



OPEN

Evaluation of spatial visual perception of streets based on deep learning and spatial syntax

Mingyang Yu¹✉, Xin Chen¹, Xiangyu Zheng¹, Weikang Cui^{1,2}, Qingrui Ji¹ & Huaqiao Xing¹

Street visual quality improvement plays an important role in urban development. An important direction for street quality research lies in accurately perceiving the spatial quality of urban streets and exploring the connection with street constituents. This study applies deep learning to extract visual elements from street view images and uses a human-machine adversarial model to rate them across six dimensions (beautiful, wealthy, safety, lively, depressing, and boring). Through spatial visualization of street quality, overlay analysis with network accessibility, and multiple linear regression, it examines the correlations between street space quality and its constituent elements. The results indicate that the streets within the study area scored highly on the dimensions of beautiful and lively, this is attributed to the reasonable greening construction which characterized by the good layout and density of greenery. Such greening not only enhances aesthetics but also provides environmental benefits. Additionally, the orderly street layout reflects well-organized spatial arrangements of street elements, such as pathways and building facades. Positive visual perception such as beautiful, wealthy, safety, lively is positively correlated with plants and pedestrians, and negatively correlated with walls. It is important to address the distinct types of streets in urban planning, including high-quality/ accessibility streets found in urban centers, high-quality/low-accessibility streets at district junctions with sparse networks, low-quality/high-accessibility streets in the southwestern center and Low-quality/accessibility peripheral areas characterized by outdated buildings. Strategies should prioritize improvements in street function, greening, building interfaces, and pedestrian connectivity. These measures will help enhance the overall spatial quality and vitality of the area. In summary, the findings provide data support for more precise urban street improvements and offer a reference for human-centered urban planning research.

Keywords Deep learning, Street images, Spatial syntax, Urban planning

Streets are essential public spaces for urban residents, providing a physical and social environment for daily interactions and recreation¹. As vital connectors between people and the city, streets shape residents' experiences, influencing mobility, safety, social interaction, and overall urban life. City managers increasingly focus on street design to enhance socio-economic and cultural activities, aiming to create more sustainable, livable environments². City managers are paying increasing attention to the design and planning of urban streets as important hubs of socio-economic and cultural activities. A deep understanding of the intricate relationship between the components of urban streets and human perception is conducive to a harmonious and sustainable urban environment. Traditionally, planners and designers relied on labor-intensive methods such as on-site surveys or static maps, which provided limited insights into the visual and spatial qualities of streets. Inadequate technology for large-scale data processing and a lack of comprehensive data sources have hindered the development of scientific and rational street planning blueprints.

The emergence of streetscape imagery has overcome the previous limitations on the availability of data sources for assessing streets^{3,4}. Streetscape images are electronic maps based on actual landscapes, and these maps provide richly detailed streetscape images with a wide range of coverage containing a large amount of information about city streets^{5,6}. Therefore, these street view images have the potential to become an important form of supporting data for assessing the visual perception of city streets. Currently, a number of Internet companies such as Google, Microsoft, Baidu, and Tencent have launched online street view services^{7,8}. In China, Baidu Maps' online Street View service already covers a large number of streets in most cities.

¹School of Surveying and Geo-Informatics, Shandong Jianzhu University, Jinan 250101, China. ²Inspur Smart City Technology Co., Ltd, Jinan 250014, China. ✉email: ymy@sdjzu.edu.cn

As a new data source, Street View images have gradually become a research hotspot. A large number of urban studies based on Street View images include 3D city reconstruction studies^{9,10}, specific scene recognition¹¹, perceptual safety assessment¹², alcohol consumption data extraction¹³, assessment of visual perception of streets¹⁴, and other related areas. Among them, visual perception of streets is the basis for exploring urban planning and quality of life of residents¹⁵. Meanwhile, with the advancement in the field of computers, it is now possible to utilize convolutional neural networks for fast and accurate fine-grained processing of street images. This technique can effectively recognize various elements such as buildings, roads, pedestrians, and greenery¹⁶. Through the combination of deep learning technology and streetscape images, it can provide refined basic data for the study of street spatial quality, and at the same time, it can quickly process large-scale data, making it technically possible to quickly and accurately measure the visual quality of streets on a large scale.

However, current research still falls short in revealing the quantitative relationship between street components and human subjective perception, lacking both systematic approaches and scalability. Consequently, an urgent research gap exists regarding how to combine emerging large-scale street view data and deep learning technologies to achieve high-precision, wide-coverage measurement of street visual quality. Against this backdrop, this study endeavors to bridge the aforementioned gap: on the one hand, advanced methods such as deep learning and space syntax are employed to comprehensively quantify street visual quality and its constituent elements; on the other hand, subjective perception dimensions are integrated with objective quantitative metrics to systematically evaluate how the street environment influences residents' daily lives and urban development. This integration enhances our understanding of the intricate relationship between street visual characteristics and residents' experiences, thereby offering more targeted optimization strategies for urban planning and decision-making.

In this study, considering the subjective feelings of people who are the main users of streets and the objective physical characteristics of streets, an efficient evaluation model of urban street visual quality is constructed by using multi-source big data such as street view images and OSM street vector data, combined with deep learning, spatial syntax and Random Forest model. It can be used for large-scale and high-detailed evaluation of the visual quality of urban streets to better provide reference for urban planning assessment and assisted decision-making, as well as the improvement of the quality of the human environment.

Literature review

Traditional street quality study

The study of street space quality has its roots in the 1960s, with seminal contributions from urban theorists such as JACOBS J and LEFEBVRE H, who emphasized the human-scale perspective in urban design. Jacobs, in her work *The Death and Life of Great American Cities* (1961), critiqued the separation of functions in cities and argued that the vitality of streets is directly linked to their ability to support diverse, pedestrian-friendly environments¹⁷. Lefebvre, in *The Production of Space* (1974), introduced the idea that the spatial organization of cities is a socially constructed phenomenon, influencing both daily life and urban interactions¹⁸. These early studies laid the groundwork for understanding the importance of human-scale urban design, focusing on the street as a space of social interaction and pedestrian use.

Building on these foundations, Kevin Lynch's influential book *The Image of the City* (1960) further explored the way individuals perceive and experience urban spaces. Lynch's work emphasized the concept of "imageability" and how streets contribute to the legibility and identity of cities¹⁹. His framework categorized urban spaces into elements such as paths, edges, districts, nodes, and landmarks, providing a systematic approach for evaluating street spaces from a psychological and sensory perspective.

As urban studies progressed, research on street quality expanded to cover various types of urban environments, including commercial districts²⁰, public squares²¹, and residential streets²². For example, studies have highlighted the role of pedestrian-friendly streets in enhancing social interaction and contributing to the economic vitality of city centers. In contrast, other research has examined the impact of traffic congestion, safety, and environmental factors on the perceived quality of streets in residential areas²³. These studies have revealed that street quality is a multifaceted concept, encompassing physical, social, and psychological dimensions.

Over the past few decades, there has been a marked shift towards more objective and systematic methods of street quality evaluation. Traditional approaches, which relied heavily on manual measurement and subjective assessment, often faced challenges in scalability and precision. For instance, methods such as surveys and visual inspections were limited by researcher biases and logistical constraints, making large-scale and detailed assessments of street quality difficult to conduct. In response to these limitations, there has been a growing trend toward integrating quantitative techniques into street quality analysis²⁴.

One significant milestone in the development of quantitative methods for street evaluation was the introduction of spatial syntax in 1984 by Bill Hillier and Julienne Hanson²⁵. Spatial syntax focuses on the topological properties of street networks, enabling researchers to quantify and visualize accessibility, connectivity, and movement patterns within urban spaces. This approach provides valuable insights into the structural organization of streets, as well as their potential for fostering social interactions and facilitating efficient transportation. Today, spatial syntax remains an essential tool in urban planning and design, with applications ranging from large-scale city planning to micro-level pedestrian movement analysis²⁶.

Street quality research incorporating big data

The rapid advancement of computer technology has greatly expanded the ways in which urban street quality can be analyzed. The diversification of data collection methods, particularly with the introduction of Point of Interest (POI) data, has enabled more comprehensive and precise quantitative evaluations of street spaces. POI data, which captures locations of notable urban features such as shops, public facilities, and cultural landmarks, has proven especially useful in urban studies. Zhang et al. (2019) leveraged POI data and public awareness tasks to map the accuracy of POI data to the linear space of streets, creating a detailed method for classifying street

types based on urban functions and use patterns²⁷. This approach marked a significant step in fine-grained street quality assessment, allowing for a more nuanced understanding of how different types of streets serve their surrounding communities. Similarly, Liu et al. (2021) used POI data to analyze the relationship between urban street characteristics and economic activity, showing how street designs influence commercial vitality in urban areas²⁸. Qin et al. (2020) explored the relationship between street vitality and urban data in tourist cities, combining POI data with Baidu heat maps and OpenStreetMap (OSM) road network data. Their study offered insights into how different types of urban spaces, such as tourist districts, are shaped by the dynamics of human activity and transportation networks²⁹. Such studies show how big data can not only support basic spatial assessments but also provide dynamic metrics for understanding the vitality and usage patterns of streets in real time. Additionally, Zhao et al. (2021) extended this analysis by incorporating weather and traffic data, showing that street vitality in tourist districts is highly sensitive to external factors such as weather conditions and public transport availability³⁰.

As the availability of data sources has grown, quantitative measurement techniques for street quality have become increasingly diverse. Geographic Information Systems (GIS) remain one of the most widely adopted methods, offering powerful tools for spatial analysis and integration of various datasets, such as road networks, POI, and demographic data. GIS-based evaluations are commonly employed to assess street accessibility, walkability, and the distribution of urban amenities. Research by Xiao et al. (2021) demonstrated how GIS-based models, integrating POI and traffic data, can be used to assess the accessibility and pedestrian comfort of city streets³¹. These approaches, coupled with demographic data, have allowed for a deeper understanding of how street designs impact the accessibility and inclusivity of urban spaces. Similarly, Wang et al. (2022) applied GIS to assess the impact of green spaces on urban street quality, finding that areas with higher green coverage tend to exhibit better pedestrian experiences and overall street satisfaction³².

Furthermore, the integration of 3D modeling and virtual reality (VR) technologies into street quality research has provided new possibilities for spatial analysis. In recent years, 3D modeling techniques have gained popularity for their ability to represent urban streets in high detail. 3D models, particularly those generated using virtual reality (VR) and augmented reality (AR) technologies, allow for immersive and interactive experiences that aid in evaluating street environments. Studies like those by Zhao et al. (2022) have explored how 3D simulations can be used to assess not only the visual appeal of streets but also their functionality in terms of pedestrian movement, traffic flow, and environmental conditions³³. This method offers a more comprehensive approach to street evaluation, incorporating both physical and experiential aspects of street quality. Furthermore, Liu and Wang (2023) developed a 3D GIS model that enables real-time evaluation of urban streets, incorporating traffic data, pedestrian flow, and environmental attributes to create a holistic street quality assessment framework³⁴.

While these advancements have enhanced the capabilities of street quality research, there remain challenges related to the vast amounts of data involved and the complexity of processing such data. Large-scale refinement of urban street evaluations, using diverse data types such as POI, heat maps, GIS layers, and 3D models, presents significant difficulties in data integration and analysis. The variability of data formats, inconsistencies in data quality, and the need for advanced computational tools to process and synthesize these complex datasets continue to pose obstacles. Nonetheless, the combination of big data and advanced spatial analysis techniques holds great potential for revolutionizing the study of urban street environments. Recent studies have also emphasized the importance of machine learning (ML) techniques to overcome these challenges. For example, Wang et al. (2023) employed deep learning algorithms to automatically classify and analyze street images and POI data, significantly improving the efficiency and accuracy of street quality assessments³⁵. Such approaches represent the next frontier in urban research, where automation and advanced analytics play a key role in handling the complexity of big data in urban planning.

Street quality research based on big data and artificial intelligence

In recent years, the rapid development of big data technologies and artificial intelligence (AI) has significantly transformed the field of urban street quality research. Traditionally, street quality assessment relied on manual evaluations and qualitative metrics. However, with the advent of big data and machine learning (ML), the scope of analysis has expanded dramatically, allowing for more efficient, scalable, and objective evaluations of urban streets. Among the most promising techniques are deep learning algorithms, particularly convolutional neural networks (CNNs), which have demonstrated substantial success in image analysis and spatial pattern recognition.

Machine learning, a concept introduced by Samuel in 1959, has paved the way for intelligent systems that learn from data and improve over time³⁶. Deep learning, a subfield of ML, has taken this further by enabling computers to process and interpret vast amounts of visual and behavioral data. Algorithms such as Fully Convolutional Networks (FCNs), ResNet and SegNet now allow for sophisticated analysis of images and spatial data. These models can extract visual features from street-level imagery, such as roads, buildings, sidewalks, trees, and green spaces, enabling researchers to assess street quality in a manner that was previously impossible^{37,38}.

The application of deep learning to urban research is particularly evident in the analysis of streetscape imagery. Through deep learning techniques, researchers are now able to automatically identify and classify various urban elements, which can then be used to quantify street quality and inform urban design decisions. A notable project, the “Place Pulse” initiative, launched by MIT’s Media Lab, collected public evaluations of cityscapes through online surveys and paired photos. This project provided a large dataset (over 1.17 million image pairs) that has become a valuable resource for understanding public perceptions of urban environments³⁹. By analyzing this data, researchers can examine how different visual elements of streetscapes (e.g., the presence of greenery, building heights, and overall design) contribute to perceptions of aesthetic appeal and urban quality.

Zhang (2020) utilized deep learning methods and the Place Pulse dataset to evaluate urban street quality in Beijing and Shanghai. By correlating visual elements with public perception scores, the study identified key

features that influence perceptions of street environments. The results highlighted the significant role of visual factors such as trees, greenery, and the built environment in shaping perceptions of street quality and urban livability. Additionally, the study considered multiple dimensions, including beautiful, wealthy, safety, lively, depressing, and boring, which all play a crucial role in shaping the overall perception of street environments⁴⁰. Other studies, such as those by Liu et al. (2021) and Li and Guo (2021), have followed similar approaches, expanding the use of deep learning to other urban quality indicators like safety, walkability, and environmental comfort^{41,42}.

In addition to visual perception analysis, AI and big data are increasingly being used to predict various factors that influence street quality. In 2021, Wang et al. applied deep learning models to predict street walkability in Beijing, incorporating factors such as street view images, traffic patterns, and environmental data⁴³. Their work demonstrated the ability of AI to assess how street design and environmental factors impact pedestrian comfort and overall street vitality. This predictive capability allows urban planners to identify areas in need of improvement and to make data-driven decisions regarding urban infrastructure.

The integration of big data and artificial intelligence in street quality research is highly relevant to current trends in urban studies, urban planning, and smart city development. As cities continue to grow and face increasingly complex challenges related to sustainability, mobility, and livability, AI and big data offer critical tools for understanding and improving urban spaces. The ability to quantify street quality, predict environmental changes, and optimize urban design based on data-driven insights is central to the development of more resilient and adaptable cities. Moreover, the insights derived from AI-driven analysis can inform policy-making and urban planning strategies, promoting the creation of more sustainable, inclusive, and livable urban environments.

As the field progresses, there is an increasing emphasis on using AI and big data to create “smart cities” where real-time data is collected and analyzed to optimize urban living. This research trend aligns with the global push towards data-driven decision-making in urban development, marking a paradigm shift in how cities are planned, designed, and experienced.

Materials and methods

Study area

This research focuses on Jinan (Fig. 1), the capital of Shandong Province, covering 7,200 square kilometers with a population of approximately 9 million. As a key political, economic, cultural, and transportation center, Jinan has seen significant urban development in recent years, the municipal government has implemented various policies and programs aimed at improving street infrastructure, environmental functions, and the urban landscape. Notably, these initiatives include road network upgrades, the expansion of green spaces, the introduction of smart city technologies for traffic management, and efforts to enhance pedestrian-friendly environments. These policies have significantly contributed to the improvement of street quality and the overall urban landscape.

Jinan was selected for this study due to its recent urban improvements and availability of high-quality street image data, which enhances the accuracy of street quality assessments. While other Chinese cities also have ample street image data, Jinan stands out due to its comprehensive urban development initiatives, making it a representative case for studying street quality in rapidly urbanizing cities.

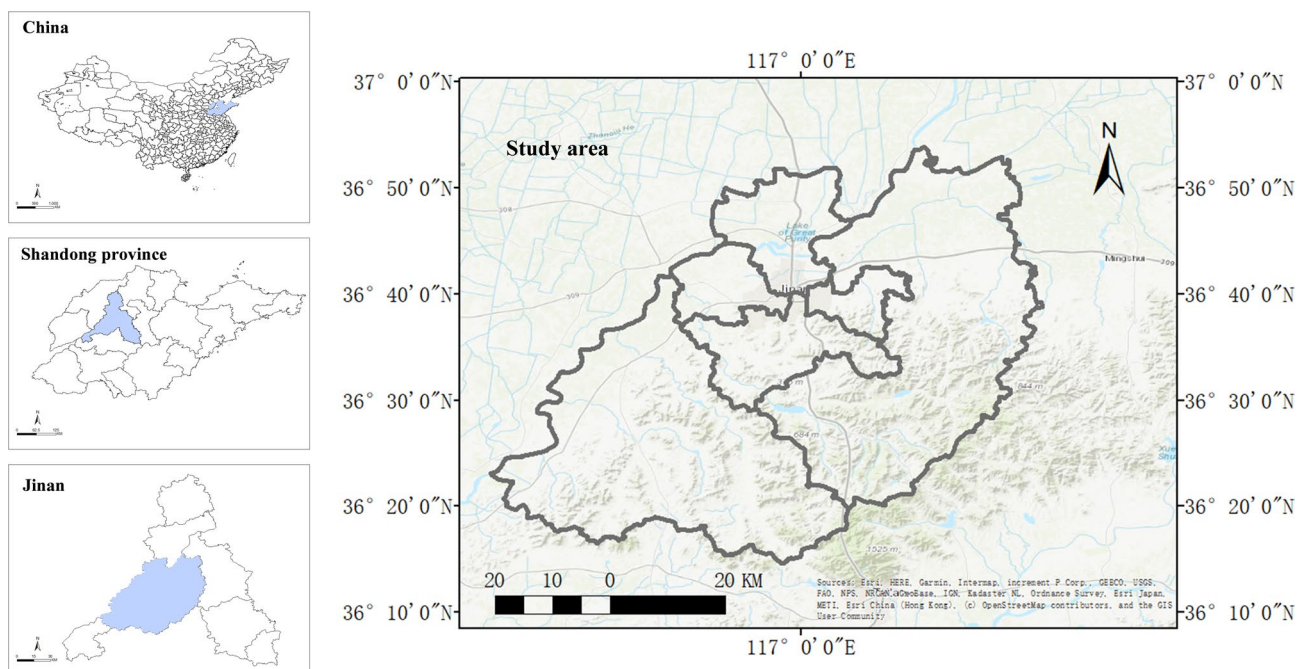


Fig. 1. Study area.

Research framework

The study proposes a large-scale quantitative assessment method for street spatial visual perception (Fig. 2) to explore the intrinsic connection between different street components and human perception and to further supplement the results of spatial perception of streets with spatial syntax. The research framework consists of three main processes: (1) Using the free and open API interface of Baidu Maps to obtain street view images, and constructing the street view image dataset in the study area. (2) The elemental composition of urban streets is extracted using the SegNet semantic segmentation model, and the human-computer confrontation model is used to quantitatively analyze the spatial visual perception of streets, and the spatial syntax is used to process the urban street network, and the accessibility of each street is measured on the basis of the 500 m accessibility radius (the average walking distance of residents). (3) The results of street accessibility analysis and visual perception scores are superimposed and analyzed to establish an evaluation matrix based on the dimensions of “quality evaluation” and “accessibility” to find out “streets with potential for renewal” in the study area. The results are used to identify “streets with renewal potential” in the study area, and to provide refined technical support for urban micro-renewal.

Constructing street view image dataset

In recent years, street view data has been widely used in urban planning studies⁴⁴, and street view images present information about urban infrastructure from a pedestrian perspective⁴⁵. Street view platforms provide APIs that allow users to batch download street view data and provide street view browsing services. In order to comprehensively measure the visual perception evaluation of street space by residents in the study area, the study set up street view data collection points at 50 m intervals. Throughout the study area, 57,527 Street View collection points were generated within the OSM street network. A total of 30,511 street view images were collected using Python and the Baidu Street View Map API (<https://api.map.baidu.com/panorama/v2?ak=YOURKEY>).

In order to accurately simulate the residents' perception, the specific parameters for retrieving Baidu street view images from the API were set as follows: the vertical angle (pitch) was set to 20° and the field of view width (fov) was set to 90°. For each sampling point, a 360° panoramic view of the street was obtained by stitching the views in four directions. An example of the downloaded street view image is shown in (Fig. 3).

Deep learning based semantic segmentation of street view images

This study uses an improved semantic segmentation model based on the encoder-decoder structure SegNet, an open-source deep convolutional neural network released in 2015 by researchers at the University of Cambridge.

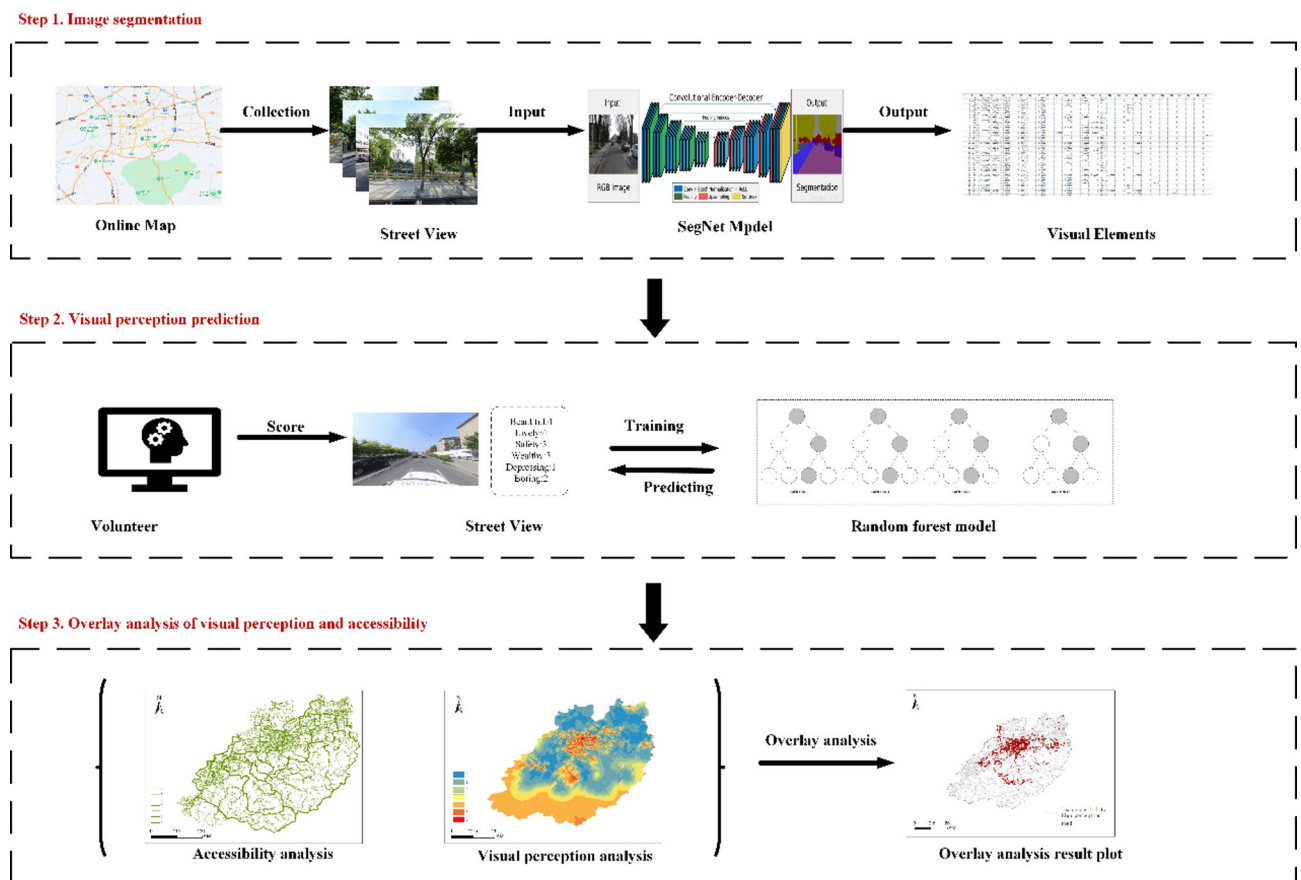


Fig. 2. Research framework.



Fig. 3. Example of the BSVIs collection process.

SegNet model is due to its demonstrated efficiency and accuracy in processing high-resolution images, and its structural flexibility allows it to effectively adapt to the complex backgrounds and diverse elements found in urban visual analysis. Compared to other potential models such as U-Net and Fully Convolutional Networks (FCN), SegNet has significant advantages in maintaining spatial information and detail recovery, which are crucial for accurately identifying various visual elements in street scenes⁴⁶. The encoder part of SegNet consists of multiple convolutional and pooling layers, which progressively reduce the size of the feature map and extract abstract features. The decoder part, on the other hand, consists of an upsampling layer and a convolutional layer, which are used to map the features extracted by the encoder back to the size of the original image and generate pixel-level classification results⁴⁷. The semantic segmentation model used in this study was trained and tested on the ADE 20 K dataset, achieving 82.538% pixel accuracy on the training dataset and 68.432% pixel accuracy on the test dataset.

The backbone encoder network in the model is ResNet50, which consists of a convolution (conv) module and an identity module. The conv module has different input and output dimensions and cannot be placed in series, whereas the identity module has the same input and output dimensions as the other modules and can be used in series. The structure of the network model is shown in Table 1. The neural network is divided into four parts: input, encoding, decoding, and output. The input layer reshapes any pixel image to a size of 416×416 , with the input image elements having three dimensions: R, G, and B. Conv2D is used to construct a convolutional layer to extract features from the input high-dimensional array. The batch normalization method proposed by Ioffe and Szegedy in 2015 is used to improve the training speed and generalization ability of the network⁴⁸. MaxPooling2D is used to reduce the image dimensions and neuron parameters without sacrificing image features. UpSampling2D is used to restore the original image size. The encoder resizes the image to a size of $43,264 (208 \times 208)$. Softmax calculates the probability of a particular semantic classification for each pixel across 150 categories.

The ADE 20 K dataset (Fig. 4) was used as the training dataset because the images contain 150 objects from everyday life, such as the sky, roads, cars, and plants. Each image is labeled with pixel-level scene segmentation labels to indicate different objects and regions in the image. Using this dataset to train the model significantly improves the experimental accuracy.

Perceptual scoring of street view images using a Human-machine adversarial scoring framework

This study refers to the human-machine adversarial scoring framework proposed by Yao to predict visual perception scores⁴⁹, which is able to more comprehensively assess the quality of different dimensions of visual perception in cities by combining the results of subjective human scoring and automatic machine scoring. Two-thirds of the sample data in the scoring model were randomly selected for model fitting, while the remaining one-third was used as test data to assess the accuracy of the overall model.

The Place Pulse project at the MIT Media Lab rated street images in six emotional perceptions: beautiful, wealthy, safe, lively, depressing, and boring^{50,51}, which are six dimensions that provide a comprehensive picture

Framework	Layer type	Output shape	Neuronal parameters
Input	Input layer	(None, 416, 416, 3)	0
	Conv2D	(None, 208, 208, 64)	9472
	Batch normalization	(None, 208, 208, 64)	256
	Activation	(None, 208, 208, 64)	0
	MaxPooling2D	(None, 103, 103, 64)	0
			
Encoder	ZeroPadding2D	(None, 28, 28, 1024)	0
	Conv2D	(None, 26, 26, 512)	4,719,104
	Batch normalization	(None, 26, 26, 512)	2048
	UpSampling2D	(None, 52, 52, 512)	0
	ZeroPadding2D	(None, 54, 54, 512)	0
			
Decoder	Batch normalization	(None, 208, 208, 64)	256
	Softmax	(None, 43,264, 150)	0
	Total parameters: 14,947,414		

Table 1. Structure of the neural network architecture.

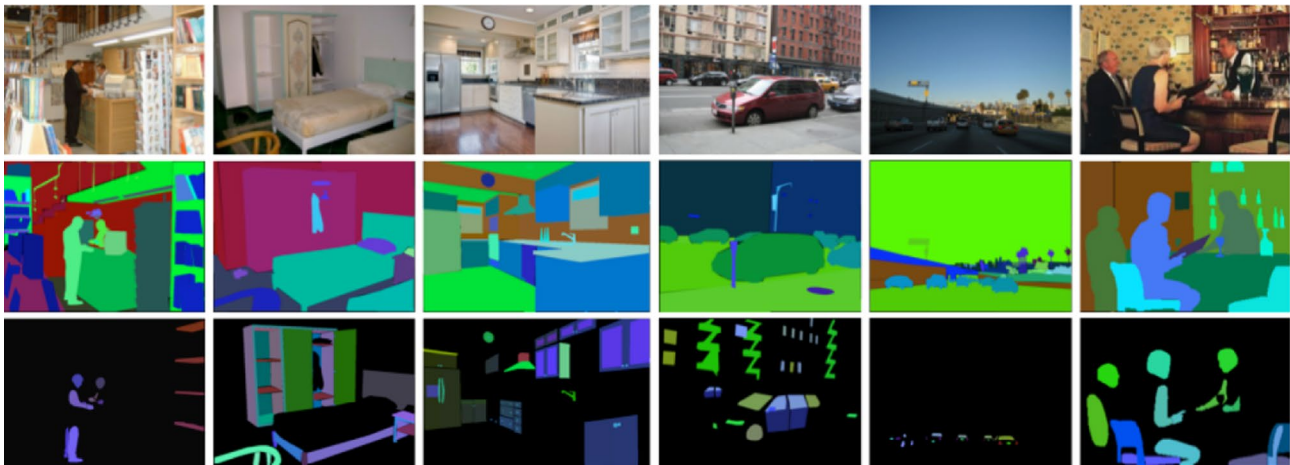


Fig. 4. ADE20K dataset (ADE20K dataset (mit.edu)).

of the quality of visual perception of streets from the residents’ perspective. Additionally, based on these six urban street perception dimensions, an increasing number of scholars have conducted extensive studies related to human perception of cities^{52,53}. A high or low score for each dimension represents the degree of perceptual recognition by residents, with higher scores indicating stronger perceptions of the dimension. We further categorized these six dimensions into positive and negative spatial perceptions to assess the quality of urban streets from the residents’ perspective. Therefore, the six perception types mentioned above were utilized to explore the quality of visual perception of urban streets with a people-oriented approach. In order to more accurately determine the perception of street quality in the study area, 128 volunteers were recruited to conduct the urban perception assessment.

The schematic diagram of using the human-computer adversarial model to assess the quality of urban streets is shown in (Fig. 5). The volunteers first used the human-machine adversarial model to rate the six dimensions of beauty, boredom, depression, liveliness, affluence, and safety on a scale ranging from 0 to 6, with higher scores representing greater congruence with the rated dimensions. This scale was chosen because it provides a balance between perceptual differentiation and ease of understanding for the volunteers. Although some studies such as Wang et al.(2022) used a scale from 1 to 100, the choice of a 0–6 range was deemed more appropriate for this context which focus on the primary emotional perceptions rather than highly granular distinctions, it facilitates broader categorization while minimizing cognitive load for participants⁵⁴.

During the implementation of the human-machine adversarial scoring framework and volunteer assessments, several potential biases could arise. Firstly, volunteer subjectivity and inconsistent scoring standards may lead to variability in the scoring results, reducing the reliability of the assessments. Volunteers might have different interpretations of the rating scales or personal preferences that influence their evaluations. Secondly, the Random Forest model, while robust, may encounter challenges such as overfitting, especially if the training data lacks

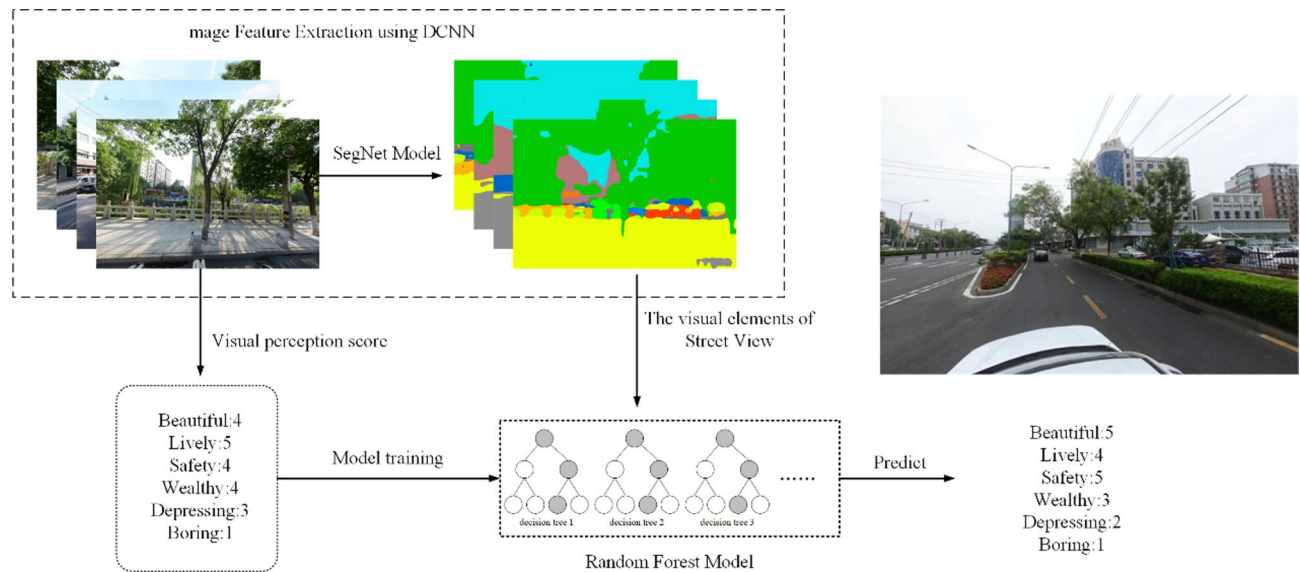


Fig. 5. Overview of the spatial perception scoring process for urban streets based on a machine learning.

sufficient diversity, which can impair its ability to generalize to new, unseen data. Additionally, the model might misclassify complex or ambiguous street view images, affecting the overall accuracy of the visual quality scores.

To address potential biases, we implemented the following strategies: Comprehensive Training and Standardization—Volunteers underwent extensive training sessions where clear guidelines and standardized scoring criteria were provided. This aimed to harmonize the understanding and application of the rating scales, thereby minimizing individual subjective differences. We utilized cross-validation to evaluate the model's performance across different subsets of data, ensuring that the Random Forest model maintained high accuracy and stability. Additionally, feature importance analysis was conducted to identify and prioritize the most influential visual elements, enhancing the model's interpretability and robustness.

Each volunteer was asked to subjectively rate the first 1,000 street view images for each dimension, after which the model constructed a random forest dataset. Random Forest, as an ensemble learning method, effectively handles high-dimensional data and captures complex nonlinear relationships between variables by constructing multiple decision trees and combining their prediction results. In this study, Random Forest was utilized to analyze the relationship between volunteer scores and the extracted visual elements in the street view images, thereby predicting visual quality scores for unscored images. Specifically, the model first used the volunteer-scored data as the training set to learn the influence of different visual elements (such as sky, buildings, plants, etc.) on the scores for each perception dimension. Then, the trained Random Forest model was applied to predict the scores for the test set, and its performance and stability were evaluated through cross-validation and feature importance analysis. This process not only enhanced the accuracy of score predictions but also improved the model's generalizability across different urban environments, enabling reliable visual quality assessments in a broader range of application scenarios. The selection of 1,000 images was based on considerations of time constraints, volunteer fatigue, and ensuring sufficient variability in the visual elements. Starting with 1,001 street view images, the model recommended scores for the specified dimensions based on the relationship between the volunteer's previous scores and the visual elements in the street view images.

Street accessibility analysis and combined street quality portfolio analysis

Spatial syntax allows complex street designs to be represented as a mathematical graph containing various nodes in order to study the characteristics of their spatial structure⁵⁵, and is also commonly used in the analysis of urban spaces with axial and segmental models⁵⁶. Although axial models have been used in previous studies, they have limitations in performing studies with large-scale urban applications⁵⁷. In particular, these models do not consider the scale of urban space⁵⁸, modeling data cannot be obtained directly from existing urban data, and the modeling time cost is large, making it difficult to cope with large spatial scales of research. In addition, this study aims to study the accessibility of urban residents during their daily trips, so it is necessary to consider the daily walking distance of urban residents as the accessibility radius, which is not supported by the axial model. Therefore, this study uses a segmentation model based on the axial model to measure the accessibility of urban streets. The segmentation model provides three modes to comprehensively analyze the topological geometry, angles and distances of the street network. The difference between these analysis modes is the different mathematical definitions of the shortest path. In the angular mode of the line segment model, the shortest path is the path with the smallest combined turning angle between two line segments, which is one of the most commonly used analytical modes in the line segment model. In his study, Hillier concluded that there is a high correlation between the deflection angle of a roadway network and pedestrian trips, and the angular mode is more in line with people's perceptions under natural trips than the other models⁵⁹. Residents do not have a God-like perspective of urban space and therefore do not deliberately choose routes that are closer together. Instead,

streets with small turning angles are perceived as long and straight, tend to have a stronger sense of direction, may be visually closer, wider in scale, and are habitually more likely to be selected⁶⁰. In contrast, Ye explored the accessibility of urban streets in Singapore using the angular pattern of segmental modeling in order to determine the distribution of greenscapes in space from a human-centered perspective⁶¹.

Based on the advantages of this model, this study utilizes it to assess the accessibility of urban streets. OSM line data was used as the raw data for spatial syntax, and GIS tools were employed to apply buffering to the roads. The centerline was then extracted from the buffer to construct a new road network. Finally, street merging, street simplification, and topology processing were performed on the road network to ensure accurate accessibility calculation. According to the accessibility formula (Eq. 1) proposed by Hillier & Hanson we calculated the accessibility value for each space⁶².

Equation (1) is as follows:

$$C_i = \sum_p^{n-1} \sum_q^n \frac{d_{pd}(i)}{d_{pd}} \quad (1)$$

C_i is the reachability value of space i , d_{pd} refers to the shortest path from space p to space q . $d_{pd}(i)$ denotes the shortest path between spaces p and q containing space i ($p < q$, $p = 1, 2, 3, \dots, n-1$, $q = 2, 3, 4, \dots, n$).

The study uses depthmapX to visualize street accessibility and applies it to the calculation of various urban street scales. Using the daily walking distance of residents as the reachability radius, a review of related studies found that the average daily walking distance of residents in first- and second-tier cities in China is about 500 m⁶³. Therefore, we set 500 m as the reachability radius and calculated the reachability of each street accordingly.

The street quality score was obtained by adding the scores of positive street perception and subtracting the negative perception score, and the street space was comprehensively evaluated by combining with the street accessibility analysis, and finally the street renewal measures were proposed by analyzing the quality characteristics of the streets under different levels of evaluation.

Analysis of results

Analysis of street view image components

The study utilizes a deep learning model for semantic segmentation of street view images to identify and categorize various street visual elements at each street data point. For each element type, the proportion within a street image is calculated as the mean value across all sampled images. The top eight elements by proportion are defined as follows:

- **Sky:** The area of the image depicting the sky, including both clear and cloudy conditions. This encompasses all visible portions above the horizon line, excluding any obstructions such as buildings or trees.
- **Building:** All structures adjacent to the street, including residential, commercial, and industrial buildings. This category includes facades, rooftops, and any architectural elements that are part of the built environment.
- **Plant:** Vegetation elements such as trees, shrubs, and landscaped greenery along the streetscape. This includes street trees, planter boxes, green walls, and any other plant-based features that contribute to the urban greenery.
- **Motorized road:** Roadways designated for motor vehicle traffic, excluding pedestrian areas. This includes lanes for cars, buses, trucks, and other motorized vehicles, as well as associated infrastructure like traffic signals and signage.
- **Vehicle:** Motor vehicles present on the streets, including cars, buses, trucks, bicycles, and motorcycles. This category captures both stationary and moving vehicles within the street view images.
- **Wall:** Walls used to control traffic flow or protect pedestrian safety, such as isolation walls at the edges of sidewalks, protective barriers in the center of roads.
- **Sidewalk:** Pedestrian pathways adjacent to the streets, designated for foot traffic. This includes sidewalks, crosswalks, pedestrian islands, and any other infrastructure intended for pedestrian use.
- **Person:** Individuals walking along the streets, captured in the images. This includes single persons, groups, and any visible human activity within the street view.

The spatial distribution of these elements is illustrated in Fig. 6, demonstrating their prevalence and arrangement across different urban street areas. By clearly defining each visual element, this study ensures that the categorization process is transparent and reproducible, facilitating consistent analysis and comparison across different datasets and study areas.

Analysis of visual perception of streets based on BSVI

The human-computer adversarial model's predicted scores for the six emotional dimensions of perception were visualized in Arcgis using kriging linear interpolation (Fig. 7). The urban streets in Jinan received high scores on beauty and liveliness owing to the well-designed greening efforts and orderly street layout. The wealthy perception score reflects the fact that the economic development of Jinan urban area is centered on Lixia and Shizhong districts, radiating to the surrounding high-tech district, Tianqiao district and other urban areas, forming an interactive relationship between the geometric central area and the peripheral areas. Second. The spatial distribution of street safety scores is somewhat similar to affluence scores, i.e., the level of economic development has a direct impact on law and order and residents' sense of security, and the more economically developed, the better the law and order is in relative terms. Most of the places with high depressing perception scores are located in old urban areas, where relatively narrow streets as well as dense building complexes cause residents' depressing perceptions to increase. Areas with high boring perception scores are mainly distributed

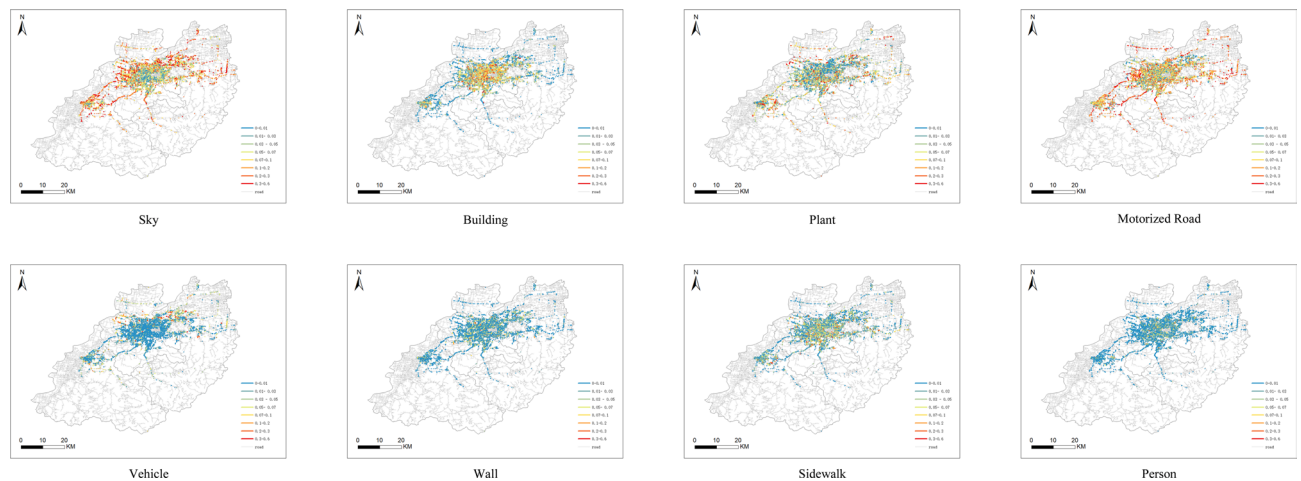


Fig. 6. Spatial distribution of streetscape constituent elements.

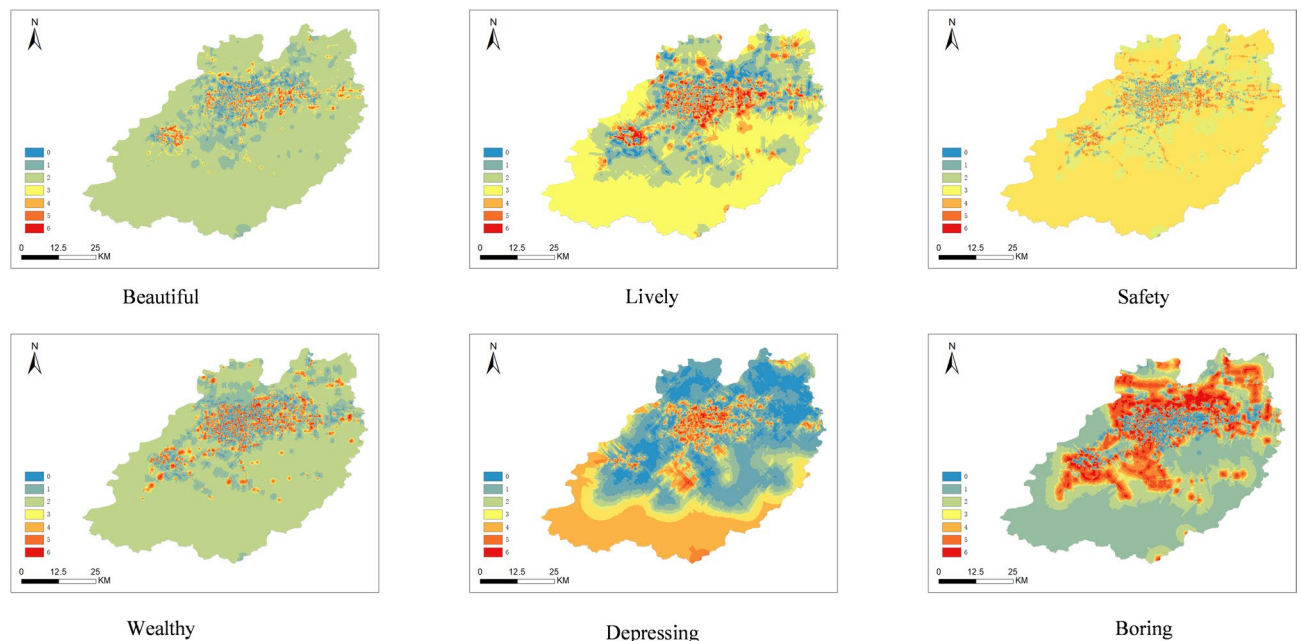


Fig. 7. Analysis of the six dimensions of emotional perception in the study area.

along the city's main roads, indicating that they are built in a monolithic way, which may be related to the urban function of the area. Instead of creating landscape features, customization and uniformity are pursued during the planning and construction of major urban roads.

Multiple regression analysis of visual perception and visual elements

This study explored the impact of various components of urban streets (sky, Motorized Roads, vehicles, plants, buildings, walls, sidewalks, and pedestrians) on different visual perception dimensions (beautiful, wealthy, safety, lively, depressing, and boring) through multiple linear regression analysis. The regression analysis results are shown in Table 2, where the asterisk next to the coefficient indicates its statistical significance level ($***P < 0.001$: indicates significant results at a 99.9% confidence level, with extremely high statistical significance, $**P < 0.01$: indicates that the result is significant at a 99% confidence level and highly significant, $*P < 0.05$: Indicates that the result is significant at a 95% confidence level).

This study utilizes regression analysis to uncover the impact mechanisms of various components of urban streets on different dimensions of visual perception, providing data-driven insights for urban planning and street design. By optimizing greenery, adjusting wall designs, improving roads and sidewalks, and promoting pedestrian activities, the visual quality of streets and residents' life satisfaction can be effectively enhanced, thereby fostering more human-centered and sustainable urban development.

	Sky	Motorized road	vehicles	Plant	Buildings	Walls	Sidewalks	Person
Beautiful	0.010	0.025**	− 0.007**	0.282***	− 0.075**	− 0.259***	− 0.086***	0.055***
Lively	− 0.298***	− 0.022***	0.039**	0.120***	− 0.393***	− 0.164***	− 0.060***	0.154***
Safety	− 0.052***	0.071***	0.0012**	0.350***	− 0.020*	− 0.179***	0.106**	0.23**
Wealthy	− 0.110***	0.075***	0.013***	0.104***	0.112**	− 0.138***	0.041***	0.033**
Depressing	− 0.139***	− 0.159***	0.012**	− 0.099***	0.250**	0.169***	0.012***	− 0.023***
Boring	0.288***	− 0.028**	− 0.026*	− 0.068***	0.236***	0.236***	0.043***	− 0.044

Table 2. Results of the multivariate linear regression analysis for the visual elements and perception scores. Beta coefficient *p<0.05, **p<0.01 ,***p<0.001

- *Optimize greenery design:* Research results indicate that plant coverage has a significant positive impact on perceptions of beauty, liveliness, and safety. Therefore, urban planners should prioritize increasing street greenery, such as planting trees and installing green walls, to enhance the overall visual quality of streets and residents’ satisfaction.
- *Adjust wall design:* Walls have a significant negative impact on multiple dimensions of visual perception, including beauty, liveliness, safety, wealth, and boredom, indicating that wall designs may need optimization. It is recommended to use more aesthetically pleasing and functional wall materials or reduce the use of walls to minimize their negative impact on visual quality.
- *Improve motorized roads and sidewalks:* Good motorized road and sidewalk design positively influences multiple perception dimensions, including beauty, liveliness, safety, and wealth. Urban planning should focus on maintaining motorized roads and expanding sidewalk designs to enhance street accessibility and visual quality.
- *Promote pedestrian activities:* Pedestrian activity has a significant positive impact on perceptions of liveliness and safety. By increasing recreational facilities on streets and establishing convenient pedestrian pathways, pedestrian activities can be promoted, thereby enhancing the overall liveliness and safety of streets.

Overlay analysis of street accessibility and street quality

The accessibility of urban streets in Jinan city is presented based on the daily walking distance of residents of 500 m (Fig. 8), the range of 0 to 6 in the map indicates the level of road accessibility, with 0 representing the lowest accessibility and 6 representing the highest accessibility. Most of the highly accessible streets are urban arterials, which bear the main traffic flow of the city, connecting urban areas with important regions, with high vehicle and pedestrian traffic, and are usually designed with multiple lanes. Secondly, compared with the central and western regions, the distribution of highly accessible streets in the southeast region is relatively sparse. With the advancement of urban development planning, urbanization in the Southeast region has accelerated, and street accessibility has been improved by increasing the number of lanes, constructing pedestrian paths, and strengthening transportation infrastructure. Overall, major transportation arteries basically cover the urban area, with a well-developed transportation network and high connectivity within and outside the region, which promotes economic development and facilitates the flow of people and goods.

Combining the measurement of street quality and the overlay analysis of street network accessibility, the aim is to evaluate the current spatial status of streets using the “accessibility-quality” evaluation dimension, and to discuss which streets have high quality and accessibility and good spatial quality of places, and which streets have high pedestrian accessibility but unsatisfactory quality, indicating that although they have good potential for pedestrian activities, they still need to be improved in terms of perceived quality. The evaluation of streets with high accessibility and good spatial quality of place, and those with high walkability but poor quality, indicates that although they have good potential for walking activities, they still need to be improved in terms of perceived quality, thus identifying potential problems in improving the quality of the streets.

In this overlay analysis, the median value of road accessibility in the study area was used to categorize accessibility into “high accessibility” and “low accessibility”, and the median value of street quality measures was used to categorize spatial quality into “high quality” and “low quality”. The median value of the street quality measurement results is used to categorize the spatial quality into “high quality” and “low quality”, and the two dimensions can be integrated to divide the streets into four major categories: high quality/high accessibility; high quality/low accessibility; low quality/high accessibility; low quality/low accessibility; and their distribution is shown in Fig. 9.

High quality/accessibility: These streets score well in both environmental quality and pedestrian accessibility, offering strong spatial potential. They are relatively few and primarily located in urban centers. High quality/low accessibility: found mainly at district junctions, these streets feature high greening rates and well-developed infrastructure, contributing to strong quality scores. However, their sparse surrounding road networks result in low pedestrian accessibility. Low quality/high accessibility: these streets, often situated southwest of the city center, benefit from good pedestrian accessibility but lack essential street furniture and greenery, leading to lower quality scores. Low quality/low accessibility: these streets require particular attention in urban planning. Predominantly located on the city’s periphery, they are characterized by aging buildings, low structures, and fragmented street networks, which hinder accessibility. To enhance these areas, urban planning efforts should prioritize functional improvements, building façade renovations, and increased greenery. Strengthening street quality and vitality while gradually expanding the pedestrian network will be key to their transformation.

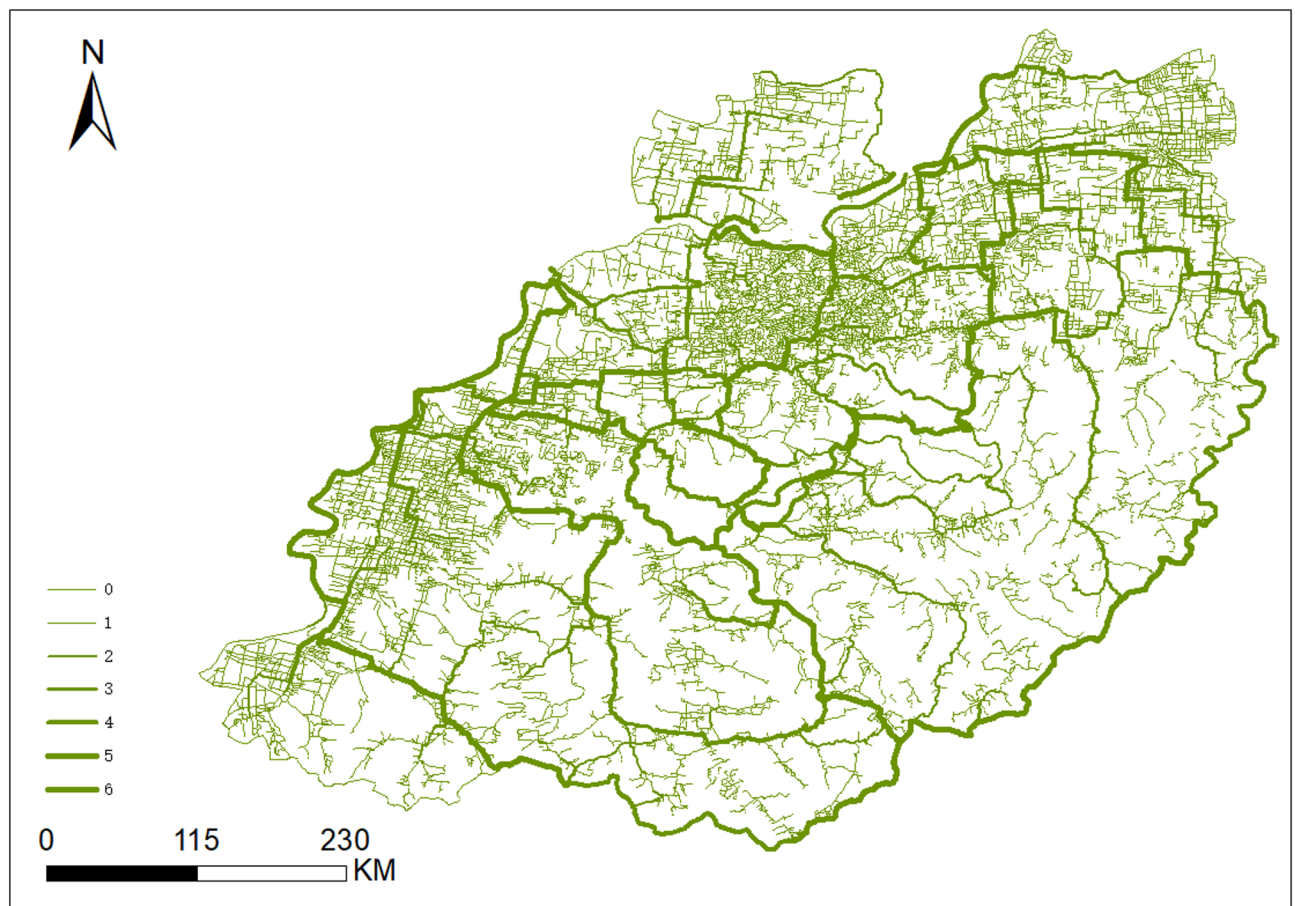


Fig. 8. Accessibility of the streets within a walking distance of 500 m for urban residents in the study area.

Conclusion

This study constructs a method for evaluating the visual perception of urban streets using spatial syntax theory and artificial intelligence technology, with a human-centered approach. The evaluation of street quality and micro-renewal potential is carried out through accessibility analysis and overlay analysis of urban streets. Additionally, the study employs a visual perception score combined with multiple regression analysis to reveal the influence mechanisms of street components on visual perception. The methodology applied in this study provides an effective way to measure the spatial quality of urban streets, offering data-driven suggestions for improving street quality. The analysis of spatial perception and visual elements can be applied to various stages of urban street development and management, contributing valuable insights for future urban planning.

As an emerging technology in urban analysis, this approach has significant advantages in large-scale, human-centered planning and design. First, in terms of data acquisition, using streetscape images to study the spatial quality and vitality of urban spaces is more time- and cost-efficient than traditional methods such as manual surveying or photography. Second, in terms of research methodology, using large-scale streetscape data for quantitative analysis offers more reliable results than traditional qualitative research or small-scale audits. Third, from a research perspective, combining objective streetscape data with residents' subjective perceptions allows for efficient and scientifically informed urban analysis, addressing urban issues in a problem-oriented manner. This approach contributes to a more rational and data-driven process in urban planning and design.

Furthermore, the findings of this study have practical applications for policymakers and urban planners. For instance, the identification of streets with high accessibility but low visual quality can inform targeted interventions to enhance these areas. By implementing targeted greening measures, such as increasing street tree density or adding green walls, policymakers can improve pedestrian safety and overall street aesthetics. Additionally, the insights gained from the multiple regression analysis can help in designing micro-renewal projects that address specific visual and functional deficiencies, thereby fostering more vibrant and sustainable urban environments.

Despite the advantages of this approach, the study does have some limitations. Due to constraints in data sources, the street view data was collected and photographed from the viewpoint of the roadway, which may introduce discrepancies when compared with the actual pedestrian perspective, as much of the public space used by people for daily activities is primarily located along walking paths. Additionally, limitations in the machine learning algorithms and the resolution of the street view data meant that certain key elements, which could impact spatial quality, were not included in this analysis. This resulted in some potential inaccuracies

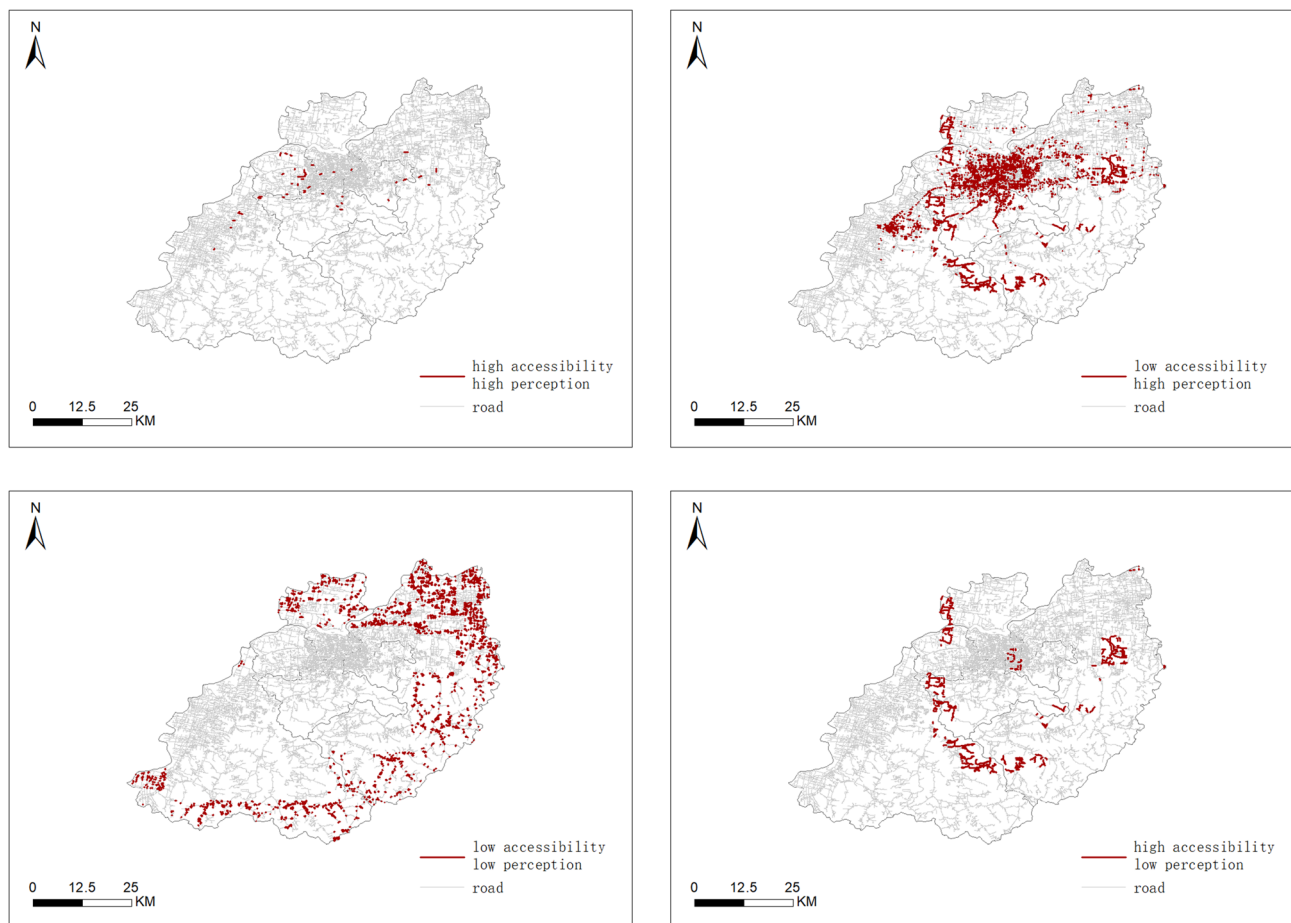


Fig. 9. Quality/accessibility distribution map.

and limitations in the quality evaluation, we will incorporate advanced analysis algorithms to address these shortcomings in the future research. Furthermore, the data from different times could be used to analysis the trends in the spatial quality of urban streets over time. By analyzing urban street planning and development from both spatial and temporal dimensions, we aim to predict future trends and improve the accuracy of urban planning decisions. Future studies could also explore the integration of real-time data sources and temporal street view images to capture dynamic changes in urban environments, thereby providing a more comprehensive understanding of how visual perception evolves over time.

Data availability

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Received: 24 September 2024; Accepted: 19 May 2025

Published online: 26 May 2025

References

- Oc, T. & Tiesdell, S. *Urban Design: Ornament and Decoration* (Routledge, 2007).
- Mehta, V. *The Street: a Quintessential Social Public Space* (Routledge, 2013).
- Yin, L., Cheng, Q., Wang, Z. & Shao, Z. Big data for pedestrian volume: exploring the use of google street view images for pedestrian counts. *Appl. Geogr.* **63**, 337–345 (2015).
- Runge, N., Samsonov, P., Degraen, D. & Schöning, J. No more autobahn! Scenic route generation using Googles street view. In *Proceedings of the 21st International Conference on Intelligent User Interfaces*, 147–151 (2016).
- Hou, Y. et al. Global streetscapes—A comprehensive dataset of 10 million street-level images across 688 cities for urban science and analytics. *ISPRS J. Photogrammetry Remote Sens.* **215**, 216–238 (2024).
- Zhang, F. & Yu, L. I. U. Street view imagery: methods and applications based on artificial intelligence. *Natl. Remote Sens. Bull.* **25**(5), 1043–1054 (2021).
- Kopf, J., Chen, B., Szeliski, R. & Cohen, M. Street slide: browsing street level imagery. *ACM Trans. Graphics (TOG)*. **29**(4), 1–8 (2010).
- Hoelzl, I. & Marie, R. Google street view: navigating the operative image. *Visual Stud.* **29**(3), 261–271 (2014).
- Torii, A., Havlena, M. & Pajdla, T. From google street view to 3d city models. In *2009 IEEE 12th international conference on computer vision workshops, ICCV Workshops*, 2188–2195 (IEEE, 2009).

10. Anguelov, D. et al. Google street view: capturing the world at street level. *Computer* **43**(6), 32–38 (2010).
11. Hara, K. et al. Improving public transit accessibility for blind riders by crowdsourcing bus stop landmark locations with Google street view: an extended analysis. *ACM Trans. Accessible Comput. (TACCESS)*. **6**(2), 1–23 (2015).
12. Li, X., Zhang, C. & Li, W. Does the visibility of greenery increase perceived safety in urban areas? Evidence from the place pulse 1.0 dataset. *ISPRS Int. J. Geo-Information*. **4**(3), 1166–1183 (2015).
13. Clews, C. et al. Alcohol in urban streetscapes: a comparison of the use of Google street view and on-street observation. *BMC Public Health*. **16**, 1–8 (2016).
14. Oh, K. Visual threshold carrying capacity (VTCC) in urban landscape management: A case study of Seoul, Korea. *Landsc. Urban Plann.* **39**(4), 283–294 (1998).
15. Li, X. et al. Assessing street-level urban greenery using Google street view and a modified green view index. *Urban Forestry Urban Green.* **14**(3), 675–685 (2015).
16. Shen, Q. et al. StreetVizor: visual exploration of human-scale urban forms based on street views. *IEEE Trans. Vis. Comput. Graph.* **24**(1), 1004–1013 (2017).
17. Jacobs, J. The death and life of great American cities. **21**(1), 13–25 (1961).
18. Lefebvre, H. The production of space (1991). In *The People, Place, and Space Reader*, 289–293 (Routledge, 2014).
19. Lynch, K. The image of the environment. *Image City*. **11**, 1–13 (1960).
20. Gehl, J. *Cities for People*. (2010). (2013).
21. Jacobs, A. & Appleyard, D. Toward an urban design manifesto. In *The City Reader*, 640–651 (Routledge, 2015).
22. Whyte, W. H. The social life of small urban spaces. (1980).
23. Hillier, W. R. G. & Shu, S. Crime and urban layout: the need for evidence. (1999).
24. Batty, M. Spatial analysis and urban form: integrating methods and techniques. *J. Royal Stat. Society: Ser. (Statistics Society)*. **166**(1), 5–22 (2003).
25. Carrión, D. & Bote, E. Street networks and accessibility: A comprehensive review of spatial syntax applications. *J. Urban Plann.* **16**(4), 312–331 (2015).
26. Zhang, T. & Lee, M. Evaluating pedestrian walkability in urban streets: A GIS-based approach. *Urban Des. Int.* **21**(3), 168–180 (2016).
27. Zhang, X., Wang, L. & Li, J. Combining POI data with public awareness tasks for street type identification. *J. Urban Stud.* **45**(3), 215–230 (2019).
28. Liu, Y., Zhang, F. & Wang, Y. The influence of street design on commercial vitality: A POI-based analysis. *Urban Plann. Rev.* **34**(2), 112–126 (2021).
29. Qin, Y., Zhang, R. & Liu, F. Quantitative evaluation of street vitality in tourist cities based on POI, Baidu heat map, and OSM road network data. *Urban Inf.* **12**(2), 108–119 (2020).
30. Zhao, X., Li, J. & Guo, L. Integrating weather and traffic data for street vitality analysis in tourist cities. *Urban Stud.* **58**(8), 1463–1480 (2021).
31. Xiao, D., Wang, X. & Huang, Z. GIS-based evaluation of street accessibility and pedestrian comfort: A case study. *Urban Des. J.* **36**(4), 320–335 (2021).
32. Wang, X., Liu, J. & Huang, L. Assessing the impact of green spaces on urban street quality using GIS. *J. Environ. Des.* **42**(1), 88–102 (2022).
33. Zhao, Q., Zhang, P. & Liu, X. Using 3D virtual reality technology for street quality assessment: A case study in urban China. *City Environ.* **25**(1), 98–112 (2022).
34. Liu, Q. & Wang, S. Real-time 3D GIS model for street quality assessment: A case study of Beijing. *Geospatial Inform. Sci.* **38**(5), 198–212 (2023).
35. Wang, H., Li, J. & Guo, Q. Deep learning for street image and POI data classification: enhancing urban street evaluation. *J. Geospatial Res.* **48**(5), 345–360 (2023).
36. Samuel, A. L. Some studies in machine learning using the game of checkers. *IBM J. Res. Dev.* **3**(3), 210–229 (1959).
37. Long, J., Shelhamer, E. & Darrell, T. Fully convolutional networks for semantic segmentation. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 3431–3440. (2015).
38. He, K., Zhang, X., Ren, S. & Sun, J. Deep residual learning for image recognition. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 770–778. (2016).
39. Zhang, H. *Understanding Human Perceptions of Street View Images Using MIT Place Pulse 2.0 Dataset* (Doctoral dissertation, Waseda University). (2023).
40. Zhang, T. Evaluating urban street quality using deep learning and place pulse dataset: A case study of Beijing and Shanghai. *Urban Stud. J.* **57**(5), 1013–1030 (2020).
41. Liu, H. & Wang, J. Deep learning for urban image analysis: A study of streetscape perceptions in new York City. *J. Urban Technol.* **28**(4), 17–33 (2021).
42. Li, X. & Guo, Y. Street view image analysis using deep learning: Understanding factors affecting urban quality perceptions. *Landsc. Urban Plann.* **204**, 103980 (2021).
43. Wang, Z., Chen, X. & Zhao, L. Predicting street walkability using AI and deep learning: A case study of Beijing. *Transp. Res. Part D: Transp. Environ.* **88**, 102616 (2021).
44. Cheng, L. et al. Use of tencent street view imagery for visual perception of streets. *ISPRS Int. J. Geo-Information*. **6**(9), 265 (2017).
45. Rzotkiewicz, A., Pearson, A. L., Dougherty, B. V., Shortridge, A. & Wilson, N. Systematic review of the use of Google street view in health research: major themes, strengths, weaknesses and possibilities for future research. *Health Place*. **52**, 240–246 (2018).
46. Badrinarayanan, V., Kendall, A. & Cipolla, R. Segnet: A deep convolutional encoder-decoder architecture for image segmentation. *IEEE Trans. Pattern Anal. Mach. Intell.* **39**(12), 2481–2495 (2017).
47. Kolhar, S. & Jagtap, J. Convolutional neural network based encoder-decoder architectures for semantic segmentation of plants. *Ecol. Inf.* **64**, 101373 (2021).
48. Ioffe, S. Batch normalization: Accelerating deep network training by reducing internal covariate shift. *arXiv preprint arXiv:1502.03167*. (2015).
49. Yao, Y. et al. A human-machine adversarial scoring framework for urban perception assessment using street-view images. *Int. J. Geogr. Inf. Sci.* **33**(12), 2363–2384 (2019).
50. Dubey, A., Naik, N., Parikh, D., Raskar, R. & Hidalgo, C. A. Deep learning the city: Quantifying urban perception at a global scale. In *Computer Vision—ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11–14, 2016, Proceedings, Part I* 14, 196–212 (Springer International Publishing, 2016).
51. Lou, A., Stancato, S. & Piga, B. E. G. Assessing in-motion urban visual perception: analyzing urban features, design qualities, and people's perception. In *Advances in Representation: New AI-and XR-Driven Transdisciplinarity*, 691–706 (2024).
52. Zhang, F. et al. Uncovering inconspicuous places using social media check-ins and street view images. *Comput. Environ. Urban Syst.* **81**, 101478 (2020).
53. Yang, J., Zhou, L. & Chen, W. Spatial patterns and multi-dimensional impact analysis of urban street. *MDPI Electron.* **13**(21), 11740 (2023).
54. Wang, L., Han, X., He, J. & Jung, T. Measuring residents' perceptions of city streets to inform better street planning through deep learning and space syntax. *ISPRS J. Photogrammetry Remote Sens.* **190**, 215–230 (2022).

55. Dawes, M. J., Ostwald, M. J. & Lee, J. H. Examining control, centrality and flexibility in Palladio's villa plans using space syntax measurements. *Front. Architectural Res.* **10**(3), 467–482 (2021).
56. Atakara, C. & Allahmoradi, M. Investigating the urban spatial growth by using space syntax and GIS—A case study of famagusta City. *ISPRS Int. J. Geo-Information.* **10**(10), 638 (2021).
57. Hillier, B. & Iida, S. Network and psychological effects in urban movement. In *International Conference on Spatial Information Theory*, 475–490 (Springer, 2005).
58. Pafka, E., Dovey, K. & Aschwanden, G. D. Limits of space syntax for urban design: axiality, scale and sinuosity. *Environ. Plann. B: Urban Analytics City Sci.* **47**(3), 508–522 (2020).
59. Lerman, Y., Rofé, Y. & Omer, I. Using space syntax to model pedestrian movement in urban transportation planning. *Geographical Anal.* **46**(4), 392–410 (2014).
60. van Nes, A., Yamu, C., van Nes, A. & Yamu, C. Analysing linear spatial relationships: the measures of connectivity, integration, and choice. *Introduction to Space Syntax in Urban Studies*, 35–86 (2021).
61. Ye, Y. et al. Measuring daily accessed street greenery: A human-scale approach for informing better urban planning practices. *Landsc. Urban Plann.* **191**, 103434 (2019).
62. Hillier, B. & Hanson, J. *The Social Logic of Space* (Cambridge University Press, 1984).
63. Lyu, Y. & Forsyth, A. Attitudes, perceptions, and walking behavior in a Chinese City. *J. Transp. Health.* **21**, 101047 (2021).

Author contributions

Mingyang Yu and Xin Chen wrote the main manuscript text together. All authors reviewed the manuscript.

Funding

This work was supported by the National Natural Science Foundation of China, grant number (No. 41801308).

Declarations

Competing interests

The authors declare no competing interests.

Additional information

Correspondence and requests for materials should be addressed to M.Y.

Reprints and permissions information is available at www.nature.com/reprints.

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Open Access This article is licensed under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License, which permits any non-commercial use, sharing, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if you modified the licensed material. You do not have permission under this licence to share adapted material derived from this article or parts of it. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by-nc-nd/4.0/>.

© The Author(s) 2025