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Seeing heritage through green and blue: Assessing the visual influence of blue-Green infrastructure (BGI) in historic urban areas (HUAs)

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ABSTRACT

Historic urban areas (HUAs) are visually and culturally sensitive environments where blue-green infrastructure (BGI) plays an increasingly important role in shaping spatial identity and environmental quality. While BGI's ecological functions are well documented, its influence on human visual perception, particularly within HUAs, remains largely unexplored. Addressing this gap, this paper proposes an integrative framework to assess how BGI affects visual experiences in heritage contexts, bridging methodological, perceptual, and user-group dimensions. By combining UAV-based photogrammetry with a three-layered perception model, the research integrates spatial analysis and empirical methods across seeing (eye-tracking), feeling (questionnaire), and understanding (interviews) layers. Street-level BGI exposure was spatially quantified and used to inform perception experiments involving both expert and general public groups. This multi-methodological, multi-layered, cross-group approach extends existing research by providing a comprehensive examination of BGI's visual impact at different cognitive levels, particularly within historic settings. Findings reveal that BGI enhances perceptual diversity, visual preference evaluation, and cognitive engagement across both groups. Although it may slightly divert attention from dominant heritage features, BGI fosters broader visual exploration and higher environmental ratings. Experts interpret BGI through more systemic and functional perspectives, while the public emphasizes emotional, aesthetic, and recreational values. Overall, this study presents a replicable framework integrating digital spatial modeling with layered perception analysis, offering new insights for evaluating and enhancing visual environments in HUAs. It supports more inclusive visual assessments and provides a basis for informed planning and selective design interventions in heritage contexts.

1. Introduction

The concept of "historic urban areas" (HUAs) was introduced in 1987, defining these areas as: "*regardless of size, any area including cities, towns, historic centers, and residential districts, as well as their natural and constructed environments* (Washington Charter, 1987)." HUAs are a crucial part of humanity's cultural heritage, playing a vital role in preserving and continuing traditional cultural history and providing unique cultural experiences over time (UNESCO, 2021). As "living" heritage, HUAs not only accommodate activities such as commerce and tourism but also increasingly incorporate urban blue-green infrastructure (BGI), including green spaces, parks, and waterways. While numerous studies have examined the effects of human activities on the visual character and experiential quality of HUAs (Dinçer, 2011; Ferreira and Ramírez Eudave, 2022; Sastre et al., 2013), the role of BGI in shaping human visual perception remains underexplored. This paper addresses this gap through an integrated approach that combines empirical perception-based methods (e.g., eye-tracking, questionnaires, interviews) with digital spatial analysis techniques, including UAV (Unmanned Aerial Vehicle)-based photogrammetry and view-based BGI quantification. To ensure diverse perspectives, participants in the perception experiments include both experts (primarily architects and landscape architects) and the general public without relevant educational backgrounds.

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1.1. Blue-green infrastructure and HUA

BGI refers to the integration of natural and artificial ecosystems, including urban green spaces, parks, gardens, wetlands, rivers, and lakes (Escobedo et al., 2019; Liao et al., 2017). It contributes to climate regulation, biodiversity, flood mitigation, and enhances physical, mental, and environmental well-being (Li et al., 2025; Macháč et al., 2022; Zhang et al., 2025).

In historic urban areas, BGI is more than a functional amenity; it is often constitutive of the urban landscape and cultural experience (Pruijt, 2004; Vallerani and Visentin, 2018). A representative case is the Jiangnan water-town tradition, where canal-edge corridors, bridge approaches, and land–water alleys structure eye-level views alongside year-round greenery from garden practices (Zuo and Zhang, 2023). Historically, these corridors functioned as water–land interfaces for social-cultural activity, and the white-wall-and-black-tile palette codified a restrained aesthetic that continues to anchor local identity (Huang et al., 2025). Beyond this illustrative case, prior research indicates that Green infrastructure (GI) within HUAs, including green spaces, parks, and urban greenery, also contributes to urban livability and reinforces cultural character (Hua et al., 2022; Stanley et al., 2012). Elements, such as ancient and heritage trees, can further enrich the historical and cultural atmosphere of these areas (Haneca et al., 2009; Rostami et al., 2015).

Previous studies on HUAs have primarily focused on two aspects of BGI: (a) its spatial integration with historic fabric and landscape evolution (Halbac-Cotoara-Zamfir et al., 2021; Wang et al., 2020); and (b) its functional roles in urban resilience and well-being (Yang et al., 2020; Zhao et al., 2024). However, despite BGI's prominence in heritage landscapes, systematic investigations into its role in shaping human visual perception and experiential qualities are almost absent. Addressing this gap is crucial for advancing heritage-sensitive landscape assessment and planning.

1.2. Visual perception research on HUAs

Visual perception plays a critical role in evaluating the environmental and cultural quality of HUAs. As carriers of cultural memory and landscape identity, HUAs have increasingly been examined in terms of how users visually engage with their spatial environment (Deghati Najd et al., 2015; Ren, 2024). Existing research can be broadly grouped into two complementary streams: perception-based and geo-spatial analytical approaches.

(a) Perception-based approaches emphasize subjective and experiential dimensions. Two primary directions are evident: *(i) User-group differences*, exploring how perceptions vary among stakeholders such as heritage professionals, planners, and the general public. These studies highlight socio-demographic factors, including age, gender, and cultural background, as key influences on visual evaluations. (Pendlebury and Townshend, 1997; Remoaldo et al., 2014). *(ii) Aesthetic and emotional responses,* investigating how urban form and landscape settings evoke feelings of beauty, nostalgia, or belonging (Chen et al., 2015; Deghati Najd et al., 2015; Jenks, 2008; Nasar, 1989; Smardon, 1988). These insights are valuable for understanding user preferences and acceptance of conservation or redevelopment strategies.

(b) Geo-spatial and computational approaches rely on digital tools to assess visual characteristics from a performance perspective. Key directions include: *(i) Visual impact assessments* of new architectural insertions or infrastructure projects, evaluated for compatibility with historic contexts using simulation and modeling techniques (Bu et al., 2022; Jiang et al., 2022; Serra et al., 2021). *(ii) Spatial cognition and visibility analysis*, using tools like spatial syntax, viewshed modeling, and GIS to understand how people navigate and perceive historic environments (Esposito et al., 2020; Tan and Ujang, 2012; Wang et al., 2022). Both approaches increasingly benefit from recent advancements in high-resolution spatial data acquisition technologies, such as UAV-based photogrammetry and point clouds derived from scanning devices (e.g., LiDAR), significantly enhancing visibility analysis and spatial cognition modeling in HUAs (Curcio et al., 2022; Zhang et al., 2021).

Although both perception-based and geo-spatial analytical approaches have yielded valuable insights, they remain largely separated in methodology and scope. In particular, little attention has been paid to how BGI structures visual experiences in HUAs through integrated spatial and perceptual analysis. Given the growing relevance of ecosystem-based design and nature-based solutions in impact assessment, embedding BGI within perception research frameworks presents a timely and underexplored direction for heritage-sensitive urban analysis.

1.3. Research gaps and research questions

Although BGI is widely acknowledged for enhancing both visual quality and ecological function in urban environment (Li et al., 2025; Macháč et al., 2022; Zhang et al., 2025), its specific impact on human visual and spatial perception in HUAs remains insufficiently understood. While previous research has recognized BGI as a product of historical processes with aesthetic and environmental value (Haneca et al., 2009; Rostami et al., 2015), few studies systematically assess how users perceive it or how it contributes to experiential qualities in heritage contexts. Another gap lies in the methodological fragmentation of visual perception studies. Research typically relies either on empirical user-based methods (e.g., surveys, interviews, behavioral observation) or on digital spatial techniques (e.g., GIS, viewshed analysis, photogrammetry), with limited integration between the two.

Recent advances in multi-view photogrammetric modeling technologies, such as Structure-from-Motion (SfM), combined with increasingly accessible and affordable UAVs, now enable the acquisition of high-resolution spatial data suitable for detailed visual analyses (Berra and Peppa, 2020; Fernández-Hernandez et al., 2015). These advancements significantly lower the technical and financial barriers for integrating empirical and digital spatial methods. UAV-based digital models can thus be effectively embedded within perception-driven research frameworks, providing reliable data support for initial scene selection and subsequent generalization of findings.

Therefore, this paper proposes an integrated framework that combines digital modeling techniques, including UAV-based 3D reconstruction and human-scale view extraction, with multi-layered perception methods including eye-tracking, questionnaires, and semi-structured interviews. The goal is to investigate how BGI influences visual perception in HUAs and how such effects vary between expert and public users. Accordingly, the study addresses the following research questions: (RQ1) How can BGI exposures and spatial characteristics be effectively measured from pedestrian perspectives in HUAs? (RQ2) How can integrated, multi-layered methods combining spatial modeling and empirical perception analysis be applied to assess BGI's visual impacts? (RQ3) How does BGI influence visual attention patterns, perceptual evaluations, and cognitive interpretations across expert and general public user groups?

This paper contributes to the field of heritage-sensitive urban visual impact assessment in two key ways. **(a) Novel thematic focus**: While previous studies have explored BGI's ecological and functional roles, this research is among the first to systematically examine its influence on human visual perception within HUAs, addressing an important and underexplored dimension in heritage landscape evaluation. **(b) Integrated framework and cross-group analysis**: The study develops an integrated approach combining UAV-based spatial modeling and multi-layered perception analysis, and systematically compares expert and general public responses to reveal differentiated perceptual structures related to BGI in HUAs, advancing methodological practices and stakeholder-informed assessment.

2. Reviewing visual perception analysis methods in urban contexts

This section reviews two complementary methodological domains that have been widely used in visual perception research related to HUAs: digital geo-spatial approaches, and perception-based methods. While the former focuses on modeling spatial structure and visibility, the latter emphasizes users' cognitive and emotional engagement. Reviewing both domains provides a foundation for identifying opportunities for methodological integration in the context of evaluating BGI in urban heritage settings.

2.1. Digital geo-spatial approaches

Geo-spatial and computational approaches often utilize spatial data and simulation techniques to analyze visibility, spatial composition, and structural patterns of HUAs, which can be categorized as:

(a) GIS-based methods: Used to quantify land cover, vegetation, hydrology, and built structures, GIS enables mapping and modeling of spatial patterns in historic contexts. Also, GIS-based viewshed/visibility analysis tools calculate the spatial visibility of elements from a given observer's location (Jerpåsen and Larsen, 2011; Sarihan, 2021), simulating what is seen from specific points in 2D or 3D terrain environments. They are useful for assessing visual accessibility and the prominence of landscape elements across an urban environment (Florio et al., 2017; Zhou et al., 2023).

(b) 3D modeling visual analysis: Using photogrammetry or LiDAR data, urban scenes can be reconstructed in 3D to simulate human viewpoints. Field of view (FOV) analyses within these models help determine the relative exposure of various visual components, such as vegetation, water, built heritage (Balsa-Barreiro and Fritsch, 2018; Prechtel et al., 2013). Recently, UAV-based photogrammetry has increasingly been employed due to its flexibility, cost-effectiveness, and ability to produce detailed, high-resolution spatial models (Berra and Peppa, 2020; Fernández-Hernandez et al., 2015). UAV-derived point clouds provide accurate spatial relationships between elements, capture complex urban morphology, and offer perspectives unavailable through traditional ground-based observations, making them particularly suitable for heritage-sensitive urban contexts (Lo Brutto et al., 2014; Pepe et al., 2022).

(c) Street-level and image-based analysis with computer vision: Techniques using street view imagery (e.g., Google Street View) combined with semantic segmentation and deep learning allow for automatic classification and quantification of visual elements like trees, sky, water, or building façades (Gao et al., 2025; Li et al., 2017; Zhang et al., 2023). These methods approximate human perspectives at the street level and have been applied to both modern urban studies and heritage districts.

The strengths of these methods lie in their objectivity, repeatability, and ability to capture spatial complexity. However, they often lack sensitivity to human perception, emotion, and cultural meaning. While they provide precise accounts of what is spatially present or visible, they reveal little about how these environments are actually perceived. This underscores the need to complement geo-spatial analysis with user-centered perception methods—particularly when evaluating the visual role of BGI in culturally significant urban settings.

2.2. Perception-based methods

Perception-based approaches explore the cognitive, emotional, and sensory dimensions of how people engage with urban spaces—revealing not just what is seen, but how it is interpreted, evaluated, and remembered. In the context of HUAs, these methods are especially valuable for capturing the layered experiences shaped by spatial form, cultural memory, and atmospheric qualities. These methods can be broadly classified into three complementary strands:

(a) Psychophysical approaches examine the physiological basis of perception, using biometric tools such as eye-tracking, EEG, or heart rate monitoring to capture unconscious reactions to visual stimuli (Braddick, 1997; Bruce et al., 2014; Xiao et al., 2024). Among these, eye-tracking has gained prominence in landscape and urban research as a non-intrusive method to analyze attention distribution and visual salience (De Lucio et al., 1996; Fang et al., 2024; Ye et al., 2022).

(b) Psychological approaches focus on how individuals evaluate and emotionally respond to environments (Leventhal and Scherer, 1987; Moser and Uzzell, 2003). Techniques such as questionnaires, semantic differential scales, and image-based scoring help measure aesthetic preferences, perceived atmosphere, and affective responses (Brosch et al., 2013; Gifford et al., 2011).

(c) Phenomenological approaches delve into the interpretive and experiential layers of perception, using interviews, self-reports, and narrative observations to explore how people assign personal and symbolic meaning to spaces (Albertazzi, 2013; Merleau-Ponty et al., 2013; Ohta, 2001; Santo-Tomás Muro et al., 2020). These methods are especially relevant in HUAs, where individual lived experience is often entangled with historical identity and cultural memory.

Together, these approaches offer a multilayered understanding of perception, tracing how people see, feel, and make sense of their surroundings. However, when used in isolation, perception-based methods present two critical limitations. First, they lack the capacity to quantify what is spatially visible from different viewpoints. Without geo-spatial data on visual exposure, such as which elements are actually seen and how prominently, subjective evaluations risk being disconnected from the physical environment. Second, the fragmented nature of perceptual data—spread across physiological signals, survey responses, and qualitative insights—makes it difficult to synthesize findings into a coherent, spatially grounded interpretation. These limitations highlight the need for integration with geo-spatial approaches. Only by combining the spatial precision of modeling tools with the experiential richness of perception-based methods can we fully understand how blue-green infrastructure (BGI) influences visual experience in culturally significant urban settings.

3. Methods

Building on the methodological insights outlined in the previous section, this study applied an integrated framework that merged the spatial precision of geo-spatial modeling with the interpretive depth of perception-based analysis to systematically examine the influence of BGI on visual experience in HUAs. The framework comprised three complementary modules (Fig. 1):

(a) Digital modeling module: A high-resolution 3D mesh model of the case area was reconstructed using Unmanned Aerial Vehicle (UAV)-based photogrammetry combined with ground-level imaging. Eye-level panoramic viewpoints were then extracted to quantify the exposure levels of GI and BI from pedestrian perspectives. These quantified spatial representations informed the selection of representative scenes for the perception experiments.

(b) Perception analysis module: This module was structured into three layers: **"seeing"** (physiological attention), **"feeling"** (subjective preference), and **"understanding"** (cognitive interpretation). It integrated eye-tracking experiments, structured questionnaires, and semi-structured interviews, providing a holistic framework for assessing the perceptual effects of BGI across user groups.

(c) Integration and generalization module: This module combined empirical results from the perception analysis with the spatial exposure levels of BGI derived from digital modeling. By establishing relationships between BGI exposure and perceptual responses, it enabled integrated assessments at the street level and predictive modeling of visual perceptual impacts in areas not directly examined through experiments.

This framework bridges digital modeling with human centered

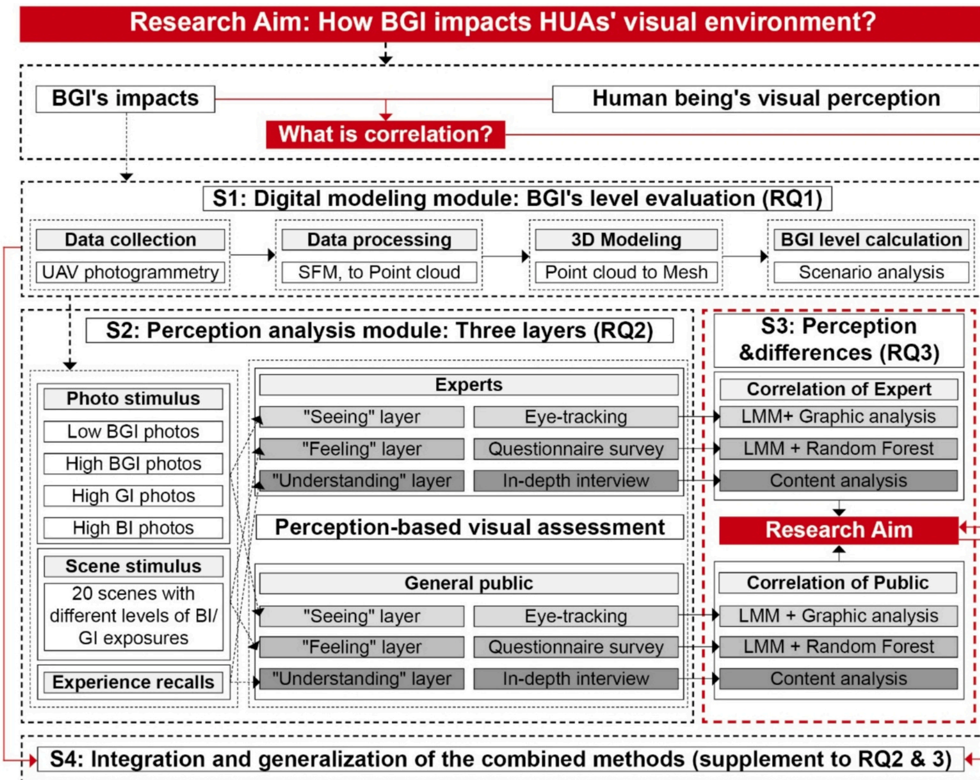

Fig. 1. The workflow of this research.

Fig. 2. The location and historic map of Pingjiang Road.

perception research, enabling both objective spatial quantification and subjective evaluation. Building on this foundation, step (a) answers RQ1 by providing spatial exposure metrics, step (b) answers RQ2 and RQ3 through multi-layer perceptual evidence and group comparisons, and step (c) supplements RQ2 and RQ3 by linking exposure to perception for integrated evaluation and scenario based prediction.

3.1. Case study area

Pingjiang Road in Suzhou, China, was selected as the case study. As a nationally protected historic street situated within the buffer zone of the UNESCO World Heritage Site "Classical Gardens of Suzhou" (Wang et al., 2015), Pingjiang Road exemplifies the Jiangnan water-town typology. The corridor is structured by canal-edge streets and bridge approaches, narrow lateral alleys that connect land and water, and a pedestrian-scale fabric of white-wall and black-tile façades (Fig. 2). These spatial and cultural features support everyday practices such as strolling, trading, neighborhood socializing, and heritage tourism, producing a layered setting in which BGI is both infrastructural and experiential.

Within this area, the primary street can be divided into two main segments (north and south). Five lateral streets connected with water channels branch off from these segments. The selected study fragment comprises the southern segment, specifically chosen due to its proximity and direct connection to Zhongzhangjia Xiang, a street whose original water channel was recently restored. This restoration differentiates Zhongzhangjia Xiang from other BGI conditions within the Pingjiang Road area, providing unique comparative value. Thus, the southern segment was selected to capture this distinctive transitional context.

3.2. 3D modeling and BGI exposure computation

To address RQ1, we quantified pedestrian-level exposure to BGI by building a high-resolution 3D semantic mesh of Pingjiang Road via an integrated aerial- and ground-based photogrammetry workflow and using it for subsequent visibility and exposure analyses. This model served as the analytical base for evaluating the exposure of BI and GI within the human visual field. Image acquisition was conducted in December 2024, using two complementary modes (Fig. 1):

(a) Aerial imaging: Low-altitude photographs were taken using a DJI Phantom 4 Pro UAV at heights ranging from 2 to 10 m, capturing rooftops, tree canopies, and canal structures.

(b) Ground-level imaging: Manual photos were captured at approximately 1.6 m—the average eye level of pedestrians—focusing on façades, vegetation, and water features within narrow alleys and walking paths.

The photogrammetric processing pipeline involved: (a) feature matching and alignment via Structure-from-Motion (SfM); (b) point cloud generation using Multi-View Stereo (MVS); (c) mesh surface reconstruction; and (d) texture mapping to retain photorealistic detail. The resulting mesh was annotated with semantic labels, assigning each surface element to one of several categories: BI, GI, or other urban components. This enabled spatially explicit quantification of BGI exposure without the need for post-rendered segmentation.

To quantitatively assess BGI exposure, pedestrian-level viewpoints were placed at 1-m intervals along the primary walking route. At each viewpoint, lines of sight (LoS) were systematically constructed horizontally at 5-degree intervals over a full 360-degree field-of-view, and vertically from 30 to 175 degrees relative to the ground plane, approximating human visual coverage. When an LoS intersected with a semantic mesh surface labeled as BI or GI, the intersection was recorded (Peng et al., 2025; Peng et al., 2024). The proportions of BI and GI visible surfaces within each viewpoint's visual field were then calculated.

Due to accuracy constraints associated with consumer-grade UAV equipment, exposure levels in the resulting semantic mesh model were simplified into categorical rankings rather than precise numeric intervals. Exposure thresholds for BI and GI were defined separately based on their distinctive visibility characteristics in urban setting. For GI, higher thresholds were applied, defined as high (G1, ≥25 %), medium (G2, 15–24.9 %), low (G3, 5–14.9 %), and none/very low (G4, <5 %), consistent with its relatively greater coverage in urban environments (Aoki, 1987; Li et al., 2021). For BI, given the absence of established thresholds in the existing literature, a proportional scaling factor of 0.3—derived from observed relative exposure ratios between BI and GI—was applied to define exposure categories (Peng et al., 2025). Therefore, thresholds were set as high (B1, ≥7.5 %), medium (B2, 4.5–7.4 %), low (B3, 1.5–4.4 %), and none/very low (B4, <1.5 %), reflecting the typically lower yet perceptually significant presence of water elements.

Based on combinations of these BI and GI exposure categories, the street was segmented into 16 distinct BGI typologies (e.g., G1B2 refers to a scene with over 25 % GI exposure and 4.5–7.4 % BI exposure). Representative scenes covering diverse spatial and environmental conditions were subsequently selected from these typologies to serve as visual stimuli in the subsequent perception experiments. At last, to verify the accuracy of this custom approach, selected viewpoint results were validated through panoramic camera simulations within the Unity environment.

3.3. Multi-layered perception-based experiments

This section addresses RQ2 by integrating measures of perception and supplies comparative evidence for RQ3 across participant groups. We implemented a three-layer experimental framework that spans the physiological, psychological, and cognitive dimensions of human experience in historic urban areas. The framework comprises three layers: (Fig. 1):

"Seeing": early-stage visual attention, assessed using eye-tracking technology;

"Feeling": intuitive preferences and evaluative judgments, measured through structured questionnaires;

"Understanding": interpretive and reflective responses, explored via semi-structured interviews.

These methods were selected for their complementarity. Eye-tracking captures unconscious attentional patterns and perceptual salience; questionnaires elicit subjective appraisals of environmental quality across multiple dimensions; and interviews reveal deeper meanings and contextual interpretations associated with BGI in heritage settings. Together, they provide a multi-faceted and integrative perspective on perception, bridging the gap between observable behavior and experiential understanding.

3.3.1. Recruitment of participants

Participants underwent the experimental tasks in a sequential manner, progressively refining the sample size at each stage. First, structured questionnaires were administered to all recruited participants (80 valid responses per group, Table 1a), enabling rapid collection of subjective appraisals. Based on questionnaire quality and participant engagement, suitable candidates (40 valid participants per group, Table 1b), who met standard visual acuity requirements (corrected or uncorrected between 0.8 and 1.5), proceeded to the eye-tracking experiment. Finally, representative participants who successfully completed the eye-tracking tasks were invited to participate in semi-structured interviews (20 per group, Table 1c).

This sequential and layered approach ensures efficient data collection, enhances data quality through rigorous participant screening, and reduces potential interference between experimental stages. By structuring the methods sequentially, the potential influence of later tasks on participants' initial responses is minimized. Furthermore, the gradual refinement of participant pools based on task-specific inclusion criteria ensures that each experimental stage involves individuals suited to provide meaningful and reliable insights.

Table 1
Participants information.

Variables	Features	Sum	Expert (80,)	General public (80)
(a) Participants for questionnaire survey:				
Age	18–22	28	11	17
	23–25	57	24	33
	26–30	44	26	18
	31–40	31	19	12
Gender	Male	83	42	41
	Female	77	38	39
(b) Participants for eye-tracking experiment:				
Variables	Features	Sum	Expert (40)	General public (40)
Age	18–22	17	8	9
	23–25	26	13	13
	26–30	26	14	12
	31–40	11	5	6
Gender	Male	38	20	18
	Female	42	20	22
(c) Participants for in-depth interview:				
Variables	Features	Sum	Expert (20)	General public (20)
Age	18–22	9	4	5
	23–25	11	6	5
	26–30	13	7	6
	31–40	7	3	4
Gender	Male	19	9	10
	Female	21	11	10

Note: Participants who did not meet the inclusion criteria have been excluded from the table (including those with poor-quality eye-tracking data or participants who completed questionnaires carelessly or randomly). For the expert group, participants were required to have academic backgrounds in architecture, landscape architecture, urban planning, or closely related fields, with at least senior-level undergraduate standing or higher. Additionally, considering that questionnaires were administered electronically and the eye-tracking experiment required familiarity with computer operations and equipment calibration—tasks potentially difficult for middle-aged and older adults—all participants were limited to individuals aged 40 or younger.

3.3.2. Questionnaire survey ("feeling" layer)

To assess users' intuitive responses to BGI in HUAs, a structured questionnaire survey was conducted as the basis for the "feeling" layer. This layer focuses on affective and evaluative judgments, capturing how different types of scenes influence participants perceived aesthetics, cultural atmosphere, and functional value. The web-based questionnaire was organized around three dimensions, each composed of multiple relatively independent items to capture distinct aspects within the same domain:

D1: Historical and cultural atmosphere; Derived from cultural memory theory (Assmann, 2011b), genius loci theory (Norberg-Schulz, 1976), and place attachment frameworks (Lewicka, 2013). These theories collectively emphasize *cultural symbolics (F11)*, *spatial memory (F12)*, and *genius loci or spirit of place (F13)*, acknowledging that cultural and spatial atmospheres form crucial perceptual foundations that must not be overlooked in heritage contexts.

D2: Spatial aesthetics; Based primarily on the classical urban aesthetics and landscape preference theories (Kaplan et al., 1989; Nasar, 1994), emphasizing *visual aesthetics (F21)* such as form, material, and color, and *ecological aesthetics (F22)* concerning the harmonious integration of natural elements. These aesthetic dimensions are vital as visual attributes fundamentally shape heritage landscapes' experiential quality.

D3: Spatial functionality; Encompasses *ecological functions (F31)*, *recreational and well-being functions (F32)*, and *spatial function (F33)*. This dimension integrates established theoretical perspectives from ecosystem services literature (Assessment, M. E, 2005), restorative environment theory (Hartig et al., 1997; Kaplan, 1992), and spatial coherence and legibility principles (Kaplan et al., 1989; Nasar, 1994). These functional aspects are critical in determining how effectively BGI enhances ecological resilience, user comfort, recreational value, and spatial legibility in heritage areas.

Each item was rated using a 1–5 interval scale with 0.5-point increments (e.g., 1.0, 1.5, …, 5.0), allowing for moderate resolution in perception-based scoring while retaining comparability across items. The questionnaire was scene-based: a total of 20 representative viewpoint scenes were selected **(Fig. 3d)**, each accompanied by 3–5 stimulus images and corresponding map locations to help participants accurately identify spatial context. The questionnaire survey was conducted in March 2025. This ensured that evaluations were grounded in place-specific memory and spatial experience rather than abstract visual judgment.

Responses were first analyzed using descriptive statistics (mean and median scores) to identify perceptual trends across scenes and user groups. To further assess the influence of BGI variables, two complementary analytical methods were employed: **(a) LMMs** evaluated the influence of BI and GI exposure levels on each perception item while accounting for inter-individual variability and repeated scene measures; **(b) Random Forest (RF)** was used to quantify the relative influence of BI and GI, with separate models for expert and public groups. Feature importance scores were calculated using Mean Decrease in Impurity (MDI). Together, these two methods provide complementary insights: LMMs establish statistically significant effects of BGI exposure, while RF analysis identifies which variables exert the strongest practical influence on perceptual variation.

3.3.3. Eye-tracking experiment ("seeing" layer)

To capture unconscious visual responses to different BGI configurations, an eye-tracking experiment was conducted as the basis for the "seeing" layer. This method focuses on early-stage visual attention and perceptual salience, providing objective data on how users scan and prioritize landscape elements in HUA environments (Dupont et al., 2014). Participants were selected and contacted based on questionnaire responses and sequentially invited for the eye-tracking experiment between March and April of the same year. Participants were presented with a series of static images simulating pedestrian views of the case area. A total of 24 images were used as stimuli: 20 images were captured at representative viewpoints previously identified in the spatial analysis (**Fig. 3d** indicates specific viewpoints and angles), and 4 additional images were selected to diversify the stimulus pool and enhance the range of visual BGI exposure **(Fig. 3d)**. Each viewpoint was represented by only one image. Since these images presented only a partial field of view rather than full 360-degree panoramas, the visual composition did not fully correspond to the modeled BGI exposure values. To ensure consistency, each image was independently reclassified based on the visible proportion of GI and BI within the photo frame, using a four-level scale: none/very low (N), low (L), medium (M), and high (H). This image-based classification was used to guide subsequent analysis and group comparison.

Each image was displayed for 20 s, preceded by a central fixation point to standardize attention. Participants were instructed to view the images naturally, simulating spontaneous observation. To support visual analysis, eight Areas of Interest (AOIs) were defined for each image, corresponding to semantic categories: *(a) historical and cultural elements, (b) commercial elements, (c) paved ground, (d) sky, (e) perspective focal points, (f) buildings and structures, (g) green infrastructure (GI),* and *(h) blue infrastructure (BI)*.

Visual attention was analyzed through fixation duration and gaze heatmaps (de la Fuente Suárez, 2020). Group-level heatmaps were generated to visualize attention distribution across AOIs. Fixation data were then analyzed using linear mixed-effects models (LMMs), which allowed for the evaluation of BGI exposure effects on visual attention while accounting for group, AOI category, and scene-level variance. Descriptive statistics such as mean and median fixation durations were also examined to support trend interpretation.

Fig. 3. (a)-(c): Visualization and modeling results; (d)-(e) Scene type classification based on BI and GI exposure.
Note: Seasonal variations were not specifically considered in this study, as the study area experiences minimal seasonal water-level fluctuations, and the dominant vegetation comprises subtropical evergreen species with negligible phenological changes (see in Fig. 3 **a-c**).

3.3.4. Semi-structured interviews ("understanding" layer)

To capture the cognitive and interpretive depth of user responses to BGI, semi-structured interviews were conducted as the foundation of the "understanding" layer. This method aimed to uncover how different user groups conceptualize the spatial, symbolic, and functional roles of BI and GI within HUAs. The interview protocol was structured around three open-ended thematic prompts, corresponding to the three perception dimensions explored in the survey: *T1 – Historical and cultural atmosphere, T2 – Spatial aesthetics*, and *T3 – Spatial functionality*.

To support memory recall and contextual grounding, participants who successfully completed the eye-tracking experiment and expressed willingness were invited to participate in the semi-structured interviews. Gender and age ratios were controlled within both participant groups (Table 1). Participants were shown selected photographs from the previous eye-tracking and questionnaire experiments. This multimodal cueing method was designed to evoke both affective and analytical reflections anchored in place-based experience. All interviews were audio-recorded, transcribed verbatim, and analyzed using a frequency-based thematic coding approach. The analysis followed a structured four-step process:

(a) Open coding: Initial concepts and expressions were tagged line-by-line from the transcripts without pre-imposed categories.

(b) Subdimension classification: The open codes were then grouped into eight perception subdimensions (the same as the questionnaire), including Genius loci, Ecological aesthetics, Recreational and well-being function, among others.

(c) Infrastructure attribution: Each coded phrase was linked to either BI or GI stimuli, based on contextual references in the participants' statements.

(d) Cognitive activation modeling: Final frequencies were synthesized into two user-specific models (expert and public), mapping the perceived activation paths from infrastructure contact through subdimensions to the three thematic categories (T1–T3).

This coding structure enabled the reconstruction of distinct perceptual pathways for each group, revealing both shared cognitive patterns and key divergences in how BGI is interpreted in a HUA setting.

3.4. Spatially explicit cross-layer integration at the street level

As a complement to **Section 3.3**, this section integrates its multi-layer perception datasets with the UAV derived spatial exposure data introduced in **Section 3.2** to deliver a unified street-scale assessment. To systematically evaluate the visual impact of BGI at the street scale, we combine empirical findings from all three perceptual layers (Seeing, Feeling, and Understanding) with the exposure metrics. The goal is to clearly link BI and GI exposure levels at street level viewpoints, categorized as high, medium, low, or none or very low, to the corresponding perceptual outcomes.

For the "seeing" and "feeling" layers, eye-tracking data (fixation duration) and questionnaire scores were explicitly structured around scenes selected based on UAV-derived exposure categories. Thus, perceptual variations inherently corresponded with these spatial categories, enabling two types of flexible, spatially explicit assessments that surpass the limitations of traditional point-based perception studies:

(a) Street-level integrated assessment: By aggregating perceptual outcomes (e.g., mean fixation duration, mean preference ratings) according to the proportional distribution of exposure categories along the entire street, it is possible to systematically evaluate the cumulative perceptual impact of BGI across the full spatial extent. This approach provides a holistic, spatially integrated evaluation of how varying BGI exposures collectively influence visual attention and environmental preferences along the street.

(b) Localized impact predictions: Using the established empirical relationships between perceptual outcomes and BGI exposure categories, perceptual impacts can be flexibly predicted at smaller scales—whether specific street segments or individual viewpoints—even if empirical data at these locations have not been explicitly collected. Such predictive capability facilitates targeted planning and enables scenario-based evaluations of BGI impacts at specific spatial locations.

For the "understanding" layer, interpretive qualitative responses from semi-structured interviews were mapped via cognitive pathways linking BGI exposure categories to specific perceptual subdimensions (e.g., ecological function, spatial memory), and subsequently to overarching themes (T1–T3). Although qualitative in nature and less directly integrated with quantitative spatial modeling, these cognitive insights were systematically anchored in the UAV-derived exposure typologies, ensuring consistent spatial referencing and coherent interpretation of cognitive meanings attributed to BGI.

Together, this spatially explicit cross-layer integration approach not only establishes a rigorous analytical linkage between spatial exposure and perceptual responses but also significantly enhances the flexibility, depth, and practical applicability of visual impact assessments within historic urban contexts.

4. Results

This section reports findings in the order of the research questions. **Section 4.1** quantifies pedestrian exposure to BI and GI and directly answers RQ1. **Sections 4.2** to **4.4** then present perception results layer by layer at the viewpoint scale, providing evidence for group differences that speaks to RQ3 and addressing RQ2 within each layer. **Section 4.5** synthesizes the evidence across layers and scales, links it to the street scale exposure metrics, and delivers a consolidated answer to RQ2 while revisiting RQ3 at a broader level.

4.1. Digital model-based classification of BGI exposure

A detailed digital model of the case area was first constructed, incorporating surface-level detail and basic semantic distinctions (BI, GI, and others) to support visibility-based analysis **(**Fig. 3**a-c)**. Based on this model, a spatial classification was conducted to evaluate the distribution and intensity of BGI across the case area. At each observation point, the proportion of visible surfaces occupied by GI and BI was calculated. The results reveal a highly heterogeneous spatial pattern of BGI distribution **(**Fig. 3**d)**: **(a) High BI** exposure was concentrated along the central, eastern and northern segments of the street, where proximity to primary canal zones resulted in extensive water visibility. These areas were characterized by strong waterfront spatial identity. **(b) High GI** exposure occurred primarily in the southern segments and northern side alleys, typically associated with street vegetation, courtyard greenery, and vertical plantings. **(c) High BGI scenes**, characterized by the simultaneous visual dominance of water and greenery, were spatially scattered across the area. These scenes typically appeared at locations where canal-edge vegetation and historic structures intersected. **(d) Low BGI** scenes were generally located in densely built-up commercial segments with limited open space or vegetation, producing enclosed and visually hardened environments.

The resulting classification map identified 15 BGI composition types based on the cross-combination of BI and GI exposure levels. From this spatial dataset, a set of representative scenes was selected to serve as the basis for subsequent perception experiments. These scenes reflected diverse combinations of water–vegetation composition and spatial context while avoiding overrepresentation of any single exposure condition (Fig. 3**d-e)**.

4.2. Results of eye-tracking experiments (seeing layer)

Eye-tracking data was collected from 40 participants in each group, using 24 images that were independently reclassified based on their visible GI and BI proportions, and focusing on two metrics: gaze heatmap and fixation duration.

4.2.1. Gaze heatmap

Gaze heatmaps overlay participants' fixation locations and durations on the image, with warmer colors indicating longer fixation time (Fig. 4). Although no dominant preference for BGI-related AOIs is observed in the overall heatmap patterns, scenes with salient vegetation still exhibit moderate visual attraction. In addition, the focus is higher on *(a) historical and cultural elements*. Notably, both groups demonstrate higher fixation on *(e) perspective focal points*. Differences emerge in the professional group, which disperses more warm areas and a varied fixation sequence, suggesting an irregular pattern rather than a uniform pattern.

4.2.2. Fixation duration

Fixation duration data were analyzed after removing outliers above 3 s. Results are averaged across all 24 photos for 8 predefined AOI categories (Fig. 5). Overall, *historical and cultural elements* received the longest average fixation time across both user groups (professionals: 0.64 s; public: 0.78 s), followed by *perspective focal points* and *buildings/structures*. In contrast, *paved ground* had the shortest fixation durations. *GI* shows moderate attention, with higher durations in scenes where vegetation is visually salient. *BI* demonstrates more variable results, influenced by scene composition. The total fixation time on *GI* is lower than that on cultural or architectural features, but still notable in scenes classified as high-GI. These findings indicate that while BGI elements can draw visual attention, particularly when prominent in the frame, cultural and architectural components remain the primary visual anchors in the historic environment.

4.2.3. Effect of BI and GI levels on fixation duration

The LMM results demonstrate that various types of AOIs exert distinct influences on visual attention in HUA environments. Among all AOIs, *historical and cultural elements* yield the highest fixation durations (Coef = 0.784, $p < 0.001$), followed by *perspective focal points* (Coef = 0.517) and *buildings/structures* (Coef = 0.318). These findings underscore the central role of culturally and compositionally salient features in shaping gaze behavior. In contrast, natural elements such as BI and GI receive less attention, while paved ground (Coef = 0.213) displays a moderate but significant effect (Fig. 6a). Beyond main AOI effects, the interaction between infrastructure exposure levels and AOI categories reveals nuanced perceptual dynamics:

(a) A negative interaction between *BI* and *historical and cultural elements* (Coef = −0.124, $p < 0.001$) indicates that increasing BI may visually compete with or overshadow cultural and historical features, reducing attention to them (Fig. 6b).

(b) *GI* positively influences attention to *GI* ($p < 0.001$), suggesting a reinforcing effect between perceptual salience and visual exposure (Fig. 6b).

(c) Additional significant interactions include *GI/BI×* *perspective*

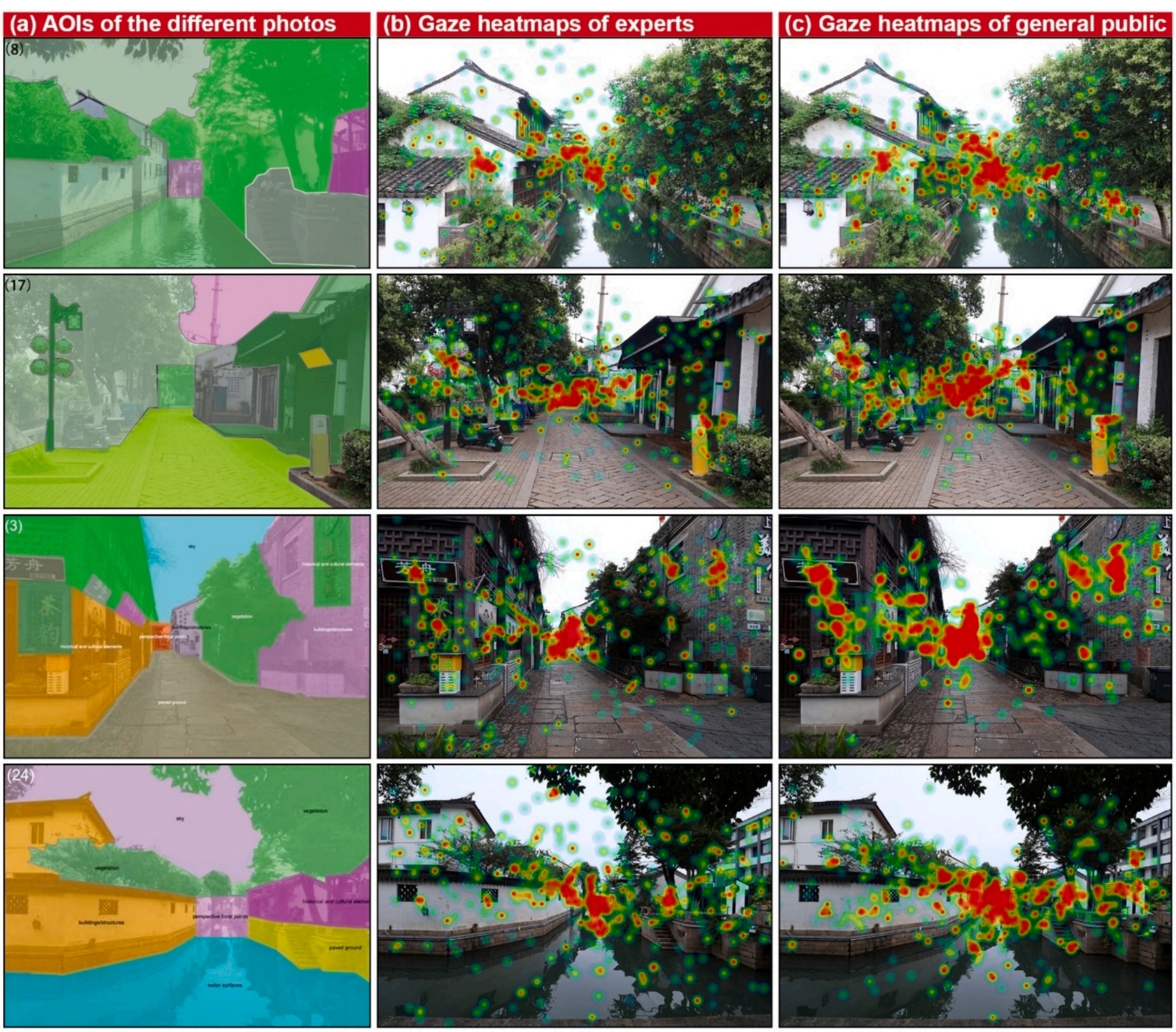

Fig. 4. Eye-tracking heatmaps: The examples of the two groups.
Note: Other heatmaps from the two groups can be found in Appendix A1.

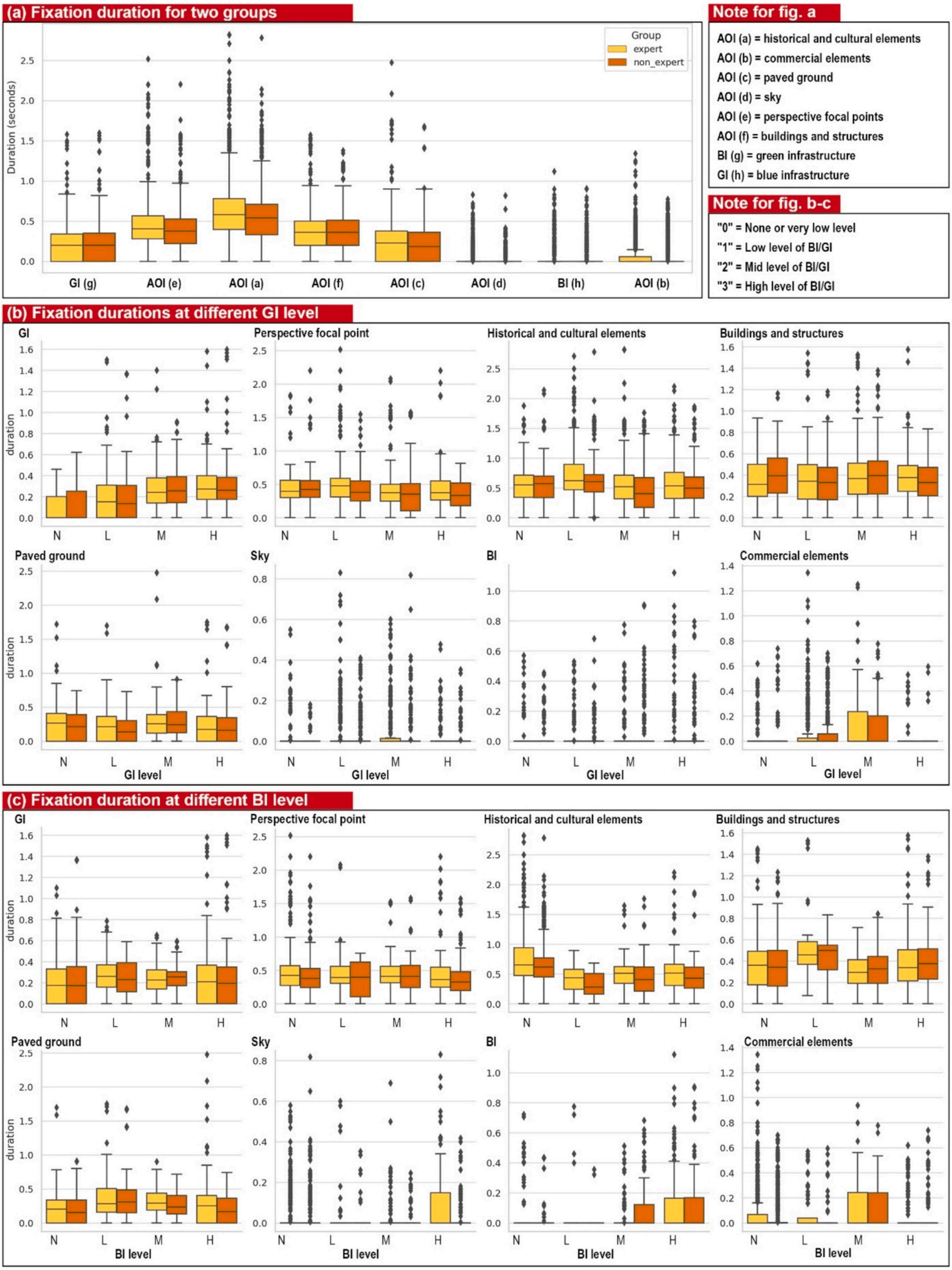

Fig. 5. Analysis results of fixation duration.

Note: Additionally, fixation durations for each AOI category under different BI/GI exposure levels are also computed for reference at (b)-(c). In addition, the table of fixation duration for each participant can be found in Appendix A2. Details of the fixation duration for each participant can be seen in Appendix A3.

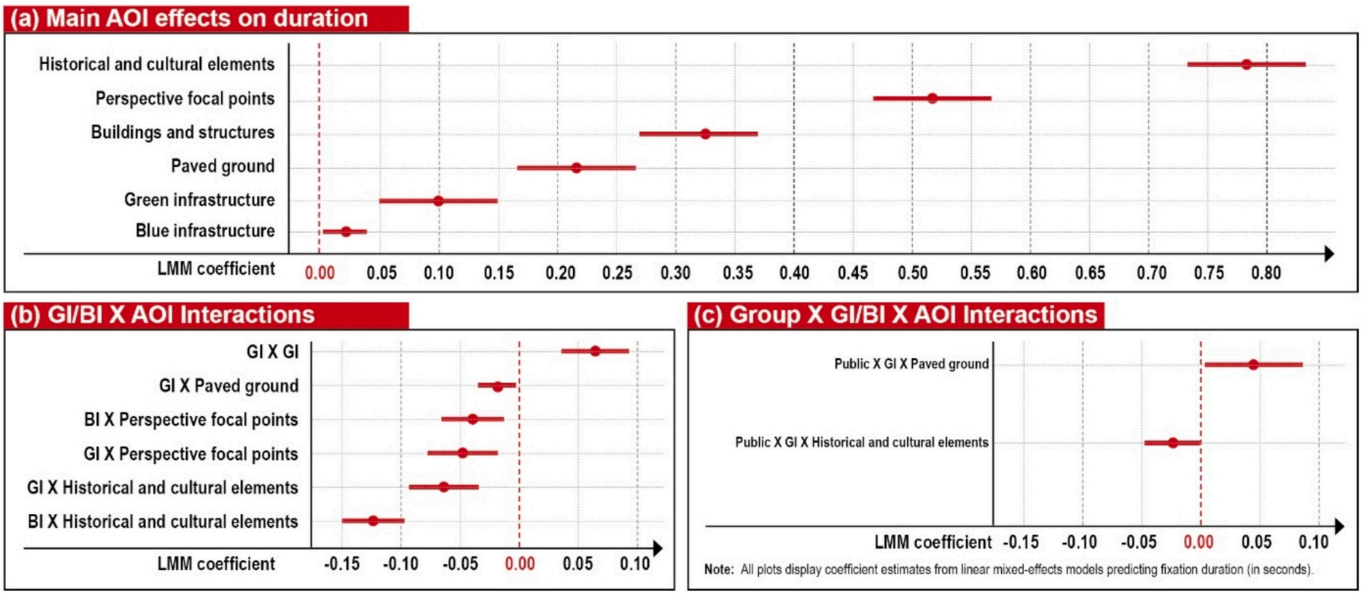

Fig. 6. Results of the LMM analysis.
Note: Details of the LMM results can be seen in Appendix A4.

focal points and *GI* × *paved ground*, illustrating that *GI/BI* may enhance or redirect spatial cognition depending on scene composition, because the gaze on *perspective focal points* and *paved grounds* always relates to spatial cognition (Fig. 6b).

The analysis also reveals notable group-level differences. Public participants exhibit significantly lower attention to *historical and cultural elements* (Coef = −0.087, p = 0.017) and *perspective focal points* (Coef = −0.079, p = 0.030) compared to professionals. This suggests that professionals are more attuned to symbolic and visual-spatial features. Interestingly, under higher GI Level conditions, the general public group demonstrates greater engagement with *paved ground* AOIs (Coef = 0.043, p = 0.042) (Fig. 6c).

4.3. *Questionnaire results (feeling layer)*

4.3.1. *Overview of response patterns*

To ensure internal consistency across repeated scene evaluations, Cronbach's Alpha was computed for each perception factor (F11–F33) separately within the expert and public groups. All 16 (8 factors, 2 groups) coefficients exceeded 0.92 **(Appendix A4)**, confirming the reliability of responses and the stability of factor structures across 20 spatial scenarios. Descriptive analysis reveals a clear alignment between perceived environmental quality and infrastructure exposure. Scenes with high combined infrastructure levels—particularly Scene 10 (BI = 1, GI = 1) and Scene 8 (BI = 1, GI = 2)—consistently received the highest average ratings from both groups. Scene 10, for example, yields mean scores of 4.73 (experts) and 4.87 (public), the highest across all evaluated scenes. In contrast, scenes with minimal infrastructure receive noticeably lower ratings, often falling below 4.0. These trends are robust across factors and user groups, indicating that both experts and non-experts consistently associate greater infrastructure presence with higher perceived value in historic urban settings. While GI exhibits a broad positive effect—particularly on ecological aesthetics and spatial memory—BI displayed more focused influence. Among public participants, BI strongly enhances perceptions of visual aesthetics and genius loci, producing mean score differences of 0.3–0.5 points between low- and high-BI scenarios (Fig. 7a).

4.3.2. *BGI influence analysis: LMM and RF*

All LMM analyses accounted for inter-individual variability and repeated scene measures to ensure robustness of estimated effects. LMM results revealed that both BI and GI have significant positive effects across nearly all perception factors, though with distinct patterns between expert and public groups (Fig. 7b): For *historical atmosphere-related factors* (F11–F13), both BI and GI are highly significant (p < 0.001). In the public group, GI has a stronger effect on F11 (*cultural/symbolics*) (coef = 0.25) than in the expert group (0.15), while BI more strongly influences F12 (*spatial memory*) among experts (coef = 0.27 vs. 0.18 in public). For *spatial aesthetics* (F21–F22), experts are more influenced by *GI*, particularly for *ecological aesthetics (F22)* (coef = 0.23). Conversely, public participants are more responsive to *BI*, especially on *visual aesthetics* (F21) (BI coef = 0.25 vs. GI = 0.21), reflecting a more visually driven perception. In functionality-related factors (F31–F33), *GI* is the dominant predictor in both groups, especially for *recreational and well-being* (F32) and *spatial function* (F33). BI shows positive but generally weaker effects.

RF analysis assesses the contribution of BI and GI without relying on statistical thresholds (Fig. 7c). Importance scores, calculated using MDI, further confirm the differential impact of BI and GI across perception factors: In the expert group, *GI* consistently ranks higher than *BI* in importance scores, averaging 0.63 across all factors. It is particularly dominant for F22 (*ecological aesthetics*) and F11 (*cultural/symbolics*), where importance reaches 0.92 and 0.88, respectively. Among public participants, *BI* emerges as a stronger predictor for specific factors, namely F21 (*visual aesthetics*) and F13 (*genius loci*), where its importance surpasses that of *GI* (0.56 vs. 0.44 and 0.52 vs. 0.39, respectively).

The convergence of LMM significance and RF importance highlights the robustness of these findings: GI has a broad and stable influence, especially among experts, while BI's impact is more factor-specific and visually driven, especially in the public group.

4.4. *Interview-based perception analysis (understanding layer)*

In total, a combined 620 coded pathways have been identified across both groups, comprising 264 codes from the public group and 356 from the expert group (Fig. 8). Across all interview responses, both public and expert groups exhibit a general preference for GI over BI, though the distribution is relatively balanced. The public group records 115 GI-related mentions and 102 for BI, while the expert group registers 119 for GI and 106 for BI.

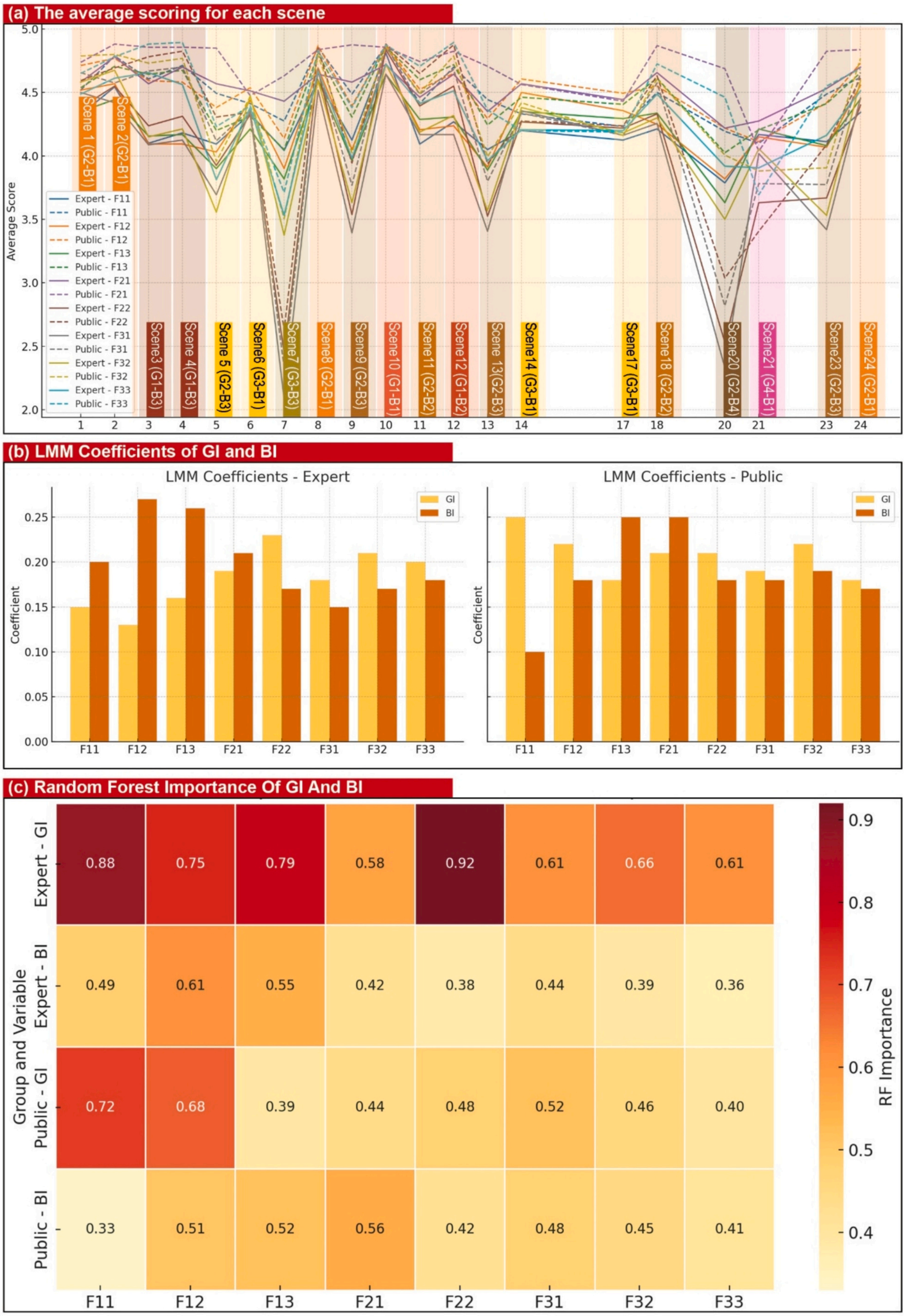

Fig. 7. Results of the questionnaire-based analysis.
Note: Details of the questionnaire results can be seen in Appendix A5.

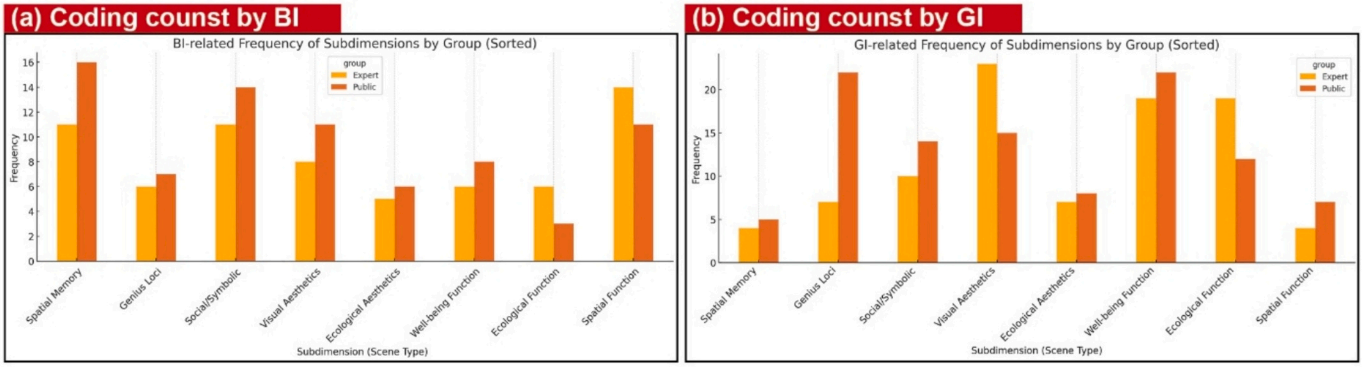

Fig. 8. Results of coding analysis.

Fig. 9. Integration and generalization at "seeing" and "feeling" layer: (a) Visual attention weights by integrating LMM and BGI exposure; (b) Preference scores enhancing estimation for the entire street by integrating RF and BGI exposure; (c) The local analysis for the different segments; (d) The local analysis for the viewpoints.

The two groups demonstrate distinct patterns in how each infrastructure type is cognitively linked to specific subdimensions. For the public group, GI is most strongly associated with *Recreational and well-being functions* (37 mentions), followed by *Visual aesthetics* (18) and *Genius loci* (21). BI is linked primarily to *Visual aesthetics* (21) and *Recreational and well-being functions* (23), with some mention of *Ecological function* (15). The expert group exhibits a more functionally and ecologically integrated mapping. GI is most commonly linked to *Ecological function* (31) and *Recreational and well-being functions* (23), whereas BI is associated with *Ecological aesthetics* (11), *Ecological function* (18), and *Spatial function* (18).

At the subdimension level, the most cited categories for the public group are *Recreational and well-being functions* (60), *Genius loci* (44), and *Visual aesthetics* (39)—highlighting an affective and sensory-driven mode of engagement. Experts emphasize *Ecological function* (49), *Recreational and well-being functions* (39), and *Spatial function* (33), reflecting a more analytic, systems-based framework. These findings underscore fundamental differences in how public and expert groups interpret BGI in HUAs at the “understanding” layer.

4.5. Cross-layer visual enhancement from BGI on HUA

This section integrates findings from all three perceptual layers with UAV-derived BGI exposure modeling to assess how BGI enhances visual experience across multiple spatial scales along Pingjiang Road. Consistent with the methodology outlined in Section 3.4, the analysis is structured into the following three subsections:

(a) Integrated street-level analysis of visual attention and preference.

Aggregated perceptual outcomes from the eye-tracking (“seeing”) and questionnaire (“feeling”) experiments reveal a coherent spatial relationship between BGI exposure and perceptual impacts at the street level (Fig. 9a, b).

Specifically, street segments characterized by higher combined GI and BI exposure exhibit systematically modified visual attention distributions, reducing fixation intensity on historically dominant AOIs (such as cultural elements and perspective focal points) and slightly shifting visual attention toward GI elements. This attentional redistribution implies subtle attentional competition effects, where increased BGI exposure may moderately draw gaze away from traditional heritage focal points. Notably, these attentional shifts remain consistent across both expert and general public groups, suggesting a generalized attentional impact of BGI exposure.

In parallel, the street-level integrated analysis of affective preference consistently demonstrates positive perceptual uplift associated with increased BGI exposure. Higher exposure levels of GI and BI strongly correlate with elevated environmental preference ratings across all perceptual factors. GI emerges as a particularly consistent and influential factor, especially among experts who link it with ecological aesthetics and spatial coherence. In contrast, BI’s perceptual contribution is more nuanced and context-specific, exerting a somewhat stronger influence among the public, particularly concerning visual aesthetics and symbolic resonance (genius loci). Collectively, this integrated analysis clearly demonstrates that the high spatial exposure to BGI significantly enhances perceptual quality across the street, simultaneously promoting broader visual exploration and elevated environmental preferences.

(b) Localized predictions of BGI impacts.

Building upon UAV-derived spatial exposure modeling, this study further conducted detailed perceptual assessments for different segments of the street, specifically divided into the southern, northern, and eastern segments (Fig. 9c).

In the southern segment, the area toward the south exhibited high levels of GI exposure and moderate BI exposure, contributing to a positive distribution of visual attention and significantly enhancing perceptual evaluations across *ecological aesthetics (F22)*, *visual aesthetics (F21)*, and *spatial functionality (F33)*, resulting in high overall preference scores (approximately 4.6–4.8). Conversely, the northern area of the southern segment, characterized by generally low levels of BGI exposure, exhibited notably lower preference ratings (approximately 3.8–4.1).

Similarly, in the northern segment, the central area demonstrated low BGI exposure levels, corresponding with reduced overall perceptual preference ratings (approximately 3.8–4.0). However, the southern and northern ends of the northern segment presented moderate BI exposure and relatively higher GI exposure, substantially improving environmental perceptions and spatial quality ratings (approximately 4.2–4.5), though still slightly below those of the southern portion of the southern segment.

For the eastern segment, high levels of BI exposure significantly elevated perceptual ratings for *visual aesthetics (F21)* and *genius loci (F13)*. Specifically, the western area of the eastern segment, with relatively lower GI exposure, exhibited somewhat reduced ratings for ecological aesthetics and spatial coherence, though overall preference scores remained relatively high (approximately 4.4–4.6). Meanwhile, the eastern area, characterized by both high GI and BI exposure, further enhanced ratings across visual and ecological aesthetics, leading to overall spatial perception scores of approximately 4.5–4.7, approaching the highest levels observed in the southern portion of the southern segment.

In addition, the environmental impact of BGI can also be assessed based on the specific areas of different viewpoints. For instance, the three viewpoints depicted in the figure show relatively low impacts of BGI on visual attention and preference, resulting in slightly lower preference scores (Fig. 9d). This UAV-based spatial-perceptual analytical approach not only facilitates systematic evaluation at the overall street scale but also enables targeted assessments and predictions for specific points or segments of varying lengths and detail. Compared with traditional perception studies based solely on individual scenes or viewpoints, this method offers significantly greater flexibility and generalizability, providing robust support for spatial planning and design decisions in heritage areas.

(c) Understanding Layer: Divergent cognitive structures anchored in BGI.

At the understanding level, both user groups construct distinct cognitive pathways from BGI to perceptual meanings (Fig. 10). Experts show a more comprehensive and balanced structure, linking both BI and GI to all three major themes—historical/cultural atmosphere, spatial aesthetics, and spatial functionality. Their interpretation is systematic, combining ecological, spatial, and symbolic dimensions. In contrast, the public group focuses more on affective and sensory experiences. Their pathways concentrate on visual aesthetics, cultural identity (genius loci), and recreational and well-being functions, reflecting a perception mode rooted in personal emotion and visual impression rather than systemic reasoning. These results highlight that while both groups recognize the value of BGI, experts approach it through functional and integrated thinking, whereas the public engages through aesthetic and experiential dimensions.

5. Discussions

By integrating UAV photogrammetry with a three-layer perceptual framework, this study offers nuanced insight into how BGI shapes visual experience in HUAs. The findings indicate that (a) the digital modeling approach supports perception analysis by providing more reliable exposure estimates, addressing RQ1; (b) explaining BGI’s influence benefits from a multi-layer design that links attention, appraisal, and interpretation, addressing RQ2; and (c) BGI appears to diversify visual attention, tends to enhance subjective perceptual quality, and activates distinct cognitive interpretations among experts and the general public, informing RQ3. The discussion that follows develops these three strands and then outlines theoretical and practical implications, limitations, and directions for future research.

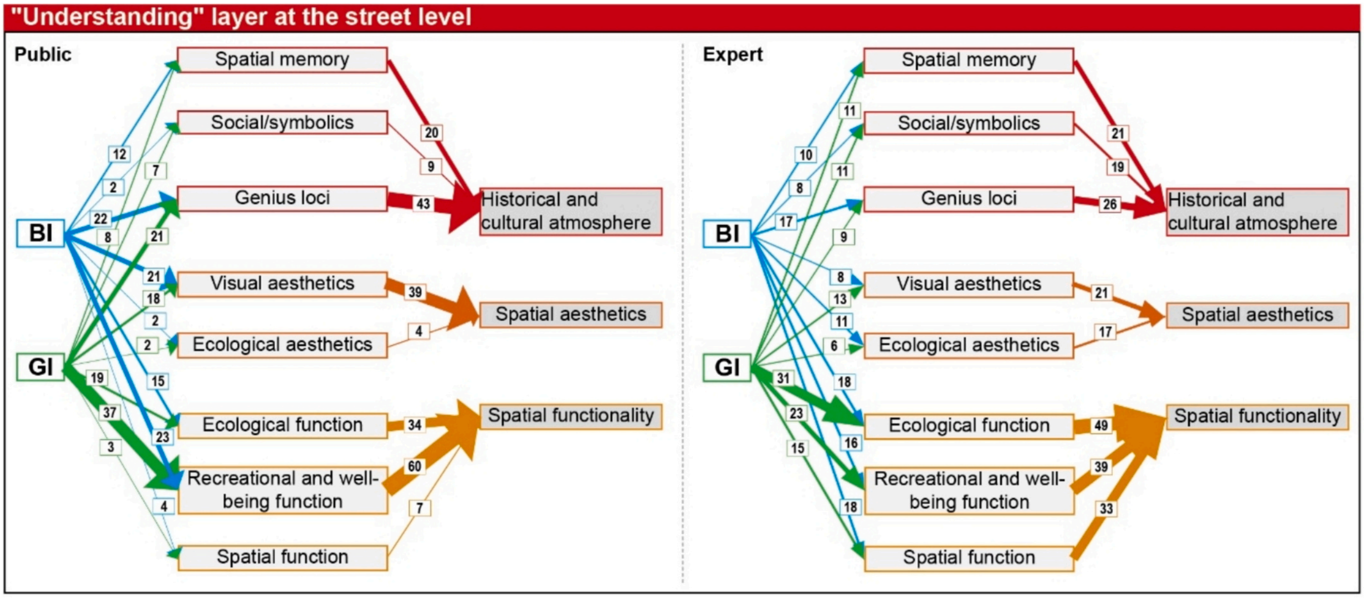

Fig. 10. Understanding layer: Cognitive pathways for both groups.

5.1. Cross methodological gaps: Combination of digital tools with empirical approaches

In recent years, the study of visual perception has been characterized by a methodological divide: quantitative, expert-driven tools such as GIS and 3D modeling dominate spatial analysis, while empirical, perception-based approaches focus on users' subjective experiences (Gulten et al., 2025; Nijhuis et al., 2011). Although both streams offer valuable insights, each has inherent limitations when used independently. Purely spatial analyses (e.g., digital modeling approaches evaluating visibility or exposure metrics) frequently neglect human subjective experiences and emotions, especially inadequate for environments embedded with complex historical or cultural meanings (Ervin, 2001). Likewise, AI-based analyses using Street View Imagery (SVI) are constrained by fixed viewpoints, coverage limitations, and inadequate adaptability to diverse historical urban settings (Fan et al., 2025; Peng et al., 2025). For instance, in many heritage-sensitive areas, comprehensive street-view datasets are unavailable, severely restricting analysis applicability. On the other hand, empirical perception/behavior-based methods alone often undervalue spatial or environmental characteristics, making their findings challenging to generalize or integrate at larger scales (Chhetri and Stimson, 2014).

In relation to RQ1, this paper contributes to bridging this gap by integrating UAV-based photogrammetry and 3D semantic modeling with a three-layer empirical framework, combining eye-tracking, questionnaire surveys, and interviews. Specifically, the UAV-based data acquisition presented here overcomes the viewpoint and coverage constraints inherent to SVI approaches, offering a non-intrusive, flexible alternative ideal for analyzing sensitive heritage contexts. The digital modeling component enables spatially explicit visibility mapping of BGI, producing scene-specific exposure metrics from pedestrian perspectives. These serve as the foundation for selecting representative visual stimuli and calibrating perceptual data at a fine-grained level. Empirical methods validate and contextualize these spatial metrics through user responses. This hybrid approach provides triangulated evidence across methods and links the objective spatial attributes of visual impact sources with the comprehensive spectrum of human perceptual responses. By correlating measurable exposure metrics with layered user perceptions, it enables a nuanced evaluation of visual impact levels that extends beyond mere geometric analysis. Although demonstrated here through the case of BGI (the influence is in general positive), the framework is broadly applicable to assessing diverse visual impact sources in different urban heritage contexts.

By demonstrating the value of cross-methodological integration, this study advances current visual assessment practices in heritage planning and Environmental Impact Assessment (EIA) (Dentoni et al., 2023). It supports a shift from static visibility simulations or isolated surveys toward multi-methodological and perception-informed evaluations, offering a more realistic reflection of how people experience complex, visually sensitive environments.

5.2. Cross perceptual layers: Seeing, feeling, and understanding

This study advances understanding of visual perception in HUAs by integrating three complementary layers, namely seeing, feeling, and understanding, into a unified analytical framework that clarifies, with respect to RQ2, how BGI relates to attention, appraisal, and interpretation. Previous perceptual assessments often focus exclusively on one isolated dimension, limiting their explanatory power. Physiological methods, such as eye-tracking, are precise in revealing patterns of visual attention at the neurological and behavioral levels. However, they inherently neglect the experiential complexity and interpretive richness of visual perception. Specifically, eye-tracking data alone cannot clarify whether visual attention reflects attraction, confusion, or even cultural significance, as identical visual attention patterns could emerge from vastly different perceptual motivations (Geise, 2011; McGrath et al., 2019). Surveys capturing aesthetic or emotional preferences rely on participants' retrospective self-reports, which are inherently influenced by memory biases, social desirability, or cultural framing effects. Nevertheless, subjective evaluations derived purely from surveys are detached from real-time perceptual experiences, making it difficult to reliably associate reported preferences with actual visual processing behaviors or spatial-environmental features (Bishop and Rohrmann, 2003; Vo et al., 2024). Qualitative cognitive studies, such as in-depth interviews or discourse analyses, excel at uncovering rich narratives and interpretive frameworks through which people understand visual environments. Yet, without grounding in measurable physiological data or systematically collected subjective ratings, these qualitative interpretations can remain speculative, contextually bounded, and difficult to generalize or systematically integrate into spatially explicit analyses (Lloyd and Gifford, 2024).

By merging physiological (seeing), affective (feeling), and cognitive (understanding) dimensions, the present study moves beyond these limitations, achieving a comprehensive and integrative analysis of visual perception. Each layer captures a distinct but interconnected facet of human experience, offering a progressively deeper view into how BGI shapes the visual environment. The seeing layer captures the immediate physiological responses through eye-tracking (Liu and Nijhuis, 2020), showing that BGI subtly diversifies visual attention without overriding cultural focal points. The feeling layer further reveals that greater BGI exposure consistently enhances subjective evaluations across aesthetic, atmospheric, and functional dimensions. Building on these sensory and affective responses, the understanding layer maps the cognitive pathways through which different user groups interpret BGI, from experts' functional-symbolic reasoning to the public's emotional and aesthetic engagement.

Together, these layers form a complementary and hierarchical structure, where sensory perception (seeing) initiates emotional appraisal (feeling), which subsequently supports deeper cognitive interpretation (understanding). This structured integration allows a multi-dimensional reading of visual experience and a gradual unfolding from surface-level impressions to meaning-making processes. Such an approach highlights both the analytical complementarity—each layer offering distinct but interconnected insights—and the progressive depth of perception, reinforcing the value of layered frameworks for nuanced visual impact assessments in culturally significant environments.

Notably, in heritage-sensitive contexts, where spatial perception is deeply embedded in cultural memory, symbolic narratives, and emotional attachments, visual impact assessment must move beyond numerical measures of visibility or the physiological tracking of gaze patterns. It must also address the experiential and interpretive dimensions that shape how individuals and groups relate to historic spaces (Assmann, 2011a; Lowenthal, 1975). Interventions (such as BGI in this study), when introduced into such contexts, interact not only with the physical environment but also with collective memory and identity, making its visual impact inseparable from affective responses and cognitive constructions of meaning (McDowell, 2016). By systematically linking seeing, feeling, and understanding, the present framework captures this complexity, offering a more holistic, culturally attuned methodology. It thus provides a critical basis for future heritage visual impact assessments that aim to respect, preserve, and enrich the experiential authenticity of historic urban landscapes.

5.3. *Cross groups differences: General public and experts*

While the three-layer framework addresses RQ3 by revealing cross-group differences between experts and the general public in visual attention, affective evaluation, and cognitive interpretation, these variations are secondary to a broader implication: the ongoing shift in heritage value assessment paradigms. Briefly, experts tend to interpret BGI interventions through multidimensional functional, ecological, and symbolic frameworks, whereas the general public's engagement is anchored in aesthetic pleasure, emotional resonance, and immediate spatial experiences.

This divergence reflects a broader and increasingly recognized shift in heritage theory and practice. Traditional models of heritage evaluation, predominantly expert-driven and focused on formally recognized values, are now expanding to incorporate diverse public perceptions and everyday experiences (Jones, 2017). Concepts such as "everyday heritage (Atkinson, 2016)," "informal heritage (Barrère, 2016)," and participatory heritage management emphasize that cultural significance is not solely determined by expert authority but emerges through lived experience, emotional attachment, and collective memory within communities (Li et al., 2020). In this context, visual impact assessment for heritages landscapes must move beyond narrowly technical or professionalized perspectives. They must systematically account for the perceptual, affective, and cognitive frameworks through which non-expert users engage with interventions in the landscape. By capturing both expert and public pathways of meaning-making, assessments can better reflect the pluralistic nature of heritage value judgments and more effectively guide the design and management of culturally sensitive environments.

5.4. *Insights for HUA development*

Building upon the cross-layer and cross-group findings, several insights emerge for the future planning and visual management of HUAs, with this case situated in a Jiangnan water-green context where BGI is closely interwoven with canals, bridges, narrow alleys, and garden traditions.

First, the layered perception model demonstrates that BGI is not merely a functional or decorative component, but a perceptual agent that modulates attention, influences preferences, and shapes meaning. Even when not the primary visual focus, BGI supports more diversified and relaxed visual scanning, contributing to environmental legibility and psychological restoration. This suggests that strategic incorporation of BGI can enhance visual coherence without overwhelming the heritage character. For example, in a newly reconstructed historic environment within the case area (Zhongzhangjia Xiang), higher levels of BGI exposure can effectively enhance people's preference for the newly created spaces, as illustrated by Scene 20. Although its score is slightly lower than other scenes with similar BGI levels, the preference rating is still higher than many areas with lower BGI exposure.

Second, by linking BGI exposure to perceptual evaluations, the study provides a framework for evidence-based visual enhancement. Scenes with moderate to high BGI exposure consistently achieved higher perceptual scores, indicating that balanced integration (not excess) is key. Overdesign or uncontrolled vegetation growth, while not present in the case area, may lead to visual clutter or loss of historical legibility, a risk noted in other studies.

Third, the differentiated cognitive responses between experts and the general public underscore the need for multi-vocal design and evaluation processes. Experts seek systemic coherence and functional performance, while the public prioritizes sensory richness and cultural resonance. Planning strategies should therefore accommodate both analytical and experiential perspectives, facilitating broader public engagement and heritage appreciation.

Finally, integrating digital modeling with empirical perception offers a practical and scalable way to manage visual environments in HUAs, particularly in Jiangnan settings. Recent advances in consumer-grade imaging and efficient modeling methods such as 3D Gaussian Splatting lower technical barriers and enable low-disturbance surveys. The approach is transferable conditionally to canal- and green-structured districts with similar sightline structures, pedestrian-scale street forms, comparable eye-level BGI placement, and heritage contexts that sustain place attachment; beyond these conditions, findings should be re-tested before use.

5.5. *Limitations*

Despite these contributions, several limitations must be acknowledged. First, the study privileges spatial metrics and quantitative evidence, and its engagement with social, historical, and ethnographic dimensions remains limited. Interpretations are therefore framed largely as context-specific associations rather than culturally situated explanations. Future work should incorporate stronger ethical engagement and reflexivity, for example by deepening community participation, expanding qualitative and ethnographic inquiry, and making researcher positionality explicit in order to situate findings within lived histories and local meanings (Muhammad et al., 2015). Second, the representativeness of the study sample was limited in terms of demographic variability (including gender, age, cultural background) and the structure of both general public and expert groups. These sampling limitations potentially constrain the broader applicability of perceptual and cognitive findings. Demographic factors (e.g., gender, age, culture) were intentionally not controlled, as the study focused primarily on perceptual differences between expert and public groups. However, future work should address these variables explicitly. Third, the integrated methodological approach employed in this study, including UAV-based data acquisition, eye-tracking, and qualitative assessments, is resource-intensive and logistically complex, limiting its immediate scalability beyond small-scale pilot studies. Future research could explore methodological simplifications or adaptations suitable for broader or larger-scale applications. Finally, the eye-tracking experiments utilized static photographs rather than mobile glasses in field settings, potentially reducing the ecological validity of perceptual data. Future research should consider employing mobile eye-tracking technology to capture more realistic perceptual responses.

6. Conclusions

This paper investigates how BGI shapes visual perception in HUAs by integrating UAV photogrammetry with a perception-based framework encompassing three layers: seeing, feeling, and understanding. Combining spatially explicit modeling with empirical methods, including eye-tracking, questionnaire surveys, and in-depth interviews, the study assessed the perceptual influence of BGI across experts and the general public.

The findings reveal that BGI contributes to HUA perception in distinct but complementary ways. At the seeing layer, BGI moderates visual attention patterns, subtly reducing the dominance of traditional focal points and encouraging more diverse visual engagement. At the feeling layer, BGI exposure correlates with consistently higher user evaluations across historical atmosphere, aesthetics, and spatial functionality. At the understanding layer, BGI serves as a cognitive trigger, activating different interpretive pathways among user groups. GI exerts a more stable and broadly positive impact, while BI exhibits more context-dependent and group-specific effects. Professionals display a balanced and systemic interpretation of BGI, whereas the general public emphasizes emotional and aesthetic connections.

Methodologically, this study demonstrates the value of integrating digital spatial analysis with perception-based empirical approaches. By systematically bridging spatial quantification and multi-layered perception analysis, it offers a novel framework that advances visual impact assessment beyond traditional singular-method approaches. The proposed cross-method, cross-layer, and cross-group framework offers a practical, replicable model for perception-informed visual impact assessment in heritage contexts. This research is among the first to explicitly examine how BGI influences visual perception in HUAs, addressing a critical but previously overlooked dimension of heritage-sensitive landscape evaluation. Beyond BGI, the framework holds significant potential for broader applications in evaluating diverse spatial interventions in culturally sensitive environments, supporting more inclusive, evidence-based, and culturally attuned planning practices. By highlighting both spatial attributes and lived perceptual experiences, the study contributes new methodological pathways for advancing visual environmental assessments that respond to the pluralistic and evolving nature of heritage conservation demands.

Declaration of competing interest

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

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eiar.2025.108301.

Data availability

Data will be made available on request.

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