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Original Research

Streetscape Evaluation Using Deep Learning in Light of Cognitive Biases

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ABSTRACT

The evaluation of Streetscapes has seen increasing development in the use of artificial intelligence and deep learning techniques to analyze Streetscape in a more objective and continuous manner. Many studies still rely on human assessments as a primary reference to verify the accuracy of intelligent models, with limited research addressing the impact of residents' spatial background and local expertise on urban evaluation outcomes. This study aims to compare the assessments of local experts and external experts in evaluating urban landscape quality based on imageability and enclosure indicators, and to analyze the extent to which each group aligns with the results of a deep learning model. The research relied on a set of urban images evaluated by urban design experts, which were then compared with the outputs of a model based on convolutional neural networks. The results showed a clear difference between the two groups, with external experts achieving higher agreement rates with the model, reaching 82.26% for the Imageability indicator and 88.71% for the containment index, compared to local experts, whose agreement rates were 69.11% and 62.60%, respectively. The results indicate that spatial familiarity and direct experience with a place may influence urban perception and produce a certain type of cognitive bias, while external evaluations tend to show a greater degree of neutrality and consistency with AI-based analysis.

Keywords: Streetscape Quality, Urban Visual Perception, Deep Learning, Imageability, Enclosure.

1. Introduction

The quality of the streetscape is considered one of the fundamental concepts in contemporary urban studies due to its direct impact on the human experience within the city. It is associated with visual comfort, sense of place, ease of movement, social interaction, as well as its role in enhancing urban identity and quality of life. Kevin Lynch pointed out that the clarity of urban elements and their visual perceptibility contribute to forming a clear mental image of the city, urban elements such as paths, edges, districts, landmarks, and nodes play an important role in shaping human perception and strengthening the visual imageability of urban environments. which enhances the sense of belonging and spatial organization [1]. Subsequent urban design studies have also emphasized that the quality of the urban environment is not limited to physical aspects alone but also encompasses cognitive and visual dimensions related to the user's experience within urban space [2].
With the rapid development witnessed in artificial intelligence and computer vision technologies, new capabilities have emerged for analyzing streetscape objectively and continuously through reliance on digital images and deep learning techniques. Street imagery platforms such as Mapillary and Google Street View have provided extensive visual databases that have facilitated researchers in studying the urban environment on large spatial scales and in a manner closer to the actual user experience within the street.
In recent years, there has been a noticeable increase in the use of convolutional neural network (CNN) models to analyze urban perception and evaluate the visual quality of streetscapes. Many studies have employed deep learning techniques to extract visual features of the streetscape and link them to human perception of elements such as visual attractiveness, safety, walkability, and the quality of the streetscape [3] [4]. These techniques

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have also contributed to the development of more objective and scalable assessment tools compared to traditional methods. Traditional methods for assessing streetscape quality often rely on manual observation, field surveys, and expert-based evaluations, which are time-consuming and influenced by subjective interpretation. In addition, the scalability of these approaches remains limited when analyzing large urban environments. Deep learning techniques provide a more efficient and objective alternative by enabling automated extraction of visual features and continuous assessment of urban scenes across different spatial contexts.

Despite the significant progress in this field, most studies primarily focus on the accuracy of the model and its statistical performance, with limited attention given to analyzing the nature of human evaluations themselves, particularly the impact of evaluators' spatial background and local experience on urban landscape assessment outcomes. Spatial familiarity and direct experience with a place affect visual perception and produce a form of cognitive bias, which leads to differences in the evaluation of urban environment quality between local experts and experts not associated with the study area [5] [6].

This research aims to compare the evaluations of local experts and external experts regarding urban landscape quality using the indicators of imageability and spatial enclosure, and to analyze the extent of agreement of each group with the results of the deep learning model. The research also seeks to understand the impact of spatial background on urban perception and to clarify the extent to which human assessments can be relied upon as an objective reference in urban artificial intelligence studies.

2. Literature Review

2. 1 Urban Scene Quality and Visual Perception

The concept of urban landscape quality is considered a multidimensional concept that is associated with the visual and cognitive experience of the user within the city. The works of Kevin Lynch have formed an important starting point for understanding the relationship between visual perception and urban organization, as he explained that the clarity of urban elements and the ease of distinguishing them contribute to forming a clear mental image of the city, which he referred to as the concept of Imageability [1].

Urban design studies have focused on the importance of perceptual and visual indicators in evaluating the urban environment, where a set of indicators related to the quality of the streetscape and walkability has been presented. Among the most prominent are spatial enclosure, visual clarity, transparency, human scale, and visual complexity [7]. These indicators have been widely adopted in studies evaluating streets and public spaces. Both Imageability and Enclosure are closely related perceptual indicators, as they contribute to shaping the visual experience and spatial understanding of the urban environment. These indicators are closely associated with urban design theory and play an important role in understanding human visual perception within streetscape environments.

In this context, urban perception indicators have become an important tool for understanding the relationship between humans and the built environment, as they help explain how individuals respond to the urban scene both visually and psychologically. Numerous studies have shown that the visual characteristics of streets, such as the continuity of facades, vegetation elements, diversity of architectural details, and urban space organization, directly influence users' perception of place quality and visual attractiveness. These characteristics are associated with the level of visual comfort, sense of safety, and walkability within the urban environment [8] [9] [10].

- **Imageability**

Refers to the ability of the urban environment to form a clear and strong mental image in the mind of the user, so that the place can be easily distinguished and remembered visually. Kevin Lynch explained that a city with high imageability is characterized by the clarity of its elements and its urban organization, which enhances spatial perception and the sense of place [11] [1]. This concept initially appeared as a perceptual concept related to the clarity of the mental image of the city, and later evolved to become a measurable indicator in studies evaluating the urban landscape and street quality. This indicator is influenced by a number of visual and urban characteristics, such as spatial enclosure, human scale, visual complexity, urban cohesion, clarity, and the connection between elements of the streetscape [12] [13].

- **Enclosure**

It refers to the degree of visual containment within the urban space resulting from the presence of surrounding vertical elements, such as buildings, trees, walls, and other elements that contribute to visually defining the boundaries of streets and public spaces. This indicator is considered one of the fundamental factors influencing the sense of place and the visual organization of the urban environment. It has been widely used in urban design literature as a measurable indicator for assessing the quality of urban spaces, particularly in studies based on expert evaluations [7]. This concept is also associated with cognitive aspects related to how spatial boundaries are defined and visually perceived within the urban environment [1].

2. 2 Artificial Intelligence and Urban Scene Assessment

In recent years, urban studies have witnessed an increasing shift towards the use of artificial intelligence and deep learning techniques to analyze the streetscape in a more objective and continuous manner. This has coincided with the rapid development of computer vision technologies and the availability of massive volumes of digital visual data. The proliferation of digital street image platforms has contributed to providing large-scale visual databases, enabling the study of the urban environment from a user's perspective within the street rather than relying on maps or aerial images. These platforms have become an important source for analyzing the visual and architectural characteristics of the urban scene in a more realistic and comprehensive manner.
Recent studies have also emphasized the growing role of street view imagery and deep learning techniques in understanding urban perception and evaluating streetscape quality across different urban contexts [14].
Many researchers have turned to using deep learning models, particularly convolutional neural networks (CNNs), to analyze street images and extract visual features associated with urban perception. These models are distinguished by their ability to recognize complex visual patterns within the urban environment, such as buildings, trees, sidewalks, and various urban elements, as well as their ability to analyze spatial relationships within the urban scene more accurately compared to traditional methods Recent research has shown that CNN-based approaches can effectively analyze visual and spatial characteristics within urban environments and support large-scale streetscape assessment processes [15]. Within the context of urban perception studies, CNN models can analyze visual indicators such as Imageability and Enclosure by learning spatial and visual patterns from streetscape images. Features related to façade continuity, vegetation presence, spatial boundaries, architectural diversity, and street proportions contribute to the automated interpretation of urban visual quality through deep learning frameworks [16].
The study by Aditya Dubey and colleagues is considered one of the first studies to use deep learning to analyze urban perception on a global scale through the Place Pulse project. They trained intelligent models on human ratings of street images with the aim of measuring the visual perception of elements such as attractiveness, safety, and liveliness within cities [3]. The study's results showed that the intelligent models were capable of predicting the perceptual qualities of the urban scene based on the visual features extracted from the images [8].
There has been an expansion in the use of artificial intelligence to analyze the quality of the urban environment. Deep learning techniques have been integrated with spatial analysis to study the visual perception of urban streets, focusing on the relationship between spatial organization and the user's visual [17]. Additionally, machine learning algorithms and Street View images have been used to develop a continuous system for visually assessing street quality, with results demonstrating the ability of intelligent models to effectively evaluate the quality of the urban landscape and link it to human perception [9].
Despite the significant advancements in this field, most studies have primarily focused on improving the accuracy of models and their statistical performance, with limited attention given to the nature of human evaluations themselves and the factors influencing them. The effects of cultural background, previous experience, and spatial familiarity of evaluators on urban scene assessment outcomes remain insufficiently studied, even though urban perception is directly linked to human experience and the cognitive interpretation of space. Therefore, there is a need for studies that combine the analysis of intelligent model performance with the understanding of perceptual differences among evaluators, particularly regarding the differences between local experts and external experts in assessing urban scene quality.

2. 3 Spatial Familiarity and cognitive Bias

Urban perception is closely linked to human experience and the user's previous knowledge within the urban environment. Understanding the streetscape is not limited to the apparent physical and visual characteristics alone, but it is also influenced by an individual's cognitive, cultural, and emotional background. Spatial familiarity is considered one of the factors affecting how the urban environment is perceived and interpreted, as individuals connected to a place may develop different cognitive patterns due to visual habituation and continuous interaction with the urban environment, which reflects on their way of evaluating the quality of the streetscape [18] [6].

The process of evaluating urban space does not rely solely on the physical characteristics of the place directly, but rather involves cognitive and psychological processes linked to memory, prior experience, and personal impressions. Urban experience is shaped through the interaction between the physical characteristics of the urban environment and the user's mental perception, which makes responses to the urban scene vary from one person to another depending on cultural and social background as well as spatial experience [19] [20].

Studies in visual perception have shown that spatial experience affects visual attention and the way architectural elements are read within the urban scene. A user familiar with a place tends to focus on meanings and spatial relationships that differ from those perceived by an external or non-connected user. This indicates that local evaluations may be influenced by factors beyond the direct visual characteristics of the streetscape, such as social attachment or daily familiarity with the built environment, whereas an external resident tends to rely more on the apparent visual features and spatial organization of the urban scene [21].

Despite the increasing importance of this topic, studies that directly address the differences between evaluations by local experts and external experts remain limited, particularly in studies that rely on artificial intelligence and deep learning to analyze urban landscape quality. Most previous studies have focused on the performance of intelligent models and their statistical accuracy, with less attention given to analyzing the nature of human evaluations and the cognitive factors influencing them. Hence, the significance of this research lies in its attempt to understand the impact of spatial background and local expertise on the assessment of urban landscape quality, and to analyze the extent to which human evaluations align with the results of intelligent models in the context of contemporary urban perception [22].

3. Method

3. 1 Research Framework

The research adopted a comparative analytical framework that combines human evaluation with artificial intelligence techniques to study the impact of spatial experience on urban scene assessment. The methodology included four main stages, beginning with the collection of street images from the study area, followed by the evaluation of these images by local and international experts based on the indicators of Imageability and Enclosure using a five-point Likert scale. Subsequently, the images themselves were analyzed using a deep learning model based on Convolutional Neural Networks (CNNs) to automatically assess the quality of the streetscape. Finally, the experts' evaluations were compared with the outputs of the intelligent model to analyze the level of agreement and to study the effect of spatial familiarity and cognitive bias on urban scene assessment.

3. 2study area

This research focuses on two main streets located in the center of Al-Kut city in Iraq. Al-Kut is situated approximately 170 km southeast of Baghdad and is considered the administrative center of Wasit Governorate. Thanks to its strategic location it serves as an important connecting point between the capital and several southern governorates such as Nasiriyah, Basra, and Amarah. Al-Kut city has experienced noticeable urban growth and increasing transportation and pedestrian-related challenges during recent decades. Several previous studies highlighted the complexity of the urban structure in the city center and the impact of urban street characteristics, movement patterns, and infrastructure conditions on pedestrian experience and urban mobility within the city [23][24].

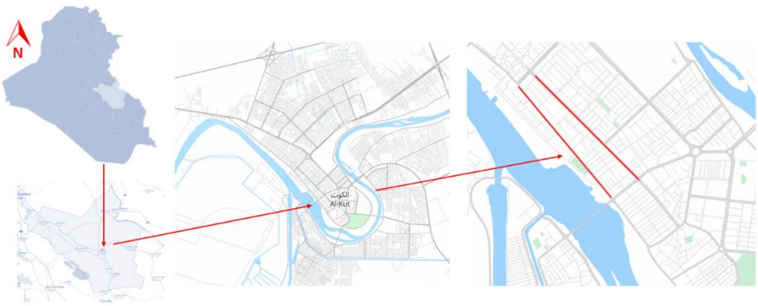

Figure 1. Study Area Location in Al-Kut City.

3. 3 Data Collection

The research relied on collecting street-level images from the study area, specifically Al-Houra and Al-Haidariya streets within the center of Al-Kut city, using the Mapillary platform. The images were captured from a pedestrian perspective in order to document the urban scene in a manner that reflects the actual visual experience of users within the street environment. In collecting the images, attention was given to capturing variations in urban features such as façade characteristics, spatial enclosure, vegetation elements, and street visual organization, in order to represent the visual and spatial diversity of the study area more comprehensively.
In addition, the model training process relied on urban images representing different visual quality levels and diverse urban characteristics in order to improve the adaptability of the model and reduce the potential influence of contextual or cultural bias during the evaluation process.

3. 4 Expert Evaluation

The research relied on human evaluation as a fundamental reference for analyzing urban scene quality and comparing the results with the outputs of the artificial intelligence model. A set of urban images was presented to a number of experts specialized in urban and architectural design to assess them based on the indicators of Imageability and Enclosure.
The experts were divided into two main groups. The first group included local experts who possessed direct knowledge and prior experience with the study area and the urban environment of Al-Kut city. In contrast, the second group consisted of non-local experts who were not directly associated with the study area and had no spatial familiarity with the selected streets.
The evaluation process relied on the five-point Likert scale, where experts were asked to assess each image according to levels ranging from low quality to high quality of the streetscape. Before starting the evaluation process, participants were provided with brief and clear definitions of the indicators used in order to achieve a greater consistency in understanding the perceptual concepts related to the urban scene. The evaluation process was conducted using structured questionnaires distributed to experts specialized in urban design. Participants were asked to evaluate each streetscape image according to the indicators of Imageability and Enclosure using a five-point Likert scale ranging from low to high visual quality.
The arithmetic mean of expert evaluations for each image was calculated to reduce individual variance among participants and achieve a more objective assessment value.

3. 5 AI-Based Assessment

To support the evaluation process and provide a more objective analytical perspective, the research adopted a deep learning model based on Convolutional Neural Networks (CNNs) to assess streetscape quality. The model was used to analyze the visual characteristics of street images and extract perceptual indicators related to Imageability and Enclosure. Before training, all images were resized and normalized to ensure consistency in the input data. Data augmentation techniques, including image rotation, brightness adjustment, and contrast variation, were applied to improve the robustness and generalization capability of the CNN model when analyzing different urban visual conditions.
The model had been previously trained using urban images that were evaluated by specialized experts, which enabled it to learn the relationship between the visual characteristics of the urban scene and human evaluations. Then, the same images that had been evaluated by the experts were analyzed using the artificial intelligence model to obtain automated predictions for each perceptual indicator. The model results were compared with the evaluations of local and non-local experts in order to investigate the influence of spatial familiarity and perceptual bias on urban scene evaluation.

- **CNN Architecture and Preprocessing**

The proposed framework was based on the EfficientNet-B3 CNN model, which was used to analyze streetscape images and extract visual features related to Imageability and Enclosure indicators. The model was pre-trained on the ImageNet dataset and adapted for the current study. Before training, the images were resized and normalized, while augmentation techniques such as rotation and brightness adjustment were applied to improve the model's ability to analyze different urban visual conditions.

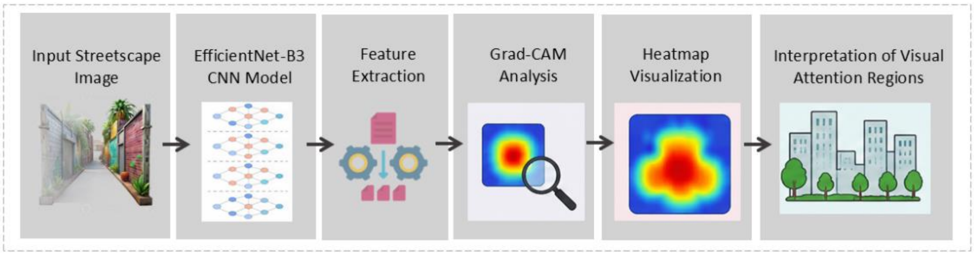

Figure 2. illustrates the main stages of the proposed CNN framework, including image preprocessing, feature extraction, and Grad-CAM-based visual interpretation.

3. 6 Comparative Analysis

The comparative analysis focused on examining the level of agreement between the evaluations of local experts, non-local experts, and the outputs of the artificial intelligence model in assessing urban scene quality. The comparison was conducted based on the perceptual indicators of Imageability and Enclosure, with the aim of identifying differences in perceptual judgments between the two expert groups and their relationship with the AI-based assessment. The analysis relied on comparing the evaluation results of the indicators with the predictions generated by the deep learning model to measure the level of consistency between human perception and automated assessment, as well as to investigate the influence of spatial familiarity and perceptual bias on urban scene evaluation, particularly regarding the differences between experts familiar with the study area and those not associated with the urban context of the site.

4. Results and discussion

4. 1 Comparison Between Local and Non-Local Expert Evaluations

The results of the comparative analysis revealed clear differences between the evaluations of local experts and non-local experts in assessing urban scene quality. The results showed that non-local experts achieved a higher level of agreement with the outputs of the artificial intelligence model compared with local experts. For the Imageability indicator, the agreement percentage between the evaluations of local experts and the outputs of the artificial intelligence model reached 69.11%, while the agreement percentage for non-local experts increased to 82.26%. The Enclosure indicator showed a lower level of agreement among local experts, reaching 62.60%, compared with non-local experts who achieved a higher agreement percentage of 88.71%. The Enclosure indicator achieved higher levels of agreement compared with the Imageability indicator for both expert groups. This may be explained by the fact that Enclosure depends more on measurable geometric and visual characteristics, such as building boundaries and street proportions, whereas the Imageability indicator is associated with more complex perceptual and cognitive factors influenced by the personal background and urban experience of the evaluators.

Table 1. Agreement Between Expert Evaluations and AI Model

Expert Group	Imageability (%)	Enclosure (%)
Local Experts	69.11	62.6
Non-local Experts	82.26	88.71

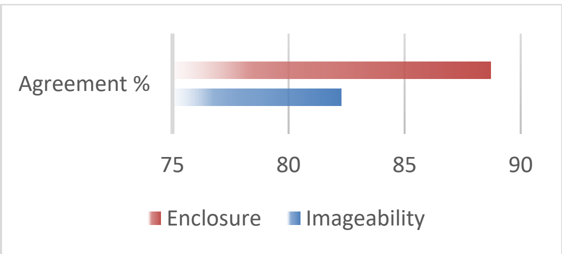

Figure 3. Agreement Between Local Expert Evaluations and the AI Model

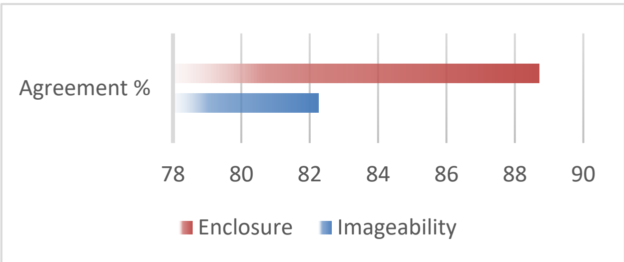

Figure 4. Agreement Between Non-Local Expert Evaluations and the AI Model

4. 2 Agreement Between Expert Evaluations and AI Model

The results revealed clear differences in the level of agreement between expert evaluations and the outputs of the artificial intelligence model in assessing urban scene quality. The comparison showed that non-local experts achieved higher levels of agreement with the AI-based assessment compared with local experts in both perceptual indicators. For the Imageability indicator, non-local experts recorded a higher level of agreement with the artificial intelligence model compared with local experts, indicating a greater level of consistency between external perceptual evaluations and the automated visual analysis of the streetscape. The Enclosure indicator showed the highest level of agreement overall, particularly among non-local experts, which indicates that this indicator can be interpreted more consistently through both human perception and AI-based visual analysis. The Enclosure indicator is more compatible with AI-based assessment compared with the Imageability indicator, because Enclosure is more strongly associated with measurable geometric and spatial characteristics, whereas the Imageability indicator depends on more complex perceptual and cognitive interpretations influenced by users' experiences and their personal perceptions of urban space.

To improve the interpretability of the CNN model, Grad-CAM visualizations were generated to identify the visual regions that most influenced the model predictions. Warm colors indicate regions with stronger influence on the prediction results, while cooler colors represent less influential regions in the evaluation process.

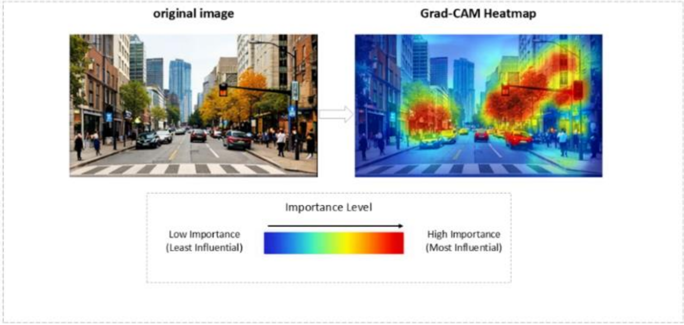

Figure 5. Example of Grad-CAM heatmap visualization highlighting the visual regions that influenced the CNN prediction during streetscape evaluation.

The Grad-CAM results showed that the CNN model focused on different visual regions depending on the evaluated perceptual indicator. For Enclosure, the model paid greater attention to spatial boundaries and building edges, while Imageability-related predictions were influenced by visually distinctive urban elements and streetscape composition.

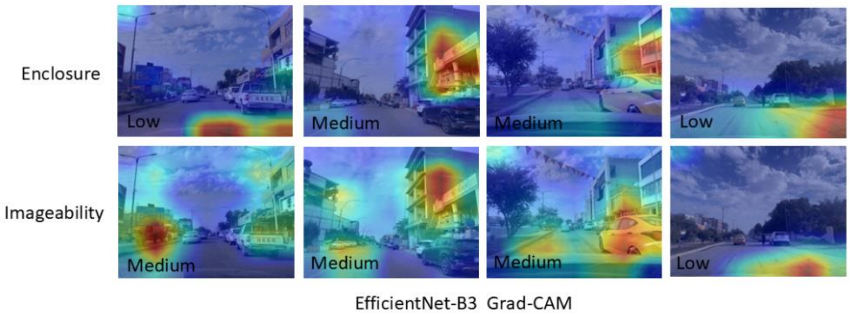

Figure 6. Grad-CAM visualizations for Imageability and Enclosure predictions generated using the EfficientNet-B3 model.

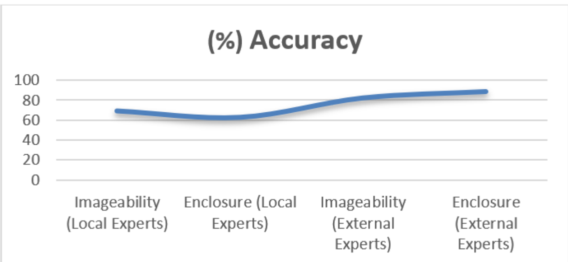

Figure 7. Comparison of Agreement Levels Between Expert Evaluations and AI Model

4. 3 Influence of Spatial Familiarity on Urban Scene Evaluation

The results showed that spatial familiarity plays an important role in shaping perceptual judgments related to urban scene quality. The comparison revealed clear differences between the evaluations of local experts and non-local experts, confirming that prior knowledge and direct experience with the study area may influence the way the urban environment is interpreted and evaluated. Local experts did not rely solely on the visible visual characteristics within street scenes during the evaluation process, but were also influenced by their previous experiences, contextual understanding, and mental associations related to the urban environment of Al-Kut city. In contrast, non-local experts relied more heavily on the visible visual and spatial characteristics within the images, which resulted in achieving a higher level of consistency with the AI-based assessment, which primarily depends on analyzing the visual characteristics of the streetscape. These results indicate that perceptual bias resulting from spatial familiarity may affect the evaluation of urban environments, particularly in studies that rely on human evaluations. Therefore, integrating artificial intelligence techniques with human evaluation may contribute to reducing subjective influences and improving the level of objectivity in urban scene assessment.

Table 2. Influence of Spatial Familiarity on Urban Scene Evaluation

Evaluation Aspect	Local Experts	Non-local Experts
Spatial familiarity	High	Low
Dependence on contextual knowledge	High	Limited
Dependence on visible urban features	Moderate	High
Agreement with AI model	Lower	Higher

The results of the research showed a clear influence of spatial familiarity on streetscape, as non-local experts achieved higher levels of agreement with the artificial intelligence model compared with local experts. The findings of this study are consistent with the growing use of visual perception indicators and AI-based approaches in contemporary streetscape evaluation research. This indicates that local experts were influenced by their previous experiences and contextual understanding of the place, whereas non-local experts relied more heavily on the visible visual characteristics within the streetscape. The results also showed that the Enclosure indicator achieved a higher level of agreement compared with the Imageability indicator, due to its association with clearer and more measurable geometric and spatial characteristics, whereas the Imageability indicator is associated with more complex perceptual and cognitive factors. These results confirm the importance of integrating artificial intelligence techniques with human evaluations in order to reduce subjective influences and improve the level of objectivity in assessing streetscape quality, particularly in studies that rely on visual perception and urban environment analysis. The findings of this study demonstrate the potential applicability of AI-based streetscape assessment in different urban environments and cultural contexts. The use of diverse urban images with varying levels of visual quality contributed to improving the robustness and adaptability of the proposed framework.

5. Conclusion

The research concluded that spatial familiarity has a clear influence on the evaluation of streetscape quality, as the results showed that non-local experts achieved higher levels of agreement with the artificial intelligence model compared with local experts. These findings indicate that familiarity with place and previous experience may influence perceptual judgments related to the streetscape. The study also showed that the Enclosure indicator achieved a higher level of agreement compared with the Imageability indicator, due to its association with clearer and more measurable visual and spatial characteristics. In contrast, Imageability was associated with more complex perceptual and cognitive factors influenced by users' experiences and mental perceptions. The findings of the research confirm the importance of integrating artificial intelligence techniques with human evaluations in order to develop more objective and accurate approaches for assessing

streetscape quality, particularly in studies related to visual perception and urban environment analysis. Future research may focus on expanding the dataset, incorporating additional perceptual indicators, and testing the proposed framework in more diverse urban environments and cultural contexts.
These findings demonstrate the importance of integrating artificial intelligence techniques with human evaluation to support more objective approaches in streetscape assessment and urban visual analysis. However, the study remains influenced by certain limitations related to dataset diversity, dependence on expert-based evaluations, and the contextual nature of urban visual perception.

Declaration of Competing Interest
The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

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Author Contributions
Roqaia Salim, Ihsan Abbas Jassim, and Manaf K. H. Altaleb contributed equally to the conception, design, analysis, drafting, and revision of this manuscript. All authors actively participated in every stage of the research and writing process, and all authors reviewed and approved the final version of the manuscript.

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