a significant contributor to decreased safety perception, as

physical deterioration signals low controllability of space and may elicit fear. Improving spatial openness and upgrading infrastructure are therefore essential interventions.

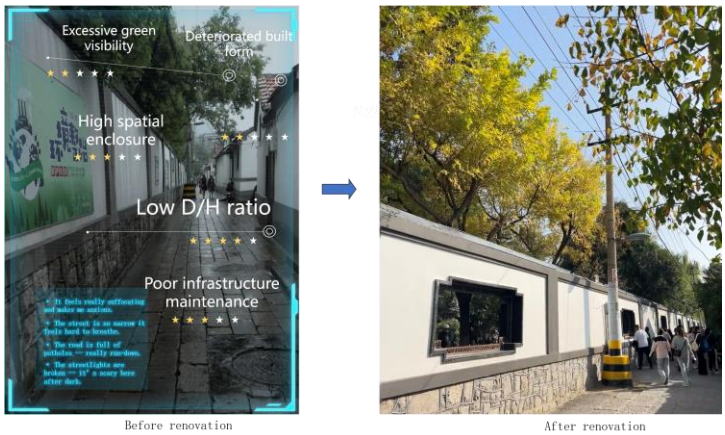


Figure 6. Spatial safety perception diagnosis for alley spaces in Xigengdao Street. Source: Authors.

Street cleanliness, green-view index, and lighting facilities also exhibit high probability values in the diagnostic results (Figure 7). According to CPTED principles, inadequate maintenance and insufficient greenery can directly reduce perceived safety. A lack of lighting may induce fear even in otherwise safe places. Diagnostic outcomes suggest that future interventions should focus on environmental maintenance, greenery improvement, and lighting enhancement [22].

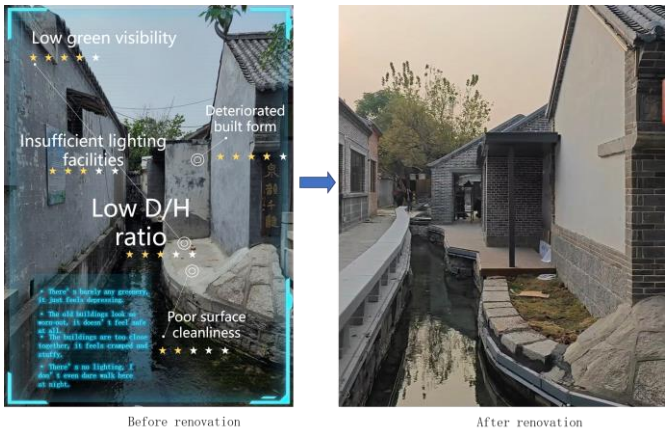


Figure 7. Spatial safety perception diagnosis for waterfront spaces along Xigengdao Street. Source: Authors.

6. Conclusion

Using crime data from the central urban area of Jinan, this study employed spatial autocorrelation to examine the spatial distribution of crime and constructed a geographically weighted regression model to analyze the social, economic, and spatial factors shaping crime patterns. The findings are as follows:

（1）Spatial autocorrelation analysis shows clear clustering of crime hot spots and cold spots within the study area. Crime distribution is strongly influenced by spatial factors. High-value clusters are concentrated in the northern part of the central city, particularly around Luokou and Beicun subdistricts, while low-value clusters appear as isolated pockets in the central-western area.

（2）Analysis of the determinants of crime distribution indicates that development intensity and land-use–related factors exert the strongest overall influence and should be prioritized in subsequent spatial governance efforts. Kernel density analysis of the high-hotspot areas further reveals four types of high-incidence spatial clusters. Targeted analysis of each cluster type was conducted, and planning strategies to suppress crime incidence were proposed across different planning scales.

（3）Based on GWR results, top-down urban renewal strategies were proposed for high-incidence areas. The most effective approach is to regulate development intensity and optimize the spatial layout of functional facilities at the district scale. Policy improvements should also aim to enhance social control and social support by increasing investment in public resources and improving the quality and equity of public services. At the street scale, measures such as streetscape coordination and infrastructural improvements can enhance the safety of the built environment.

（4）Drawing on the Bayesian Network diagnosis of public perceptions of spatial safety, bottom-up renewal strategies were proposed. First, to address poor spatial order, infrastructure should be regularly maintained to ensure clean and orderly environments. Second, spatial controllability should be improved through the repair and reinforcement of existing gates, fences, and boundary-defining elements, thereby strengthening territoriality. Third, micro-scale urban renewal should be used to enhance green-view index and adjust enclosure levels, maintaining appropriate visual permeability and environmental coherence. Finally, fostering inclusive communities and strengthening community-based safety programs can help build robust social networks.

In summary, this study analyzes the spatial pattern of crime in Jinan's central urban area through statistical crime analysis and public participation–based safety diagnosis. The findings clarify the key factors influencing urban safety and propose both top-down and bottom-up strategies for improvement, offering methodological support for enhancing spatial safety in comparable urban contexts.

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