

Article

Evaluation of Pedestrian-Perceived Comfort on Urban Streets Using Multi-Source Data: A Case Study in Nanjing, China

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Abstract: Urban street comfort is a crucial measure of street environmental quality. However, traditional evaluations primarily focus on physical elements, often neglecting pedestrian perceptions. In this study, considering five core evaluation dimensions—safety, mobility, aesthetics, perceptibility, and convenience—an innovative quantitative evaluation model is proposed to assess pedestrian-perceived comfort on urban streets by integrating physical environmental factors and subjective experiences. This analysis comprises two steps: evaluation indicator extraction and weight application. Indicators are extracted from multi-source data (street-view images, real-time traffic data, points of interest, and pedestrian surveys) using a deep learning method. A comprehensive weighting method combining entropy weight and the analytic hierarchy process is used to determine the relative importance of each factor. This study focuses on Nanjing as a case study, and the results reveal significant variations across the five dimensions and their 11 secondary indicators. Street environment safety (0.143) is critical for street safety, while the degree of street traffic congestion (0.121) dominates street mobility. Street aesthetics is primarily influenced by building enclosure (0.105), and street convenience is strongly affected by the number of surrounding bus stops (0.260). Spatial analysis indicates higher comfort levels in urban centers due to well-developed infrastructure, whereas peripheral areas face challenges from inadequate facilities. Notably, areas around parks demonstrate elevated pedestrian-perceived comfort levels, highlighting the importance of green spaces. Overall, the proposed evaluation system provides new insights from the perspective of pedestrian experience and offers valuable guidance for urban planning and policy.

Keywords: pedestrian-perceived comfort; urban street; multidimensional evaluation; multi-source data; combined weighting method



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1. Introduction

With the gradual shift toward “human-centered” concepts in recent years, enhancing pedestrian-perceived comfort has become critical for improving walking environments. Perceived comfort is closely associated with high-quality pedestrian environments [1,2]. Some researchers have adopted measurement indicators like safety, comfort, fluidity, and convenience to measure pedestrian perceptions. In particular, comfort, which represents a pleasant state resulting from the physiological and psychological harmony between individuals and their

environment [3], is an important indicator for assessing the walkability of urban streets [4]. Although comfort has been addressed in previous studies, it has primarily been treated as a component of walkability and has rarely been studied as an independent factor.

Recently, pedestrian comfort has been studied primarily from two perspectives. The first aspect examines external factors contributing to pedestrian discomfort during extreme temperatures, such as climatic conditions (e.g., high temperatures, heatwaves, and humidity levels). Additionally, urban design elements—such as street design parameters, tree species, shadows, and urban canyon geometry—play a significant role in mitigating or exacerbating the effects of extreme temperatures. These design factors influence local microclimates, providing shade, altering airflow, and modifying heat exposure, thereby impacting pedestrian comfort levels [5–7]. The second perspective identifies built environment attributes that affect the comfort of pedestrian walking, including sidewalk materials, greening, trash bins, and streetlights [8]. However, both perspectives primarily focus on the physical environment of streets and cannot fully account for the experience of walking on a specific street or clarify individual perceptions of the physical environment. Pedestrian-perceived comfort emphasizes subjective experiences, assessing the sensory and emotional comfort of urban streets experienced by pedestrians [9]. Sensory comfort refers to people's satisfaction with environmental attributes related to their senses, including the unobstructed view and width of the street, greening, and sky view proportion [10], all of which are closely related to street comfort. Emotional comfort refers to the positive emotions that a street can provide to pedestrians, including feelings of safety, refuge, familiarity, and privacy [11–13]. However, most previous studies focus on a specific dimension, ignoring the subjective multidimensional characteristics of pedestrian perception.

Although questionnaires provide direct feedback on pedestrian-perceived comfort, they are time-consuming and have limited sample sizes and slow update rates [14]. The advent of big data has led urban researchers to embrace multi-source datasets, including global navigation satellite system data, location-based social network data, mobile signaling data, and street-view images (SVIs) [15]. In particular, SVIs are closely related to human visual perception at the street level and reflect the actual street environment [16–18]. Some researchers have proposed evaluation systems considering spatial indicators extracted from such datasets, emphasizing aspects of connectivity, convenience, comfort, conviviality, and conspicuousness [19]. Moura et al. (2017) [20] proposed two additional factors of coexistence and commitment to incorporate pedestrian policy promotion by local authorities and communities. Additionally, various approaches such as direct perception scoring by experts [21], analytic hierarchy process (AHP) methods [2], and factor and cluster analysis [22] have been used. However, a unified concept and quantitative model to comprehensively evaluate pedestrian-perceived comfort are still lacking.

Therefore, we aimed to develop a quantitative evaluation model for assessing pedestrian-perceived comfort on urban streets based on multi-source data. Specifically, we defined pedestrian-perceived comfort on urban streets as the visual and psychological comfort experienced by pedestrians based on the works of Cheng et al. (2017) [23] and Yang et al. (2021) [18]. This definition incorporates pedestrians' subjective perceptions of street physical environments (e.g., traffic lanes, landscapes, and sky), the quality of the neighborhood environment (e.g., aesthetics and cleanliness), and perceived safety of the street. According to this definition, we established an evaluation system encompassing five core dimensions: perceptibility, safety, aesthetics, mobility, and convenience. Each dimension reflects a critical aspect of pedestrian-perceived comfort in urban environments. These dimensions were chosen for their relevance to pedestrian-perceived comfort and their significant roles in shaping street environments. Perceptibility focuses on sensory experiences, including noise and olfactory disturbances. Safety considers both subjective

perceptions and physical factors affecting pedestrian protection. Aesthetics reflects the visual appeal of urban streetscapes, while mobility evaluates traffic conditions and their impact on pedestrian comfort. Convenience emphasizes the accessibility and connectivity of street infrastructure. To provide a detailed assessment, 11 specific indicators were selected, grounded in prior research and urban planning principles. These indicators were derived from diverse data sources, including SVIs, point-of-interest (POI) data, real-time traffic data, and questionnaire survey responses. A combined weighting approach, integrating the entropy weight method (EW) and the AHP, was applied to ensure balanced and rational indicator weights. Finally, the spatial variation in pedestrian-perceived comfort was analyzed across Nanjing's main urban area, offering valuable insights for urban planning and policymaking.

This study contributes to the field in three significant ways: (1) proposing a comprehensive evaluation framework that integrates objective environmental measures with subjective pedestrian perceptions, (2) developing a replicable methodology leveraging multi-source data adaptable to other cities, and (3) offering actionable insights for urban planners through spatial analysis of pedestrian comfort dimensions. This framework deepens the understanding of pedestrian-perceived comfort and supports evidence-based urban planning and policymaking.

2. Literature Review

Urban streets play an important role in urban morphology, occupying a central position in urban development [24]. A comfortable urban street may lead to pleasant experiences for pedestrians. Therefore, conducting a comprehensive pedestrian comfort evaluation of the streets within a region is beneficial for providing better and more efficient decision support for policymakers.

Pedestrian-perceived comfort is fundamentally a subjective perception shaped by multiple sensory and emotional factors. Sensory comfort primarily refers to the level of satisfaction pedestrians derive from environmental attributes (e.g., unobstructed views, greenery, and the width of streets) [10]. Liu and Kang (2018) [25] demonstrated a strong positive correlation between audiovisual comfort and street width-to-height ratio, highlighting the importance of urban design in enhancing sensory experiences. Beyond sensory comfort, emotional comfort also plays a crucial role in pedestrian experiences. It encompasses feelings of safety, refuge, familiarity, and privacy, which are influenced by both physical and social elements of the urban environment [11–13]. For example, safety, as a key component of emotional comfort, is largely determined by traffic conditions and crime rates. Research has shown that measures like pedestrian refuge islands can enhance perceived safety, whereas longer crossing distances reduce perceived safety [26,27]. Furthermore, the surrounding environment (e.g., well-maintained lawns and the absence of garbage) can reduce crime rates and improve the sense of security.

Additionally, the thermal environment significantly impacts pedestrian comfort, especially in dense urban areas. Yang et al. (2016) [7] quantified street design parameters to evaluate their impact on thermal comfort in Singapore's central business district, providing foundational insights into the role of urban planning in mitigating heat stress. Building on this, Morakinyo et al. (2017) [6] studied the effects of tree species and building shadows on thermal comfort in Hong Kong, highlighting the synergy between natural and built environments. Li et al. (2020) [28] introduced the concept of frontal area density in 3D building models, linking architectural design to both thermal comfort and air quality. More recently, Ren et al. (2022) [29] incorporated human physiological indices to assess the contributions of urban street trees to thermal comfort in Changchun, China.

With the advent of data-driven approaches, multi-source geospatial datasets, particularly SVI datasets, have become valuable tools for evaluating pedestrian comfort. Gu et al. (2018) [30] used SVIs and POI data to develop metrics for evaluating street walkability in several Chinese cities. Sun (2020) [31] proposed a comprehensive evaluation system for street walkability and the green view index (GVI) in Nanjing's central urban area. Larkin et al. (2021) [17] integrated urban perception with SVIs to identify the built environmental factors associated with urban safety, vitality, and aesthetics, providing a nuanced understanding of street environments. Furthermore, Yang et al. (2021) [18] integrated SVIs and POIs to develop a spatial comfort indicator system for urban streets. While these studies primarily relied on static datasets such as POIs and SVIs, the integration of real-time traffic data remains underexplored, suggesting a potential direction for future research to capture dynamic, time-sensitive factors in pedestrian comfort assessments.

The determination of weights for indicators is critical in evaluating pedestrian comfort, as it directly impacts the outcomes of the evaluation model. Weighting methods can be broadly categorized into subjective and objective approaches. Subjective methods, such as the AHP [32] and the Delphi method [33], rely on the knowledge and experience of experts to assign weights. Although these methods are widely used due to their simplicity and ability to incorporate expert insights, they can be subject to bias, as decisions are influenced by subjective judgment [34]. In contrast, objective methods, such as the entropy weight (EW) method [35,36] and the Technique for Order Preference by Similarity to an Ideal Solution [37], assign weights based on the statistical properties of data. The EW method, in particular, has been widely applied in urban research due to its ability to quantify the information entropy of data and assign appropriate weights. However, objective methods often overlook the contextual knowledge and preferences of decision-makers, which may limit their applicability in complex urban environments. To address these limitations, researchers have increasingly combined multiple methods. For example, Chen et al. (2024) [38] integrated the AHP and Fuzzy Comprehensive Evaluation to establish a measurement system, while Chen et al. (2023) [39] combined the AHP and EW to improve flood risk assessments in Wuhan, China. Building on these efforts, this study adopts an EW–AHP approach, minimizing the geometric distance method to calculate weights, owing to its simplicity and superior performance.

Although significant progress has been made in understanding pedestrian comfort, few studies have focused on pedestrian-perceived comfort. Therefore, we designed a comprehensive evaluation system to assess pedestrian-perceived comfort using multi-source data combined with a deep learning model by combining the AHP and EW to assess pedestrian-perceived comfort, offering valuable insights for urban planners and policymakers.

3. Materials and Methods

3.1. Study Area

Nanjing (31°14' N–32°27' N, 118°22' E–119°14' E), located in Jiangsu Province, has a well-developed transportation network, a high proportion of green space coverage, and notable ecological benefits. Positioned at the confluence of the Yangtze River Economic Belt and the Belt and Road Initiative, Nanjing has received considerable research attention. As the backbone of urban morphology [24], streets facilitate traffic flow and social activities, and connect various urban functional zones. Therefore, we chose streets as our research units to study Nanjing's pedestrian-perceived comfort. Figure 1 presents the 2369 streets analyzed in this study.

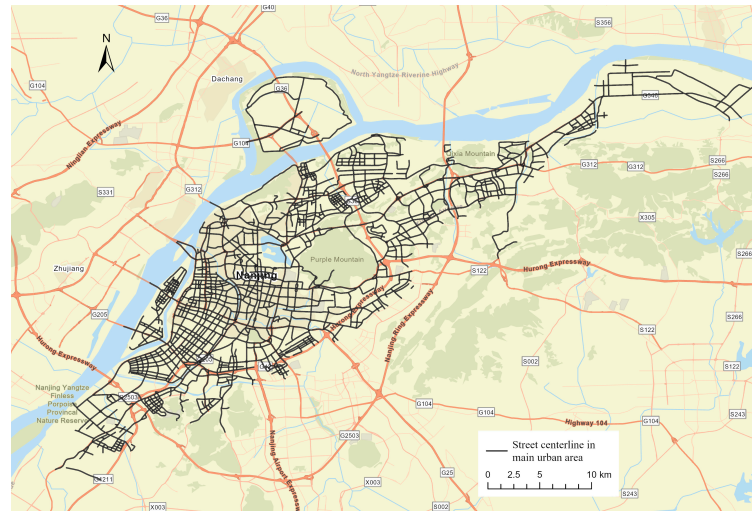


Figure 1. Partial streets in the study area.

3.2. Research Framework

The overall workflow of this study comprised two parts (Figure 2). First, data collection was performed, wherein SVIs were classified using the DeepLab V3 model to extract specific indicators, and real-time traffic and POI data were obtained from AMap. Street safety scores were predicted using the random forest regression method. Second, an evaluation model was constructed by integrating multi-source data into an indicator system. Subsequently, a novel method combining subjective and objective factors was used to assign weights to each indicator, resulting in a pedestrian-perceived comfort evaluation model for urban streets.

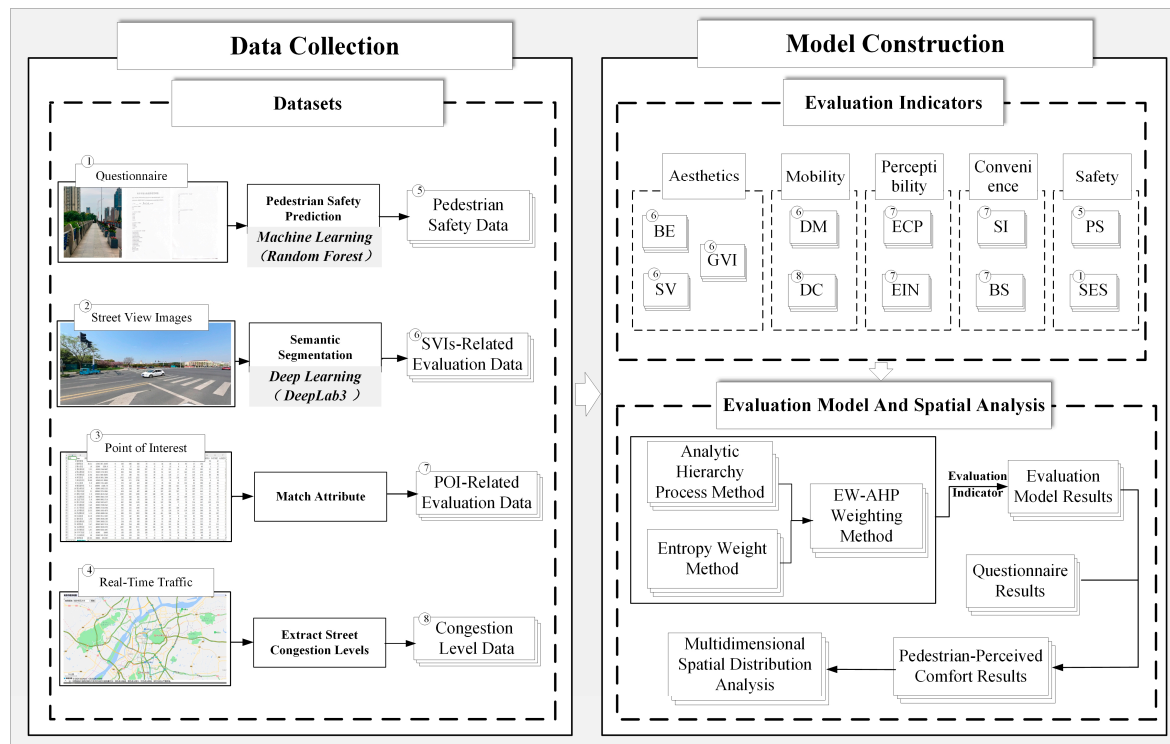


Figure 2. Research flowchart (Note: for the specific codes of the indicators used in this flowchart, please refer to Appendix A).

3.3. Data Collection

3.3.1. Questionnaire Data Collection

To collect relevant data for evaluating pedestrian comfort and safety, an inductive approach was employed to identify key evaluation indicators. A group of twelve experts from diverse fields—including urban planning, geoinformatics, environmental psychology, and transportation engineering—were consulted to provide insights into the factors that influence pedestrian perceptions of street environments. Based on expert input, a comprehensive questionnaire was developed, focusing specifically on two critical factors: street safety and comfort. The indicator selection process highlighted several key factors influencing pedestrian perceptions. Among these, street environment safety (SES) and pedestrian safety (PS) emerged as the most influential indicators, with 130 and 108 selections, respectively, out of a total of 172 respondents (Supplementary Materials, Table S1). Other notable indicators included degree of street motorization (DM) (87 selections), degree of street traffic congestion (DC) (95 selections), and Green View Index (GVI) (73 selections). These indicators collectively reflect the multidimensional nature of pedestrian-perceived comfort, encompassing aspects such as safety, mobility, aesthetics, perceptibility, and convenience.

To ensure a representative sample, 14 streets across Nanjing were selected, covering various functional zones such as commercial, residential, and mixed-use areas. The survey targeted respondents who were familiar with these streets to capture their subjective perceptions of safety and comfort. A total of 172 valid questionnaires were collected, with each street receiving a minimum of 10 responses. The final scoring results for the selected streets indicate substantial variation in pedestrian perceptions. For instance, Caochangmen Avenue in the Gulou District received consistently high scores for safety and comfort (8 and 9, respectively), while Huanshan West Road in the Yuhuatai District scored significantly lower (4 and 4, respectively). These variations underscore the diverse nature of urban street environments and their impact on pedestrian experiences (see Supplementary Materials, Tables S1 and S2). To protect participant privacy, verbal informed consent was obtained prior to the survey. All participants were informed of the study's objectives and the confidentiality of their responses.

3.3.2. Street-View Image Collection

Following Long (2017) [39], sampling points were selected using an equidistant method (150 m) based on the road network. This ensured the acquisition of points distributed across the study area, with each road segment having an equal chance of inclusion. Pedestrians tend to perceive environments within a relatively short distance and the 150 m distance aligns well with typical pedestrian behavior patterns while ensuring adequate spatial coverage. Road network data were obtained from the OpenStreetMap platform (<https://www.openstreetmap.org>), focusing on major urban roads above the tertiary level.

SVIs were collected between March and September 2021 from the Baidu Map Open Platform (<https://lbsyun.baidu.com>, accessed on 21 September 2021). At every sample point, SVIs were captured in four horizontal directions: 0°, 90°, 180°, and 270°. After excluding incomplete or missing images, 31,104 valid SVIs were acquired from 7776 locations in the study area (Figure 3). To ensure the reliability of the SVIs, we conducted a rigorous validation process that included geolocation accuracy checks, image quality control, technical specifications review, and strict adherence to data privacy regulations.



Figure 3. Renamed SVI samples.

3.3.3. Point-of-Interest and Real-Time Traffic Data Collection

POI and real-time traffic data were obtained from AMap (<https://ditu.amap.com>, accessed on 13 December 2023), representing 5639 valid real-time traffic records and 11,500 relevant POIs. For the RT data, the traffic congestion status was categorized into five levels—unknown, smooth, moderate, congested, and severely congested—based on actual conditions. These levels were encoded as values ranging from one to five. The POI data were categorized into four types—pollution and chemical enterprises (including chemical metallurgy and gas stations), industrial noise enterprises (including factories and automobile repair shops), bus stops, and intersections.

3.3.4. Spatial Matching of Data

Since some data were collected at different times, spatial matching remained valid despite the temporal differences due to the relatively stable nature of urban street traffic conditions. The real-time traffic congestion data were spatially matched to the corresponding locations where the SVI data were collected, ensuring the alignment of both datasets. This matching approach ensured that street-level conditions were comparable despite time differences. Similarly, POI data were integrated into the analysis based on georeferenced street coordinates, while questionnaire responses from pedestrians familiar with the selected streets were linked to the corresponding street segments. While data collection occurred at different times, any temporal discrepancies were mitigated by cross-checking with historical traffic data, which allowed for the validation of environmental conditions and ensured their relevance. The stable nature of urban traffic, supported by this cross-checking process, enabled valid comparisons across datasets. This integration of objective (traffic and POI) and subjective (questionnaire) data provided a comprehensive understanding of the factors influencing pedestrian experiences.

3.4. Evaluation Indicator Extraction

3.4.1. Semantic Segmentation of SVIs

To efficiently and accurately extract visual information for assessing pedestrian-perceived comfort on urban streets, a semantic segmentation model was employed to identify the key indicators in the SVIs (e.g., sky, roads, trees, vegetation, cars, shrubs, sidewalks, traffic lights, poles, and buildings). DeepLab-series models, particularly DeepLab V3 and DeepLab V3+, have demonstrated outstanding performance for semantic segmentation. Experimental validation indicated that DeepLab V3 and DeepLab V3+ yielded similar accuracies; however, DeepLab V3+ required more processing time. Therefore, we selected DeepLab V3 for the semantic segmentation of SVIs (Figure 4).

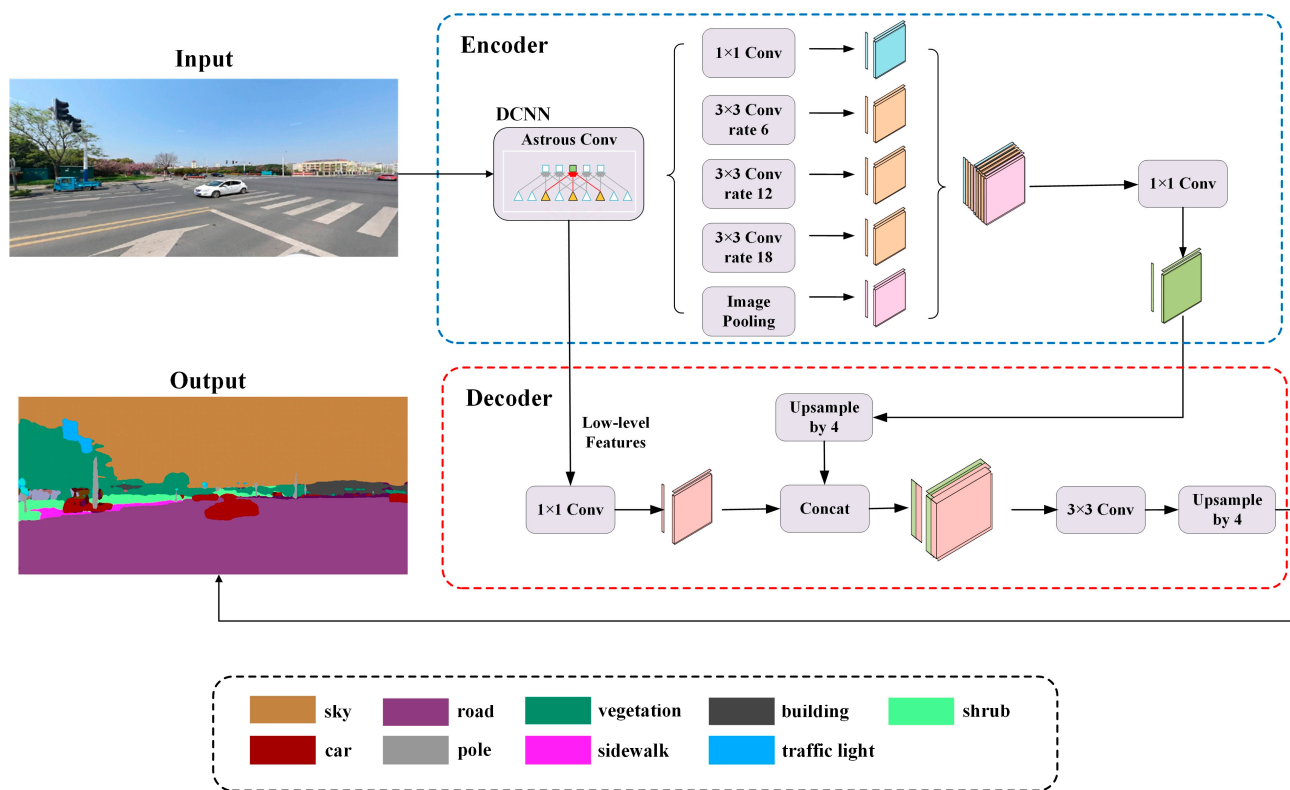


Figure 4. Structure of the DeepLab V3 Network.

The Cityscapes dataset contains 2975 training images, 500 validation images, and 1525 testing images collected from 50 cities. Cityscapes is extensively used because it provides high-quality pixel-level annotations of urban street scenes and includes 34 street scene categories (e.g., sky, road, and cars) [40]. We selected 19 types of streetscape elements as a training set to extract the key features surrounding the streets in Nanjing. The training process was conducted on a Windows 10 PC equipped with an NVIDIA GeForce GTX 1080 Ti GPU and Intel Core i7-11700 CPU, supported by an NVIDIA CUDA 11.3 and cuDNN v8.4.0 environment. We used a batch size of eight and an initial learning rate of 0.0001. After 1000 epochs of training, the model achieved an overall accuracy of 0.9440, mean accuracy of 0.7860, and mean intersection over union of 0.6966.

Considering the similarities in urban landscapes between the Cityscapes dataset and Nanjing's main urban area, we applied the optimal weights obtained from training the semantic segmentation model on the SVIs of Nanjing's main urban area, despite the presence of minor architectural style differences. Semantic segmentation was performed on 31,104 SVIs in Nanjing and was generally successful.

3.4.2. Calculation of Evaluation Indicators

To establish a scientific evaluation system for pedestrian-perceived comfort, indicators selected by over 20% of questionnaire respondents were retained. After processing, 11 indicators were included in the final evaluation (Table S3). Based on expert opinions, questionnaire data, and study area conditions, the indicators were categorized into five dimensions: street perceptibility, safety, aesthetics, mobility, and convenience.

(1) Street perceptibility

Street perceptibility refers to pedestrians' immediate sensory experiences of the street environment, including factors such as environmental noise and olfactory disturbances. Environmental noise and unpleasant odors have been shown to significantly affect pedestrian comfort and behavior [41,42]. Audition and olfaction are more important media for

perceiving the environment [43,44]. Odor nuisance issues are particularly worrying when more industrial activities exist near residential areas [45]. Some studies have shown the impact of unpleasant odors on the living comfort and well-being of residents living near odor emission sites [46,47]. This study selected two indicators—(1) the number of enterprises involved in chemical pollution and (2) the intensity of industrial noise—to evaluate potential environmental disturbances, considering the prevalence of industrial activities in the study area. These indicators were chosen based on their relevance to urban street environments and their potential to reflect specific discomfort factors. Table A1 (Appendix A) provides detailed descriptions and calculation methods for these indicators.

(2) Street safety

Street safety is a critical component of pedestrian-perceived comfort, encompassing two aspects: pedestrian safety (PS) and street environmental safety (SES). These, respectively, reflect residents' subjective evaluations of street safety conditions and the actual impact of street physical design on pedestrian protection [3,48]. Due to limited questionnaire data on safety, which only covered 14 representative streets, a random forest algorithm was applied to predict the safety of the remaining streets. The SES values obtained from the questionnaires served as the dependent variable in the model, while predictors included the GVI, PS, BE, DM, and SI. These indicators represent dimensions closely tied to pedestrian-perceived safety's physical and psychological aspects. The random forest algorithm was selected for its robustness in handling nonlinear relationships and high-dimensional data, which align with the complexity of street safety factors. The obtained mean squared error was 1.0595, indicating a good model fit. During model training, hyperparameters were optimized via grid search, and all features were standardized to ensure consistent scales. The relevant indicators and their calculations are described in Table A2 (Appendix A).

(3) Street aesthetics

Street aesthetics evaluate the perceptual appeal of environmental features, focusing on the visual attractiveness of streets and their surroundings. Key elements include buildings, vegetation, and urban landscapes [49]. Visually pleasing environments have been shown to enhance pedestrian satisfaction, encourage walking, and improve overall perceptions of streets [50]. In this study, aesthetic indicators were selected to reflect the unique characteristics of the study area, including the green view index, the proportion of sky view, and building enclosure. These indicators are widely recognized for their association with pedestrian perceptions in urban environments. Table A3 (Appendix A) details the selected indicators and their calculation methods.

(4) Street mobility

Street mobility assesses the capacity of streets to accommodate motorized traffic, focusing on the degree of street motorization (DM) and street traffic congestion (DC). DM measures the smoothness and convenience of vehicle movement on urban streets [18], where higher DM values correspond to reduced traffic volumes and enhanced pedestrian comfort. Conversely, lower DM values indicate higher congestion, often linked to delays and dissatisfaction. Traffic congestion is a critical factor affecting urban mobility and directly impacts pedestrian-perceived comfort [51]. Consequently, a comprehensive assessment of street mobility necessitates evaluating both DM and DC. In this study, DM and DC were assessed using indicators specifically for the local traffic conditions of the study area. Detailed descriptions of these indicators and their calculation methods are provided in Table A4 (Appendix A).

(5) Street convenience

Street convenience reflects the role of infrastructure in supporting pedestrian activities, emphasizing connectivity and accessibility as core dimensions [52,53]. Connectivity relates to the ease of navigating from origins to destinations, significantly influencing

pedestrian route choices [54]. Accessibility, on the other hand, emphasizes the proximity of transit facilities, such as bus stops, that support pedestrian mobility. To evaluate convenience, this study used two indicators: the number of street intersections (SIs) and the number of surrounding bus stops (BSs). These indicators were selected for relevance with pedestrian-perceived comfort and ease of navigation. Detailed descriptions of these indicators, along with their calculation methods, are provided in Table A5 (Appendix A).

3.5. Evaluation Methods

A comprehensive evaluation model for pedestrian-perceived comfort on urban streets was constructed based on the calculated indicators. The EW–AHP method determined the weights of these indicators, integrating subjective and objective criteria for a comprehensive evaluation. This process is explained below.

Step 1: Normalization

Each indicator was standardized to ensure comparability. We employed the min-max method to standardize the data [55]. Positive and negative indicators were standardized separately, with Equations (1) and (2) applied to positive and negative indicators, respectively.

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

$$x_{norm} = \frac{x_{max} - x}{x_{max} - x_{min}} \quad (2)$$

Here, x_{norm} denotes the standardized data of the indicator factor, x denotes the raw data, x_{max} is the maximum value, and x_{min} is the minimum value.

Step 2: EW Method

The EW method objectively determines indicator weights based on data information, forming the basis for multi-indicator evaluations [15]. The EW calculation is given in Equations (3)–(5).

$$W_i = \frac{(1 - E_i)}{\sum_{i=1}^n (1 - E_i)} \quad (3)$$

$$E_i = -\frac{1}{\ln m} * \sum_{j=1}^m P_{ij} * \ln(P_{ij}) \quad (4)$$

$$P_{ij} = \frac{x_{ij}}{\sum_{j=1}^m x_{ij}} \quad (5)$$

Here, E_i is the information entropy, m is the number of sampling points, n is the total number of indicators, W_i is the weight of the i th indicator, x_{ij} is the value of the j th sample point for the i th indicator, E_i is the entropy value of the i th indicator, and P_{ij} is the proportion of the j th sample point in the i th indicator.

Step 3: AHP Method

The AHP assigns weights based on expert judgment [2] through three steps: decomposition, comparative judgment, and synthesis. The consistency ratio (CR) is used to verify the consistency of the results. If the CR does not exceed 0.10, then the judgment matrix is considered to have acceptable consistency; otherwise, it must be readjusted. The CR is calculated by dividing the consistency index (CI) by the random index (RI). The formulae for the CI and RI are presented in Equations (6) and (7), respectively. The AHP is detailed in Tables S4–S11.

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (6)$$

$$CR = \frac{CI}{RI} \quad (7)$$

Here, λ_{max} is the maximum eigenvalue of the judgment matrix, n is the order of the matrix, and RI is obtained using randomly generated reciprocal matrices.

Step 4: EW-AHP Weighting Coefficients

As AHP determines the judgment matrix based on subjective experience and EW relies excessively on the inherent patterns in data, an EW-AHP weighting method was adopted to determine indicator weights with reduced subjectivity. To ensure a balanced and robust weighting scheme, the geometric distance between the weights from the two methods was minimized to determine the optimal combined weights. The distribution rules for the combined weighting coefficients are defined in Equations (8) and (9) [18]:

$$W_{PC} = aW_{EW} + bW_{AHP} \quad (8)$$

Here, W_{PC} represents the combined weighting of pedestrian-perceived comfort (PC), W_{EW} and W_{AHP} are the weights obtained from the EW and AHP, respectively, and a and b are the weighting coefficients satisfying $a + b = 1$. The coefficients a and b are determined by minimizing the geometric distance between W_{EW} and W_{AHP} [56]:

$$\begin{cases} \text{Minimize :} & d(W_{EWM}, W_{AHP}) = \sqrt{\sum_{k=1}^n (W_{EW, k} - W_{AHP, k})^2} \\ \text{Subject to :} & a + b = 1 \end{cases} \quad (9)$$

Here, $d(W_{EWM}, W_{AHP})$ is the geometric distance between the two sets of weights, and n is the number of indicators. The coefficients a and b are then calculated as

$$a = \frac{1 + d(W_{EWM}, W_{AHP})}{2}, \quad b = \frac{1 - d(W_{EWM}, W_{AHP})}{2}. \quad (10)$$

This approach ensures that the combined weights W_{sc} reflect both subjective judgments and objective data patterns.

Step 5: Scoring

The weighted sum model is one of the popular applied multiple criteria decision-making methods for evaluation [57]. Based on the weighted values, a multidimensional comprehensive evaluation model was constructed to assess pedestrian-perceived comfort on urban streets in the study area.

$$P = \sum_{i=1}^n W_i * X_i \quad (11)$$

Here, P represents pedestrian-perceived comfort on urban streets, wherein a higher score is better; W_i is the weight of the i th evaluation indicator (normalized combination); X_i is the score of the i th evaluation indicator; and n is the total number of evaluation indicators.

3.6. Spatial Analysis Method

Empirical Bayesian kriging (EBK) is an advanced geostatistical method that improves upon classical kriging techniques [58]. EBK is particularly useful for handling datasets with moderate-to-large non-stationarity, wherein variogram models may vary across different regions of the study area [59]. This method creates a spectrum of variograms that account for the error introduced by estimating a variogram model [28]. Unlike other classical kriging methods, EBK automatically calculates adjusted parameters through subset construction and simulation processes, enhancing performance [60].

In this study, EBK was applied to interpolate pedestrian-perceived comfort on urban streets across the study area. The input data consisted of discrete sampling points, spaced at 150 m intervals along urban streets. These sampling points represent the loca-

tions where pedestrian-perceived comfort indicators were directly measured or estimated. The assessment indicators were calculated specifically for these discrete points. Using EBK, these indicators were then interpolated to generate continuous predictions of pedestrian-perceived comfort across unsampled locations. The interpolated results were aggregated to provide a continuous, spatially explicit assessment of pedestrian-perceived levels for the entire street sections in the study area.

4. Results

4.1. Spatial Autocorrelation Analysis

Figure 5 presents the Pearson correlation coefficients for eleven indicators: pedestrian safety (PS), street environmental safety (SES), degree of street motorization (DM), degree of street traffic congestion (DC), green view index (GVI), proportion of sky visibility (SV), building enclosure (BE), number of enterprises producing chemical pollution (ECP), number of enterprises producing industrial noise (EIN), number of street intersections (SIs), and number of surrounding bus stops (BSs). The matrix in Figure 5 provides a comprehensive overview of the pairwise relationships among these indicators, revealing several noteworthy correlations.

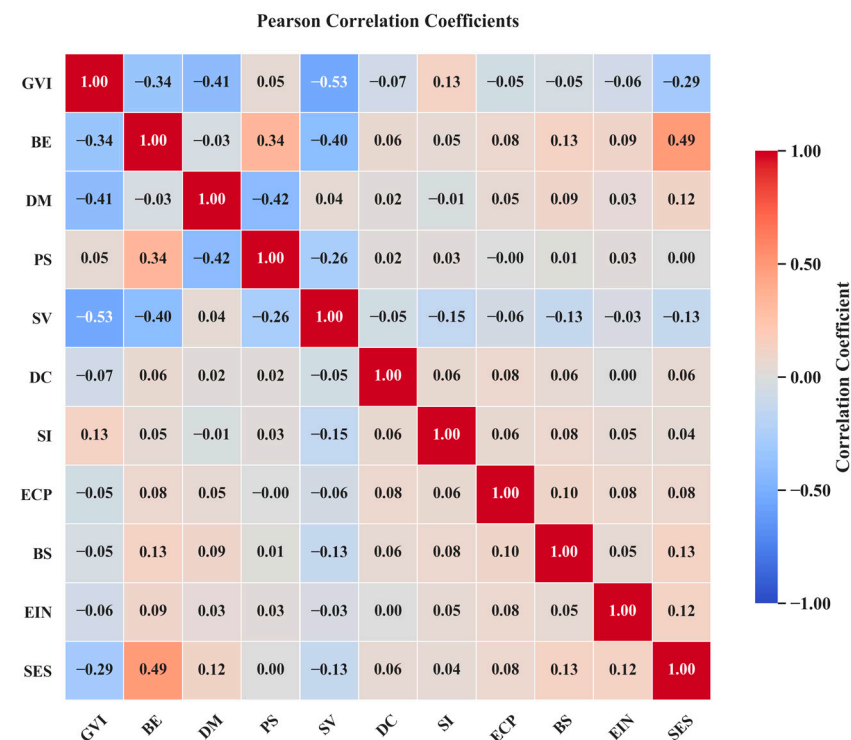


Figure 5. Correlation coefficients between eleven indicators.

(1) Moderate correlations

The analysis identifies several moderate correlations. GVI is negatively associated with SV (-0.53), suggesting that areas with higher greenery coverage often exhibit reduced sky visibility, potentially due to dense vegetation or tree canopies. GVI also shows a moderate negative correlation with DM (-0.41), indicating that greener areas may correspond to lower motorization levels. Conversely, BE demonstrates a moderate positive correlation with SES (0.49), implying that urban areas with higher building enclosure are often perceived as safe for pedestrians. Furthermore, DM is moderately negatively correlated with both PS (-0.42) and GVI (-0.41), illustrating the complex interactions between motorization, pedestrian safety, and urban greenery.

(2) Weak correlations

Other indicators predominantly display weak correlations. For instance, PS exhibits a weak negative correlation with SV (-0.26), reflecting a minor association between pedestrian safety and sky visibility. DC demonstrates negligible correlations with most indicators, with the highest being a weak positive correlation with ECP (0.08). Similarly, SI and ECP exhibit weak positive correlations with BE (0.05 and 0.08 , respectively). Additionally, SI, BS, and SES show weak negative correlations with SV (-0.15 , -0.13 , and -0.13 , respectively).

4.2. Weights of Evaluation Indicators for Pedestrian-Perceived Comfort

To evaluate pedestrian-perceived comfort on urban streets, we utilized the EW-AHP method, which combines the subjective strengths of the AHP method and the objective reliability of the entropy weight (EW) method. Detailed calculation steps, including the EW method (Equations (3)–(5)) and the AHP method (Equations (6) and (7)), are described in Section 3.5. The final weights were determined by combining both methods (Equations (8)–(10)), with optimization coefficients $a = 0.711$ and $b = 0.289$, indicating a stronger reliance on the entropy weight method.

Table 1 presents the weights of the evaluation indicators calculated using the EW-AHP method. For instance, pedestrian safety (PS) was assigned an EW weight of 0.144 and an AHP weight of 0.333 , resulting in an EW-AHP weight of 0.143 . Although PS has a lower EW weight, its higher AHP weight reflects its importance as perceived by experts. Similarly, street environmental safety (SES) received a lower EW weight (0.037) but a higher AHP weight (0.667), resulting in an EW-AHP weight of 0.108 . This finding underscores the critical role of SES in pedestrian-perceived comfort and highlights the importance of expert judgment in the AHP method.

Table 1. Weights of evaluation indicators.

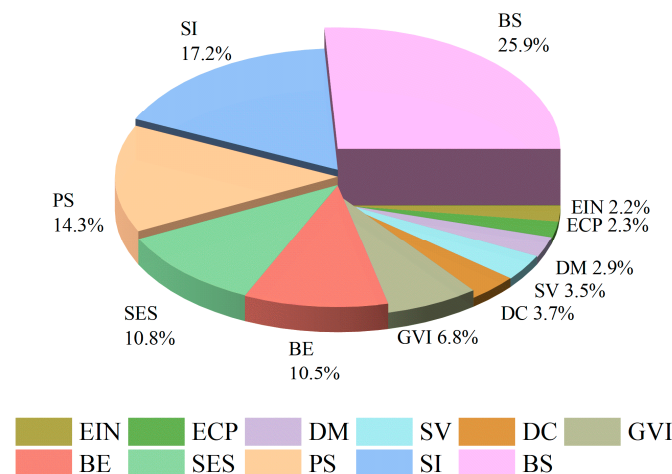
Dimension	Indicator	AHP	EW	EW-AHP
Street safety	Pedestrian safety	0.333	0.144	0.143
	Street environmental safety	0.667	0.037	0.108
Street mobility	Degree of street motorization	0.333	0.020	0.029
	Degree of street traffic congestion	0.667	0.009	0.037
Street aesthetics	Green view index	0.549	0.064	0.068
	Proportion of sky view	0.211	0.037	0.035
	Building enclosure	0.241	0.133	0.105
Street perceptibility	Number of enterprises producing chemical pollution	0.500	0.003	0.023
	Number of enterprises producing industrial noise	0.500	0.500	0.022
Street convenience	Number of street intersections	0.333	0.333	0.172
	Number of surrounding bus stops	0.667	0.667	0.260

In this study, the AHP model was constructed with a three-layer structure: a top-level goal layer (pedestrian-perceived comfort on urban streets), a criterion layer (five first-level indicators: street safety, mobility, aesthetics, perceptibility, and convenience), and an indicator layer (eleven second-level indicators). Table 2 summarizes the final weights of each indicator, revealing the relative importance of these factors in shaping pedestrian-perceived comfort.

Table 2. AHP weights of evaluation indicators.

Goal	Criterion	Weight	Indicators	Weight
Pedestrian-perceived comfort on urban streets	Street safety	0.421	Pedestrian safety	0.333
			Street environmental safety	0.667
	Street mobility	0.157	Degree of street motorization	0.333
			Degree of street traffic congestion	0.667
	Street aesthetics	0.143	Green view index	0.549
			Proportion of sky view	0.211
			Building enclosure	0.241
	Street perceptibility	0.143	Number of enterprises producing chemical pollution	0.500
			Number of enterprises producing industrial noise	0.500
	Street convenience	0.136	Number of street intersections	0.333
			Number of surrounding bus stops	0.667

Figure 6 shows the weight distribution of the indicators determined by the EW-AHP method. The number of surrounding bus stops (BSs), with the highest weight of 25.9%, is the most influential factor, emphasizing its importance in street convenience assessment. Pedestrian safety (PS) and street environmental safety (SES) were assigned weights of 14.3% and 10.8%, respectively, reflecting the critical role of street safety in pedestrian-perceived comfort. Despite the low weights of the number of enterprises producing industrial noise (EIN, 2.2%) and the number of enterprises producing chemical pollution (ECP, 2.3%), street perceptibility remains a critical dimension for urban planners in assessing pedestrian-perceived comfort on urban streets.

**Figure 6.** Weight distribution of standardized indicators. (Round to one decimal place).

4.3. Construction and Validation of an Evaluation Model

The evaluation model for pedestrian-perceived comfort (PC) on urban streets was constructed using weighted indicators, as shown in Equation (12):

$$PC = 0.143PS + 0.108SES + 0.029DM + 0.037DC + 0.172SI + 0.260BS + 0.068GVI + 0.072SV + 0.070BE + 0.086ECP + 0.085EIN \quad (12)$$

Here, PS, SES, DM, DC, SI, BS, GVI, SV, BE, ECP, and EIN are normalized indicator values (refer to the Appendix for the code). The coefficient represents the weight of the

indicator determined by EW-AHP. PC represents the overall pedestrian-perceived comfort score integrating normalized indicator values and weights to calculate. This model quantitatively synthesizes multidimensional factors influencing pedestrian-perceived comfort, covering safety, mobility, environmental quality, and convenience.

To validate the accuracy of our experimental results, a validation study was conducted using subjective comfort scores derived from 172 questionnaire responses corresponding to the surveyed street segments. These survey-derived comfort scores were compared with the model evaluations. The results yielded a correlation (r) of 0.726 with a significance level (p -value) of less than 0.01 (Figure 7), indicating a strong positive correlation between the variables. Therefore, the evaluation results closely align with the actual levels of pedestrian-perceived comfort observed on the streets in Nanjing's main urban areas, emphasizing the effectiveness and precision of the proposed evaluation system.

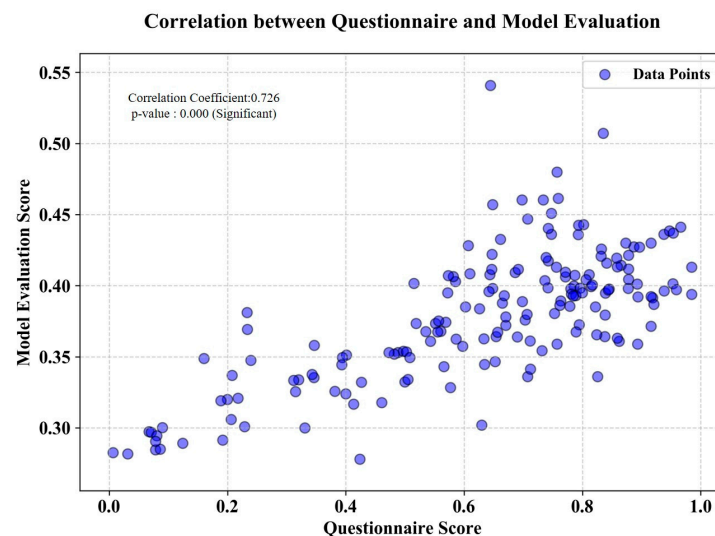


Figure 7. Correlation between questionnaire survey results and model evaluation.

4.4. Spatial Distribution of Pedestrian-Perceived Comfort

EBK results were categorized into five classes using the natural break method [61]. Table 3 presents detailed classification criteria and Figure 8 presents the spatial distribution of pedestrian-perceived comfort.

Table 3. Classification of pedestrian-perceived comfort levels.

Pedestrian-Perceived Comfort Level	Values
Low Comfort	$0.29 \leq p < 0.35$
Moderate Low Comfort	$0.35 \leq p < 0.37$
Moderate Comfort	$0.37 \leq p < 0.39$
Moderate High Comfort	$0.39 \leq p < 0.42$
High Comfort	$0.42 \leq p \leq 0.56$

Specific colors represent pedestrian-perceived comfort levels on urban streets. Dark green (high comfort) denotes the highest level of comfort, indicating areas characterized by superior ambient conditions and minimal traffic congestion. Green (moderate high comfort) indicates a relatively high level of comfort with potential minor traffic congestion or environmental discomfort. Yellow (moderate comfort) reflects streets that may experience moderate congestion issues such as occasional mobility challenges or other environmental discomfort. Orange (moderate low comfort) represents streets with comfort detractors such as frequent traffic congestion, noise disturbances, or suboptimal aesthetic surroundings. Red (low com-

fort) represents the lowest level of comfort, potentially caused by heavy traffic, poor street maintenance, high noise pollution, or inferior environmental quality.

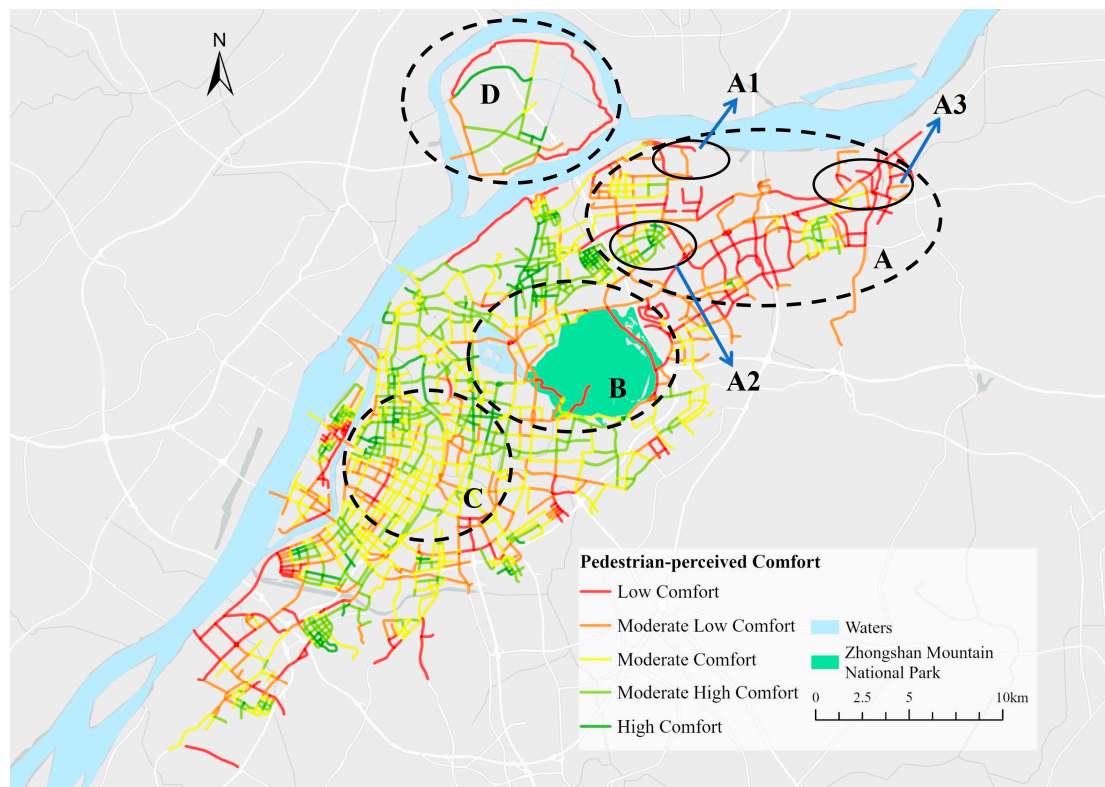


Figure 8. Spatial distribution of pedestrian-perceived comfort on urban streets. (Note: The eastern part of Qixia District was excluded due to missing SVIs. Areas A, B, C, and D denote the selected analysis areas, and A1, A2, and A3 are sub-areas within area A).

One can see higher pedestrian-perceived comfort levels in the city center and lower levels in the periphery. The city center, with its concentration of high-quality development resources and spatial qualities, exhibits excellent performance in terms of transportation, services, environment, and safety, resulting in higher comfort levels. Conversely, the peripheral zones exhibit lower pedestrian-perceived comfort levels, indicating poor conditions.

5. Discussion

5.1. Evaluation of Pedestrian-Perceived Comfort on Urban Streets

As shown in Figure 8, comfort levels vary significantly in the peripheral study area of the Qixia District (area A). Qixia Mountain (area A1), a well-known attraction, provides a scenic environment along Qixia Avenue. The extant literature indicates that natural quiet spaces, like parks and rural areas, have enhanced comfort levels [62]. However, this area experiences substantial daily traffic, including numerous trucks. An increase in the number of trucks may be related to traffic safety concerns, which also affect pedestrian perceptions. Wang and Yu (2019) [63] found that 80% of people believe that heavy trucks on the road impact road safety. By contrast, Xianlin University City (area A2), which is known for its high-density educational institutions, enjoys well-maintained streets and an agreeable environment. These factors contribute to high pedestrian-perceived comfort levels, as observed around Nanjing Normal University. This finding aligns with previous research indicating that poor aesthetics can detract from walking experience [62]. Conversely, in commercial areas, like the Golden Eagle Lakefront and Big Famous Shop Park, the presence of street stores, advertisements, and diverse demographic compositions contribute

to suboptimal street conditions, compromising pedestrian safety and comfort. These findings align with the existing literature linking advertisements, shops, and signboards with negative effects on the pedestrian environment [64]. In region A3, high vehicular traffic on the Shugang and Baohua Avenues also detracts from pedestrian-perceived comfort. In areas with heavy traffic, people must be constantly aware of their surroundings, which can reduce their comfort [65]. Furthermore, the health risks associated with motor traffic have been well documented [66] and the negative auditory experience of traffic further exacerbates discomfort [67].

Streets adjacent to landscape elements, like mountains and bodies of water, are often influenced by terrain and construction challenges, which can result in a lower road network density, larger block sizes, and increased proportions of dead-end streets and T-intersections. Such intersections increase the risk of pedestrian–vehicle collisions [68]. However, mountain and water elements typically enhance ecological richness, leading to higher green space ratios in the surrounding areas. Consequently, urban streets near such elements exhibit higher green view rates and greater sky views, which positively affect the overall street environment. For example, areas near Zhongshan Mountain National Park (area B) exhibit a high green view index, accompanied by relatively expansive sky visibility, contributing to a visually pleasing environment [69]. Prior research also indicates that vegetation positively affects street comfort [70]. However, notable tourist attractions, like Zhongshan Mausoleum and Ming Xiaoling Mausoleum, attract large crowds, leading to high traffic flow and reduced street mobility. Therefore, on some popular streets, such as Lingyuan Road and Huanling Road, the level of pedestrian-perceived comfort is affected because they attract a large number of tourists. The influx of tourists not only increases congestion but also places additional strain on existing infrastructure, potentially diminishing the overall pedestrian experience. Regardless, effective traffic management measures ensure an overall high level of pedestrian-perceived comfort. This observation is consistent with existing research on traffic congestion detracting from tourism experiences by reducing the time available for participation in activities and creating negative perceptions [71]. The pedestrian-perceived comfort levels around the Inner Ring North Line circular interchange are notably lower, primarily due to its proximity to Nanjing Railway Station and its connection to Xuanwu Avenue. This interchange is characterized by complex traffic conditions, including heavy traffic flows and intricate road layouts, which contribute to a less conducive environment for pedestrians. Moreover, the area's strategic function as a major transportation hub exacerbates these challenges, as the concentration of vehicular movement increases the likelihood of safety risks, further diminishing pedestrian comfort in this area.

Central Nanjing (area C) exhibits a relatively high level of pedestrian-perceived comfort. This region is characterized by an abundance of premium resources and infrastructure, particularly in the vicinity of Xinjiekou. Despite the presence of an intricate road network and substantial pedestrian traffic, the implementation of pedestrian underpasses and consistent presence of traffic police have effectively promoted pedestrian comfort and safety, contrasting with studies indicating that urban centers with heavy traffic and busy streets often lead to negative perceptions [72]. Conversely, the pedestrian-perceived comfort along Jiangdong Zhonglu, particularly in the vicinity of the Nanjing Olympic Sports Center, is relatively low despite its strategic location and proximity to significant urban infrastructure. This can be attributed to frequent events held at the stadium, resulting in increased pedestrian traffic and congestion, which adversely affect the pedestrian experience. On the other hand, peripheral regions, especially along the Yangtze River, exhibit lower levels of pedestrian-perceived comfort, which can be attributed to inadequate infrastructure, suboptimal traffic management, and the challenges of the riverside environment, which may contribute to pedestrian insecurity.

Jiangxinzhou (area D) is renowned for its pleasant natural surroundings, contributing to relatively high levels of pedestrian-perceived comfort. The positive impact of natural environments on human health and emotions is well established, with the presence of green spaces and natural scenery associated with enhanced well-being and positive emotional responses [73]. However, despite its appealing environment, Jiangxinzhou faces challenges in terms of accessibility. Being situated on an island, the area is somewhat isolated from the rest of the city, and its transportation infrastructure remains relatively under-developed. As a result, the surrounding areas experience lower comfort levels due to limited connectivity and potential difficulties in accessing key urban amenities. This highlights the importance of both environmental quality and transportation infrastructure in shaping overall pedestrian comfort, particularly in more peripheral areas of the city like Jiangxinzhou.

5.2. Integrated Recommendations

Our findings align with previous research highlighting the importance of safety and comfort [64]. Based on these findings, we propose several urban management strategies.

First, enhancing pedestrian infrastructure (e.g., increasing pedestrian refuges and widening sidewalks in high-density areas) is essential for improving safety and comfort. Strengthening the physical separation between pedestrian pathways and roadways by installing additional barriers is also recommended. This intervention is supported by studies that have demonstrated a direct correlation between infrastructure improvements and increased pedestrian satisfaction [74]. Moreover, prioritizing interventions in areas with low pedestrian comfort scores, as identified in this study, can maximize the impact of limited resources.

Second, greenery significantly enhances aesthetic appeal and provides multiple environmental benefits, including the mitigation of urban heat islands and improved air quality. Integrating vegetation along streets and in public squares aligns with the perceptibility and aesthetic dimensions of pedestrian comfort. For instance, increasing the green view index in peripheral areas where comfort levels are lower can reduce disparities and improve urban livability [75].

Third, the strategic deployment of traffic police, expansion of pedestrian pathways, and implementation of speed limit interventions in high-traffic zones can foster a secure environment and improve perceptions of safety. These measures are associated with the public perception of safety and positively contribute to livability [76].

Finally, engaging local communities in the urban planning process ensures that infrastructure improvements align with residents' needs and expectations [77,78]. Community involvement fosters more effective urban design solutions, addressing both sensory and emotional dimensions of comfort. Participatory approaches can also enhance the social acceptance of interventions and strengthen public trust in urban policymaking [18].

By aligning these recommendations with broader urban sustainability goals, such as equitable resource distribution and climate resilience, policymakers can ensure long-term improvements in pedestrian-perceived comfort. The proposed interventions address immediate pedestrian concerns while contributing to the sustainability and livability of urban spaces.

6. Conclusions and Future Work

This study presents a novel framework for evaluating pedestrian-perceived comfort on urban streets using multi-source data and the EW-AHP method to assign weights to indicators. By addressing the common issues of data gaps and single-dimension assessments in current evaluation systems, this approach provides a more comprehensive understanding of pedestrian comfort.

We defined pedestrian-perceived comfort on urban streets and developed an evaluation indicator system based on five dimensions—street perceptibility, safety, aesthetics, mobility, and convenience—and 11 specific indicators. Our findings revealed that the number of surrounding bus stops significantly influences pedestrian-perceived comfort, whereas industrial noise has a relatively minor impact. Spatial analysis revealed that central areas with higher-quality development and better infrastructure offer higher pedestrian-perceived comfort levels compared with peripheral regions, where inadequate infrastructure and poor traffic management contribute to lower comfort.

These findings have important implications for urban planning and policy. The proposed evaluation system can help urban planners better understand the multidimensional aspects of pedestrian-perceived comfort, guiding decisions on infrastructure priorities and resource allocation. Policymakers can use these insights to develop targeted interventions like improving street safety through widened sidewalks and pedestrian barriers; enhancing aesthetics with increased greenery; promoting mobility by optimizing traffic management; improving perceptibility by reducing pollution, thereby creating more livable, sustainable urban environments; and improving the convenience of streets by increasing the number of surrounding bus stops.

Despite these contributions, further refinement is needed. Future research should integrate a temporal dimension to explore variations in pedestrian-perceived comfort levels across different times of the day (e.g., rush hours versus off-peak hours) and between weekdays and weekends. Additionally, incorporating a broader range of SVIs and conducting more comprehensive field surveys will enhance the model's robustness and applicability. Efforts should also be directed toward adapting the model for applications across various urban environments, ensuring its transferability and generalizability.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/ijgi14020063/s1>, Questionnaire survey: Survey on the Pedestrian-Perceived Comfort of Streets in Nanjing; Table S1: Selection Results of Questionnaire Indicators; Table S2: Scoring Results of the Street Survey (Partial); Table S3: Scale of Pairwise Comparison for the AHP; Table S4: Criteria Layer Weights; Table S5: Consistency test results summary; Table S6: Weights for Street Safety Indicators; Table S7: Weights for Street Mobility Indicators; Table S8: Weights for Street Aesthetics Indicators; Table S9: Weights for Street Perceptibility Indicators; Table S10: Weights for Street Convenience Indicators; Table S11: Weight of Each Indicator; Table S12: AHP Measurement of Street Comfort Index Weights; Table S13: Weight of Each Indicator (entropy); Table S14: Weight of Each Indicator (EW-AHP). References [2,79] are cited in the Supplementary Materials.

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Data Availability Statement: The data in this study are openly available. Points of interest (POI) and RT real-time traffic data (RT) were obtained from the application programming interface (API) of Amap, available at <https://ditu.amap.com>; road network data were obtained from the OpenStreetMap platform (<https://www.openstreetmap.org/#map=5/35.59/134.38>, accessed on 13 December 2023); SVIs were collected from the Baidu Map Open Platform (<https://lbsyun.baidu.com>, accessed on 21 September 2021). The questionnaire survey data cannot be provided.

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Conflicts of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

Table A1. Definitions and calculations of street perceptibility indicators.

Dimension	Indicators	Description	Calculation	Sources
Street perceptibility	Number of enterprises producing chemical pollution (ECP)	Number of enterprises per street that can cause chemical pollution, measuring the direct impact on residents' sense of smell and environmental health.	Number of chemical enterprises, metallurgical industries, and gas stations within a 300 m radius around each sampling point on the specified street.	POI
	Number of enterprises producing industrial noise (EIN)	Number of enterprises per street that potentially generate industrial noise, measuring the direct impact on pedestrians' auditory disturbance and noise pollution levels.	Number of factories and automotive repair enterprises within a 200 m radius around each sampling point on the specified street.	POI

Table A2. Definitions and calculations of street safety indicators.

Dimension	Indicators	Description	Calculation	Sources
Street safety	Pedestrian Safety (PS)	Quantitative assessment of pedestrian sidewalks and non-motorized lane usage, combined with pedestrian distribution, providing a basis for improving PS.	$PS = \frac{C_{sidewalk} + C_{bike} + C_{person}}{C_{svi}}$ $C_{sidewalk}$ is the number of pedestrian sidewalk pixels in SVIs; C_{bike} is the number of non-motorized vehicle pixels; C_{person} is the number of pedestrian pixels; and C_{svi} is the total number of pixels.	SVIs
	Street Environmental Safety (SES)	Evaluation of pedestrians' subjective sense of safety in urban street environmental factors, including lighting, surveillance equipment, and other elements.	Pedestrian scores for street safety were obtained from the questionnaire.	Questionnaire

Table A3. Definitions and calculations of street aesthetics indicators.

Dimension	Indicators	Description	Calculation	Sources
Street aesthetics	Green view index (GVI)	Reflects the extent of vegetation coverage in SVIs. It is crucial for enhancing urban environmental aesthetics and promoting mental well-being among residents.	$GVI = C_{plant} / C_{svi}$ C_{plant} is the number of green vegetation pixels in SVIs and C_{svi} is the total number of pixels.	SVIs
	Proportion of sky view (SV)	Quantifies the proportion of sky visibility at specific points, significantly influencing residents' spatial perception.	$SV = C_{sky} / C_{svi}$ C_{sky} is the number of sky pixels in SVIs.	SVIs
	Building enclosure (BE)	Quantifies building layout and height on both sides of the street, influencing the degree of spatial enclosure, which affects pedestrians' spatial experience and the comfort of public spaces.	$BE = C_{building} / C_{svi}$ $C_{building}$ is the number of building and wall pixels in SVIs.	SVIs

Table A4. Definitions and calculations of street mobility indicators.

Dimension	Indicators	Description	Calculation	Sources
Street mobility	Degree of street motorization (DM)	Reflects the city's traffic structure and motorization level. This information is of paramount significance for guiding traffic planning and promoting sustainable transportation development.	$DM = \frac{C_{car}}{C_{car} + C_{road}}$ C_{car} refers to the number of pixels representing motor vehicles in SVIs; C_{road} denotes the number of pixels representing streets.	SVIs
	Degree of street traffic congestion (DC)	Combines indicators such as traffic volume, vehicle speed, and vehicle density, and is used to evaluate unobstructed traffic flow and efficiency.	Obtained through real-time traffic data from AMap.	Real-time traffic data

Table A5. Definitions and calculations of street convenience indicators.

Dimension	Indicators	Description	Calculation	Sources
Street convenience	Number of street intersections (SIs)	Evaluates the complexity and connectivity of the urban traffic network, and directly impacts traffic flow efficiency and pedestrian crossing safety.	Calculated using POI data.	POI
	Number of surrounding bus stops (BSs)	Reflects the convenience of public transportation around urban streets. It is crucial for enhancing residents' convenience and expanding the coverage of the urban traffic network.	Calculated using POI data within a 100 m radius.	POI

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