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Public Perception, Representational Trust, and Scheme Support in AI-Visualized Urban Regeneration: Evidence from Industrial Heritage Public Spaces

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Abstract

Visual generative artificial intelligence (visual GenAI) is increasingly used to communicate urban regeneration proposals, but how public evaluations relate to scheme support remains insufficiently understood. Using the Fengtian Factory in Shenyang, China, this study examined three AI-visualized industrial heritage regeneration schemes across three scenes within the Stimulus–Organism–Response framework. A total of 360 participants evaluated all nine stimuli in a fixed sequence, yielding 3240 evaluation records. Multilevel confirmatory factor analysis, multilevel structural equation modeling, participant-level cluster bootstrap, and repeated-measures analysis of variance were used. Perceived cultural authenticity and perceived realism were positively associated with perceived trust in visual representation; trust, cultural authenticity, and affective comfort were positively associated with scheme support. The exhibition-oriented scheme received the highest cultural authenticity and trust ratings, whereas the shaded relaxation-oriented scheme received the highest affective comfort ratings. Despite these differences in perceived cultural authenticity and affective comfort, overall scheme support did not differ significantly across the three schemes. Perceived realism also showed no significant between-scheme differences. Scheme contrasts showed oppositely directed indirect associations with support through cultural authenticity and trust and through affective comfort. These findings distinguish evaluations that differentiate among schemes from evaluations associated with trust and support, informing the assessment of AI-visualized industrial heritage regeneration.

Keywords: visual generative artificial intelligence; urban regeneration; industrial heritage; public perception; representational trust; public support

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1. Introduction

Industrial heritage constitutes important material evidence of urban industrialization. Its buildings, production facilities, and spatial fabric record modes of production and trajectories of urban development during particular historical periods, while also embodying accumulated place-based memories and cultural meanings [1–3]. With the decline of traditional industrial functions, adaptive reuse has become an important approach to linking heritage conservation with sustainable urban development [4]. Unlike the regeneration of ordinary urban spaces, industrial heritage regeneration requires the coordinated consideration of heritage value continuity, contemporary functions, and spatial-

environmental improvement [5,6]. Previous studies have identified the effective reuse of developed land, conservation of historical and cultural values, and community participation as important conditions for sustainable industrial heritage reuse [7,8]. Industrial heritage regeneration therefore involves not only physical design decisions but also how the public understands, evaluates, and accepts different regeneration directions.

Involvement of the community encourages community members and other stakeholders to deliberate on their needs and planning options [9]. The public's level of professional expertise influences how they perceive spaces that have not yet been constructed [10]. Although virtual and augmented reality as well as interactive planning tools have made proposed spaces easier to understand, they often require specialist skills and equipment and can be costly to develop [11]. Visual generative artificial intelligence (visual GenAI) offers another option. It can quickly create different design scenarios using text prompts and image editing. AI-generated images may offer a starting point for exploring and discussing design ideas. They could also help the public take part in planning from an early stage [12].

As visual GenAI is increasingly incorporated into urban design and planning practice, AI-generated images are becoming media through which the public understands, discusses, and evaluates future spatial proposals. In industrial heritage settings, evaluations of AI–AR co-creation encompass authenticity, well-being, and preservation intention [13], while expert feedback informs criteria for evaluating AI-assisted regeneration proposals [14].

Previous studies have examined the use of multimodal large language models (MLLMs) to interpret and evaluate images of urban spaces and buildings. The GPT-4 assessment of urban attractiveness shows strong overall agreement with human ratings, although geographical differences persist [15]. ChatGPT-4o has also been used to assess the perception of street view changes [16]. GPT-4V's assessment of architectural atmosphere in virtual urban environments generally matches the most common human responses. There are still differences in emotional resonance and perceived grandeur [17]. Facade similarity was also examined by comparing human assessments with baseline ChatGPT assessments and assessments guided by 15 properties of Alexander's life structure [18]. Heritage-related features extracted from facade images using GPT have also been combined with building register data in machine learning models to classify buildings according to their heritage value [19]. These studies mainly deal with AI-assisted assessment of the built environment, while this study employs GenAI as a visualization medium to communicate the proposed regeneration schemes, with an empirical focus on the public assessment of the proposal itself.

However, how public evaluations of cultural authenticity, affective comfort of public space, and perceived realism relate to representational trust and scheme support in the context of industrial heritage regeneration remain underdescribed. To address this gap, the study examined these associations for three site-referenced, AI-visualized regeneration directions.

AI-visualized regeneration schemes can be conceptualized as external stimuli associated with cognitive, emotional, and trust assessments and subsequent scheme support. We used a stimulus-organism-response (S–O–R) framework to guide the analysis. The regeneration scheme type was stimulus (S) and scheme support was response (R). The organism (O) includes perceived cultural authenticity, affective comfort of public space, perceived realism, and perceived trust in visual representation. We study the relationship between these variables.

The study addresses the following research questions:

RQ1: Are there significant differences in perceived cultural authenticity, affective comfort of public space, perceived realism, perceived trust in visual representation, and

scheme support among the three selected AI-visualized regeneration schemes under the stimulus and presentation conditions used in this study?

RQ2: At the within-participant level, what structural associations exist among perceived cultural authenticity, affective comfort of public space, perceived realism, and perceived trust in visual representation, and how are these psychological evaluations associated with scheme support?

RQ3: Are the three types of AI-visualized regeneration schemes significantly and indirectly associated with scheme support through each of the following pathways: perceived cultural authenticity–perceived trust in visual representation, perceived realism–perceived trust in visual representation, and affective comfort of public space?

The Fengtian Factory in Shenyang, China, retains identifiable industrial buildings and historical spatial relationships, providing a suitable context for examining public evaluations of AI-visualized industrial heritage regeneration schemes. Using this site to address the research questions, the study makes three contributions to research on AI-visualized urban regeneration. First, it examines public evaluations of specific industrial heritage regeneration proposals, rather than focusing on the adoption of generative AI tools or the visual quality of AI-generated images alone. Second, it distinguishes psychological evaluations associated with perceived trust in visual representation and scheme support from those that vary across the selected regeneration schemes. Third, it identifies how differences in perceived cultural authenticity and emotional comfort coexist with non-significant differences in overall scheme support, as well as indirect and conditional direct associations in opposite directions in estimated models. Together, these contributions provide a more differentiated understanding of how the public evaluates AI-visualized industrial heritage regeneration proposals.

2. Theoretical Framework and Research Hypotheses

2.1. Theoretical Foundation: The Stimulus–Organism–Response Model

The S–O–R model helps explain the relationship between external stimuli, internal psychological state, and later behavioral responses [20]. The model was first developed in environmental psychology. Its organism (O) component can include emotional experience and cognitive evaluation [21,22]. Researchers later applied the model in studies of consumer behavior and digital experiences such as virtual reality [23,24].

Research on spatial regeneration has shown that environmental quality, spatial experience, and place characteristics can be associated with participation and use behaviors through internal states such as satisfaction, pleasure, and sense of belonging [25]. Studies of AI-generated content have reported similar S–O–R relationships. In one study of AI-generated videos, visual anomalies were linked to eeriness and perceived realism. Both were also associated with behavioral intention through perceived trust [26]. The S–O–R framework may offer a way to study the links among AI-generated visual representations, psychological evaluations, and subsequent responses.

Industrial heritage encompasses multiple attributes, including material space, historical and cultural significance, and place meaning. Regeneration schemes for industrial heritage may prompt several psychological responses from the public at the same time. These include judgments about authenticity and value as well as emotional reactions and feelings of connection to place. Existing studies have incorporated variables such as authenticity experience, perceived value, emotional responses, and place attachment into the S–O–R framework to explain the relationships between environmental characteristics of industrial heritage, internal psychological states, and subsequent behavioral responses [27,28]. This suggests that the material and cultural characteristics of industrial heritage can enter the individual's cognitive and affective evaluation as external stimuli and correlate with subsequent behavioral responses. These studies provide a basis for applying

the S–O–R framework to public evaluations of AI-visualized industrial heritage regeneration schemes. This earlier work helps justify studying the relationships between cultural authenticity, emotional experience, representational trust, and scheme support.

Therefore, the S–O–R model was adopted as the overall analysis framework in this study. The three AI-visualized regeneration schemes serve as external stimuli (S). Perceived cultural authenticity, affective comfort of public space, perceived realism, and perceived trust in visual representation form the organism component (O). Scheme support forms the response (R). The framework aims to examine how the schemes relate to cognitive evaluations, affective experiences, trust judgments, and scheme support. The proposed structural relationships are illustrated in Figure 1.

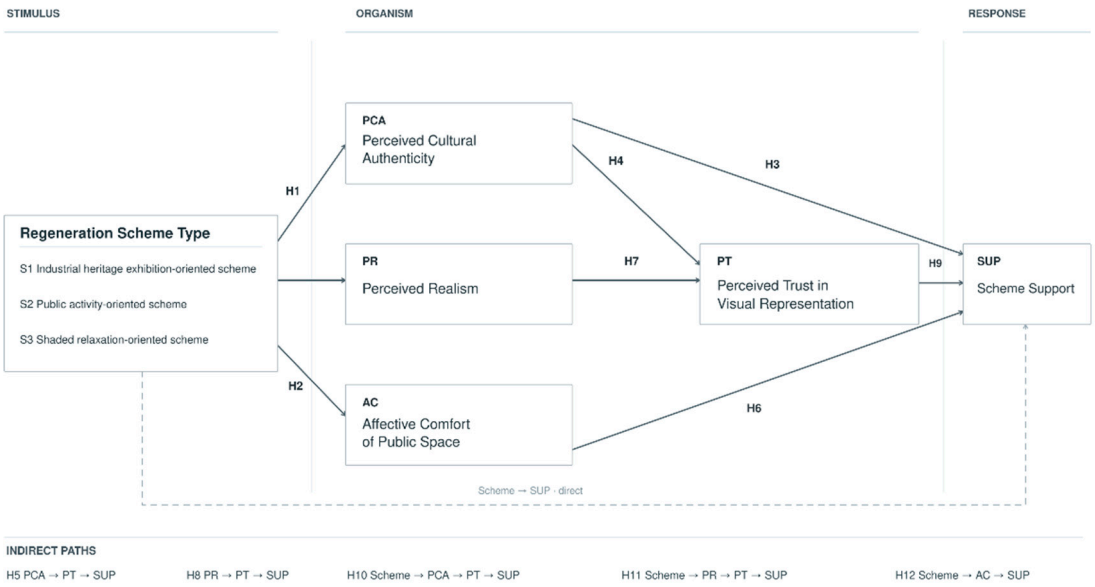


Figure 1. Structural model within the S–O–R framework.

2.2. Hypothesis Development

2.2.1. Regeneration Scheme Type

The preservation of physical remains is only part of the regeneration of industrial heritage. Another is to bring the historical and cultural information preserved in these monuments into the way people understand and experience sites. Studies based on place theory have shown that the protection and reuse of industrial heritage can enhance the public's understanding of heritage culture and strengthen place identity, and an important role of spatial regeneration is to transform previously implicit historical and cultural information into spatial expressions that can be perceived and identified [29]. We can consider different regeneration schemes as external stimuli in the S–O–R framework. Each scheme brings together a different combination of design priorities. We also examined whether public evaluations of cultural meaning and emotional spatial experiences differ across schemes with different design cues.

The regeneration of public spaces within industrial heritage is not organized around a single objective, but simultaneously involves different levels of spatial tasks, including the expression of industrial heritage culture, the improvement of site environment and the restructuring of public uses. Recent studies on adaptive reuse of industrial heritage have developed comprehensive assessment frameworks covering environmental, economic, and socio-cultural dimensions [3], while post-occupancy assessments of industrial heritage parks further distinguish cultural values, ecological environment, public spaces,

functional facilities, and public participation as separate assessment dimensions [30]. Industrial buildings, machinery, and raw materials can embody important aspects of a place's industrial history and local identity. However, the mere preservation of these monuments is not sufficient to fully realize their cultural significance. Their historical significance also needs to be further conveyed through the organization of presentation, narrative and cultural messages [31]. At the same time, the authenticity of cultural heritage is not only related to the continuity of its material form, but also to whether its historical and cultural connections and cultural significance are clearly conveyed [32]. At the environmental level, converting abandoned or underutilized industrial land into green space can produce multiple environmental benefits while providing spatial conditions for recreation and daily public activities [33]. Vegetation and greenery elements in industrial heritage landscapes are also positively correlated with public visual interest and length of stay [34]. Relevant environmental studies have further shown that the spatial configuration of vegetation is closely related to visual comfort and emotional experience, and appropriate canopy and greening structures correspond to more positive emotional evaluation and greater perceived comfort [35]. At the same time, the regenerated public space in industrial heritage sites also performs social functions such as daily interaction, entertainment and collective activities, and its spatial organization and functional facilities are closely related to public activity participation and social interaction experience [30]. Based on these studies, this study establishes three regenerative directions for AI visualization stimulus materials: oriented to industrial heritage exhibitions (S1), public activity-oriented (S2), and shaded relaxation-oriented (S3). These regenerative directions reflect different design priorities, expressed through differences in functional focus and spatial organization of the proposed interventions.

Accordingly, the following hypotheses are proposed:

H1. *Perceived cultural authenticity differs significantly across regeneration scheme types.*

H1a. *Perceived cultural authenticity is higher for the industrial heritage exhibition-oriented scheme than for the public activity-oriented scheme.*

H1b. *Perceived cultural authenticity is higher for the industrial heritage exhibition-oriented scheme than for the shaded relaxation-oriented scheme.*

H2. *Affective comfort of public space differs significantly across regeneration scheme types.*

H2a. *Affective comfort of public space is higher for the shaded relaxation-oriented scheme than for the industrial heritage exhibition-oriented scheme.*

H2b. *Affective comfort of public space is higher for the shaded relaxation-oriented scheme than for the public activity-oriented scheme.*

2.2.2. Perceived Cultural Authenticity (PCA)

Perceived cultural authenticity refers to an individual's subjective evaluation of whether cultural heritage and its cultural expressions preserve and convey recognizable historical and cultural characteristics [36]. Cultural heritage authenticity is not limited to judgments of material authenticity; previous research has further distinguished objective, constructive, existential, and postmodern authenticity, indicating that public evaluations of heritage authenticity also involve subjective interpretations of heritage meanings and experiences [37]. Human evaluations of AI-generated cityscapes have considered both visual realism and fidelity to local urban identity, highlighting the relevance of local knowledge to judgments of representational fidelity [38]. For AI-visualized industrial

heritage regeneration, perceived cultural authenticity concerns the public's judgment, based on the presented site information and visual content, of whether a scheme preserves and conveys the site's recognizable historical and cultural characteristics. Research on AI-generated visual content has found that evaluations of the extent to which generated content accurately and faithfully represents its referent are significantly associated with user trust, with trust mediating the relationship between such evaluations and subsequent behavioral intentions [39].

Perceived cultural authenticity may be associated not only with support for heritage conservation and development directions but also with trust judgments. Previous research has linked perceived authenticity with place attachment and support-related evaluations in heritage tourism contexts [40]. Related studies have shown that higher evaluations of cultural authenticity are positively associated with destination attachment, which in turn corresponds to a stronger willingness to support the development of cultural heritage tourism [41]. Evidence from the converse perspective of cultural representation further indicates that perceived distortions in cultural essence, cultural representation, and cultural construction at cultural heritage sites enter into a "risk–trust–behavioral intention" relational structure and are significantly associated with lower subsequent behavioral intention [42]. These findings suggest that public judgments regarding whether heritage cultural content and its expression maintain authenticity may be further linked to subsequent support orientations through trust evaluations.

Accordingly, the following hypotheses are proposed:

H3. *Perceived cultural authenticity is significantly and positively associated with scheme support.*

H4. *Perceived cultural authenticity is positively associated with perceived trust in visual representation.*

H5. *Perceived cultural authenticity has a significant positive indirect association with scheme support through perceived trust in visual representation.*

2.2.3. Affective Comfort of Public Space (AC)

Affective comfort of public space reflects the positive affective evaluation individuals form when encountering a spatial environment, particularly in terms of perceived calmness, relaxation, comfort, and safety. Spatial layout, natural elements, and overall environmental characteristics can influence the public's subjective evaluations of public spaces in terms of comfort, safety, and environmental preference [43,44]. Evaluations of existing streetscapes and public squares presented through 360-degree videos have included ratings of pleasantness, relaxation, and perceived safety alongside preferences for architecture and public-space design [45]. High-quality urban environments can alleviate stress and improve mood, while environments with greater restorative qualities are generally more likely to elicit positive environmental evaluations and preferences [46,47]. Accordingly, in this study, the affective comfort of public space refers to the public's subjective affective evaluation of whether the future public space depicted in a regeneration scheme would provide experiences of calmness, relaxation, comfort, and safety.

Positive affective-comfort experiences not only influence the public's immediate evaluation of a space but may also strengthen behavioral tendencies to approach, use, and accept that environment. Higher levels of environmental comfort are closely associated with positive behavioral intentions such as revisiting and recommending [48]. In the context of urban regeneration, residents' evaluations of spatial conditions, including buildings, infrastructure, traffic, and the public environment, are significantly associated with their willingness to participate in regeneration [49]. Therefore, in the regeneration of

industrial heritage public spaces, when the public anticipates that a future space will provide a calmer, more relaxing, comfortable, and safer environmental experience, such an evaluation may be associated with a stronger intention to support the regeneration scheme.

Accordingly, the following hypothesis is proposed:

H6. *Affective comfort of public space is significantly and positively associated with scheme support.*

2.2.4. Perceived Realism (PR)

Perceived realism (PR) refers to an observer's subjective judgment of how visually plausible, natural, and close to real-world experience a visual representation appears [50]. In environmental visualization, overall realism is not the only factor that determines how the visual representation represents the real environment. Descriptions of key visual elements relevant to scene judgment are also important. Higher levels of detail often contribute to the effectiveness of visual representation, with descriptions of scene elements such as foreground vegetation and ground being particularly important [51]. Therefore, in this study, perceived realism refers to the public's subjective cognitive evaluation of whether the architecture, spatial features, and environmental elements depicted in the AI-generated regeneration scheme appear natural, real, and close to the visual experience of the real world.

When judging the credibility of AI-generated visual content, viewers may take advantage of perceived realism. How realistic an image looks affects how one judges the accuracy and certainty of the results it shows [52]. Public assessment of planning and design visualizations also involves judgments on authenticity and credibility, as well as preferences for the environmental scenarios shown [53]. In the context of digital virtual representations, the mode of visual presentation can simultaneously influence users' judgments of realism and trust, and certain dimensions of perceived realism can also significantly predict trust levels [54]. Further research on AI-based virtual content has shown that perceived realism is involved in the formation of user trust and subsequent behavioral intention, while trust can in turn be associated with behavioral tendencies such as purchasing [55]. Accordingly, in the context of AI-visualized industrial heritage regeneration, higher perceived realism may be associated with greater trust in the visual representation and, through that trust, stronger scheme support.

Accordingly, the following hypothesis is proposed:

H7. *Perceived realism is positively associated with perceived trust in visual representation.*

H8. *Perceived realism has a significant positive indirect association with scheme support through perceived trust in visual representation.*

2.2.5. Perceived Trust in Visual Representation (PT)

Trust refers to a positive attitude formed when individuals, under conditions involving uncertainty and vulnerability, believe that a particular entity can help them achieve their goals [56]. Trust in technology is primarily grounded in judgments of a system's competence, reliability, predictability, and stability and influences whether users are willing to act on or rely on system outputs. In the context of artificial intelligence, factors such as the representational form of AI, its level of capability, transparency, and reliability have all been identified in previous research as important factors associated with user trust [57]. In the field of AI-based interactive applications, trust is also an important psychological factor closely associated with users' acceptance and adoption of technology [58].

For AI-generated content, trust extends beyond evaluations of the generated output itself and is closely related to whether users are willing to accept the content and rely on it in subsequent judgments. Existing research on AI-generated content has shown that trust in generated outputs is significantly associated with higher levels of information adoption and with subsequent acceptance and adoption behaviors [59,60]. In the context of AI-generated visual content, trust is also regarded as a key dimension of user evaluation, alongside users' engagement, interaction, and acceptance responses to the content [61]. Accordingly, in the context of AI-visualized industrial heritage regeneration, perceived trust in visual representation refers to the public's judgment of the credibility of an AI-generated image as a visual representation of a future spatial condition, rather than general trust in AI systems. Research on image credibility has examined the role of source cues in viewers' judgments [62]. Studies of environmental visualization have also examined how the presentation of visual information shapes viewers' evaluations [53]. These perspectives position PT within the broader literature on perceived image credibility, with a specific focus on confidence in AI-visualized representations of proposed future spaces.

Accordingly, the following hypothesis is proposed:

H9. *Perceived trust in visual representation is significantly and positively associated with scheme support.*

2.2.6. Scheme Support (SUP)

Scheme support refers to the positive attitude and behavioral tendency that individuals form toward the implementation or further advancement of a development initiative, policy, or spatial intervention after evaluating its anticipated benefits, costs, and local impacts. Resident support is generally closely associated with evaluations such as perceived benefits, perceived costs, and community satisfaction [63]. In heritage-led urban regeneration, public evaluations of regeneration policy attributes closely correlate with policy support [64]. In cultural heritage contexts, perceived cultural authenticity is closely related to residents' place attachment, while stronger place attachment is further associated with greater willingness to support cultural heritage development [41].

In the context of AI-visualized industrial heritage regeneration, when viewing regeneration schemes that have not yet been implemented, the public forms judgments about whether to accept, endorse, and support different regeneration directions. Accordingly, this study defines Scheme Support as the public's inclination, based on the spatial and cultural information presented in the AI-visualized scheme, to accept the scheme, support its implementation, and recommend its adoption as a potential regeneration direction for the outdoor public space of the Fengtian Factory. As an overall attitudinal and behavioral tendency formed during scheme evaluation, this construct is positioned at the response stage of the S–O–R model and is structurally related to internal psychological evaluations, including perceived cultural authenticity, the affective comfort of public space, perceived realism, and perceived trust in visual representation.

2.2.7. Structural Relationships Among Psychological Evaluations Within the S–O–R Framework

Within the S–O–R framework, external stimuli, individuals' internal affective and cognitive states, and subsequent behavioral responses are organized into a theoretically ordered relational structure. External cues in generative visual content can be associated with internal evaluations of content authenticity, reliability, and affective experience, while psychological states such as trust may in turn be related to subsequent behavioral tendencies.

Accordingly, the following hypotheses are proposed:

H10. *Scheme type is significantly and indirectly associated with scheme support through the sequential pathway of perceived cultural authenticity and perceived trust in visual representation.*

H11. *Scheme type is significantly and indirectly associated with scheme support through the sequential pathway of perceived realism and perceived trust in visual representation.*

H12. *Scheme type is significantly and indirectly associated with scheme support through affective comfort of public space.*

3. Research Methods

3.1. Study Area

In this study, Fengtian factory located in Tiexi District, Shenyang City, Liaoning Province, China was selected as the case site. Shenyang is a representative old industrial city in China, and the modern industrialization process has produced a large number of industrial relics. Among them, Tiexi Industrial Zone developed into a highly concentrated industrial production area in the 20th century, and has become an important area for the protection and reuse of industrial heritage in Shenyang [65,66]. Fengtian Factory is located in Tiexi District, and its industrial history can be traced back to "Fengtian Factory of Daxin Trading Company". The base was subsequently reorganized and became the production base of equipment manufacturing enterprises such as Shenyang Metallurgical Machinery Repair and Manufacturing Factory. With the advancement of industrial structure adjustment in Tiexi Old Industrial Zone, the original production functions have been gradually relocated, and the factory area has entered the stage of protection and reuse. At present, the official inventory has identified Shenyang Metallurgical Machinery Repair and Manufacturing Factory as a provincial industrial heritage in Liaoning Province. Fengtian factory and its location within Shenyang are shown in Figure 2.

After the factory was vacant for many years, the local government began to repair and renovate the site in 2017. The site has gradually become an industrial and cultural space open to the public. Although Fengtian Factory has been repaired for the purpose of preservation, it still retains its original physical features and spatial layout. These features provide a practical basis for keeping site conditions consistent when comparing different plans later in the study. After conducting a field investigation, we selected three outdoor spaces in the public-accessible area as experimental scenes (Figure 3). These spaces have undergone relatively limited regenerative interventions, retaining clearly identifiable industrial character and offering potential for further improvements in public spaces. They preserve the visual foundation of real industrial heritage environments and allow the construction of different AI visualization regeneration schemes without significantly changing building volumes, spatial boundaries or dominant industrial features.

The case also provides an urban context well-suited to public assessment research. Tiexi industrial heritage has undergone a long-term transformation from production space to new urban function, and its protection and reuse require the coordination among heritage value, spatial environment quality and public demand. Research on Tiexi industrial heritage has indicated that government played a pronounced leading role in earlier conservation processes, whereas workers and other important stakeholders were insufficiently involved. More recent research on industrial historical spaces in Shenyang has likewise incorporated the coordination of environmental quality, heritage value, and local memory, together with community needs, into the evaluation of industrial heritage regeneration [67]. The Fengtian Factory therefore provides a context of practical relevance for examining how the public evaluates AI-visualized regeneration schemes for industrial heritage and public spaces.

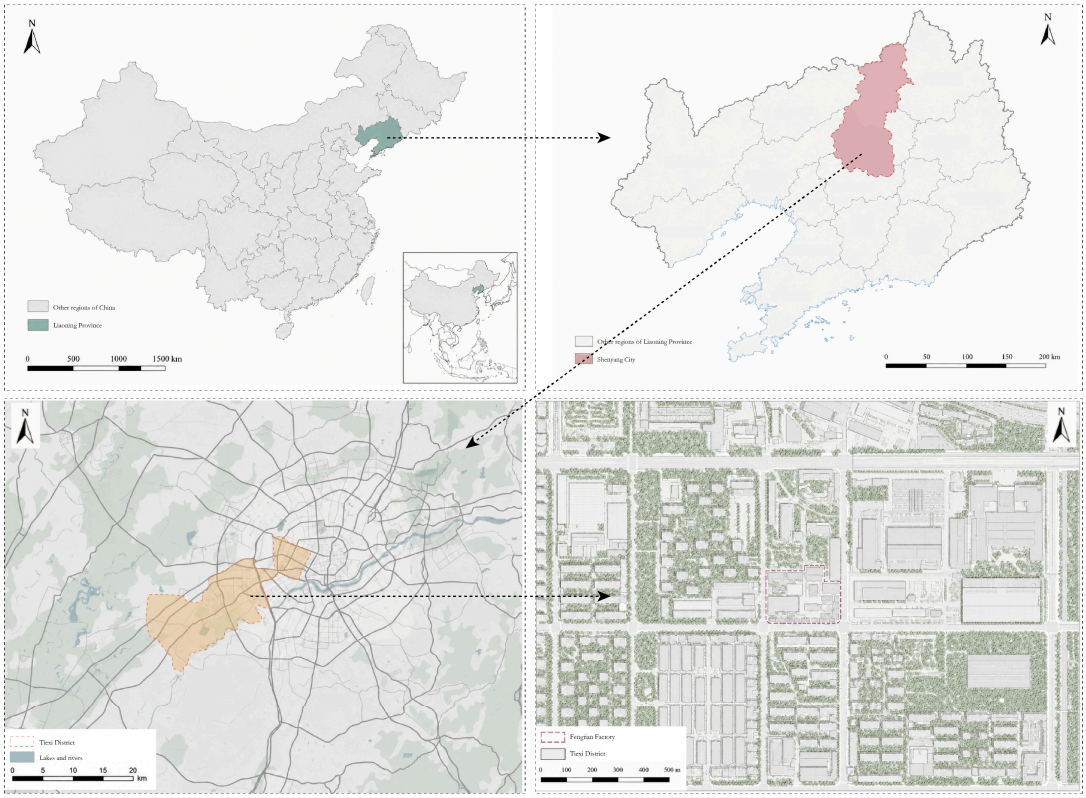


Figure 2. Location of Fengtian Factory in Shenyang, China.



(**a**) (**b**) (**c**)

Figure 3. Existing conditions of the three selected outdoor public-space scenes at Fengtian Factory: (**a**) O1; (**b**) O2; (**c**) O3.

3.2. Generation of Stimulus Materials

The experimental stimuli were generated on July 10, 2026, using the built-in image-generation functionality of ChatGPT (OpenAI, San Francisco, CA, USA). All generated images had a resolution of 2048 × 1365 pixels and were not manually edited after generation. To enhance the comparability of the different AI-visualized regeneration schemes and to control, as far as possible, visual differences unrelated to the research objectives, this study employed a modular prompt framework to construct the experimental stimuli. The framework for stimulus generation is shown in Figure 4. Photographs of the actual Fengtian factory site were used as basic visual input, and different regeneration targets were transformed into spatial elements that could be visually recognized in the generated images.

Within each scene, the three schemes were generated from the same original site photograph and followed the same shared prompt requirements. The shared control module specified consistent framing and spatial structure, as well as the locations where

regeneration interventions were permitted. The prompts required the retention of major industrial heritage features, including red-brick factory buildings, industrial structures, historic doors and windows, material textures, and traces of weathering. They also specified comparable weather, lighting, and rendering styles to limit visual differences unrelated to the schemes. Vegetation and shading were allowed to vary when required by the scheme-specific design objectives.

The scheme-specific prompt module defines three design directions. (1) An ongoing heritage exhibition and interpretation system is the focus of S1. (2) The S2 emphasizes open and flexible group activity spaces, with modular seating and lightweight shade structures. (3) S3 prioritizes tree planting, landscaped walking routes and scattered seating. Its intended use is for quiet, shady relaxation. Both S2 and S3 include greenery, seating, and open space. The difference is how the elements are arranged. S2 supports group activities, while S3 prioritizes quiet rest.

Applying S1, S2, and S3 to each of the three scenes yields nine "scene × scheme" conditions.

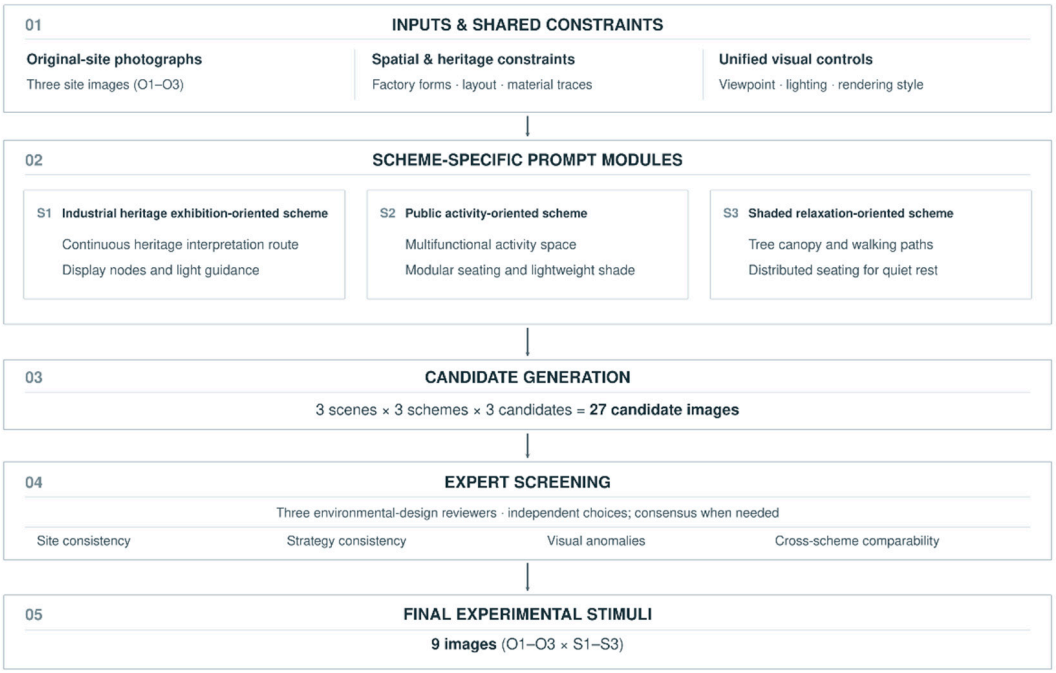


Figure 4. Modular prompt framework and stimulus-generation workflow.

Because generative AI can produce different outputs even with the same prompt, three candidate images are independently generated for each "scene × scheme" condition, resulting in a total of 27 candidate images. Then, three reviewers with professional backgrounds in environmental design examined the candidate images and independently provided their preferred choices. The evaluation process included three candidate-level screening criteria and a cross-scheme comparability assessment of the selected image sets. The first is site consistency, which refers to whether the original architecture, spatial relations and main industrial heritage features have been retained. The second is strategy consistency, which refers to whether the image clearly represents the regeneration direction corresponding to this condition. The third is the degree of visual anomaly, which refers to whether there are obvious AI-generated anomalies, such as building deformations, incorrect components, distorted proportions, or random text. Cross-scheme comparability was assessed for the selected S1–S3 image set within each scene, considering viewpoint, degree of photorealism, lighting, and overall image quality. When all three reviewers agreed, the

preferred image was directly selected as the final stimulus. When their preferred choices differed, the three reviewers discussed the candidates and reached a consensus on the final selection. Ultimately, one image per condition was retained, yielding nine formal experimental stimuli (Figure 5). Qualitative screening aims to improve the applicability and visual comparability of stimuli. The purpose is not to establish complete equivalence for all image-specific visual features. Complete prompts, candidate images, and generation records are all retained to ensure traceability of the stimulus construction process.



Figure 5. Final AI-visualized experimental stimuli across three scenes and three regeneration schemes. Rows correspond to scenes O1, O2, and O3, respectively, and columns correspond to the industrial heritage exhibition-oriented scheme (S1), public activity-oriented scheme (S2), and shaded relaxation-oriented scheme (S3), respectively: (**a**) O1S1; (**b**) O1S2; (**c**) O1S3; (**d**) O2S1; (**e**) O2S2; (**f**) O2S3; (**g**) O3S1; (**h**) O3S2; (**i**) O3S3.

3.3. Questionnaire Design and Measurement

The main experiment used a within-subject repeated measures design. All participants watched three types of AI visualized regeneration schemes in three outdoor scenes at the Fengtian factory, generating a total of nine sets of visual stimuli. Each stimulus set consisted of one photograph of the existing site and one corresponding AI-visualized regeneration image. The photograph of the existing site was used solely as a reference to the current site conditions, helping participants identify the relationship between the existing spatial setting and the visualized post-regeneration condition; it did not constitute a non-AI regeneration scheme or an experimental control condition. After viewing the AI-visualized image for each scheme, participants immediately completed the questionnaire items corresponding to that scheme before proceeding to the next stimulus set. Within each scene, comparability of the existing site context, major building features, viewpoint, and perspective was sought through the shared prompt requirements and candidate-image screening procedure.

The target population includes adults aged 18 or above who have living experience in Shenyang. Prior to formal investigation, the study protocol was approved by the Northeastern University Ethics Committee (approval number NEU-EC-2026B095S; July 20,

2026). All participants provided informed consent prior to participation. This eligibility requirement is used to place the assessment in a shared local urban setting. Because each participant evaluated all nine stimulus sets, each participant served as their own reference for comparisons of different scheme conditions.

The questionnaire consisted of two parts. The first collected basic demographic information and the second contained 16 items measuring five underlying constructs: perceived cultural authenticity, affective comfort of public space, perceived realism, perceived trust in visual representation, and scheme support. The measurement items and their sources are shown in Table 1. All measurement items were scored using a seven-point Likert scale. These scales are largely adapted from established measurement tools in previous studies and adapted to context for the visual assessment of AI-generated industrial heritage regeneration schemes. In order to improve the clarity of the project wording and its applicability to the research context, the original English items were translated and adapted into Chinese, which was subsequently reviewed and revised by six experts (including those with academic backgrounds in foreign languages) for semantic accuracy, clarity of expression, and appropriateness of context. Before the formal evaluation began, all participants received standardized instructions and were asked to evaluate based only on photographs of the existing venue, currently presented AI-generated regenerated images, and corresponding contextual information about the venue.

The experiment was conducted through an online questionnaire platform. A scenario-based demonstration procedure was employed that allowed participants to evaluate three regeneration schemes in succession in the same spatial environment before moving on to the next scene. This arrangement reflects the study's focus on the public evaluation of alternative regeneration proposals in a shared site setting. The questionnaire was administered for all participants using a single standardized presentation sequence: O1S1, O1S2, O1S3, O2S1, O2S2, O2S3, O3S1, O3S2, and O3S3. Therefore, they all saw the same visual stimuli in the same order. This standardized presentation ensured a common exposure order but did not eliminate potential order effects. The image-presentation format, response interface, and measurement-item structure also remained consistent across evaluations. As scheme order was not randomized or counterbalanced, the resulting comparisons reflect evaluations under the specified presentation conditions.

Table 1. Measurement Constructs, Items, and Their Reference Sources.

Construct	Content	References
Perceived Cultural Authenticity (PCA)	PCA1: This scheme reflects the core cultural meanings of Fengtian Factory's industrial heritage. PCA2: The industrial cultural content presented in this scheme is consistent with the historical context of Fengtian Factory. PCA3: This scheme preserves the cultural characteristics of Fengtian Factory as an industrial heritage site.	[68]
Affective Comfort of Public Space (AC)	AC1: I find the public-space environment presented in this scheme calming. AC2: I find the public-space environment presented in this scheme relaxing. AC3: I find the public-space environment presented in this scheme comfortable. AC4: I find the public-space environment presented in this scheme safe.	[69]
Perceived Realism (PR)	PR1: I think the buildings, spaces, and environmental elements shown in the scheme image closely resemble those in a real-world environment.	[26]

Perceived Trust in Visual Representation (PT)	PR2: I think the overall presentation of the buildings, spaces, and environmental elements in the scheme image appears natural. PR3: Overall, the scheme image gives me a visual impression similar to that of a photograph of a real environment. PT1: I consider the overall visual representation of the regenerated public space in the scheme image to be reliable. PT2: I consider the visual representation of the buildings, spaces, and environmental elements in the scheme image to be trustworthy. PT3: Overall, I consider the visual presentation of the scheme image to be trustworthy.	[26]
Scheme Support (SUP)	SUP1: I am willing to accept this scheme as a reasonable form of regeneration for the Fengtian Factory. SUP2: I support implementing this regeneration scheme at the Fengtian Factory. SUP3: I am willing to recommend this scheme as a regeneration proposal for the Fengtian Factory.	[70]

3.4. Data Analysis

Data analysis was performed using IBM SPSS Statistics 27.0 and Mplus 9.1. Nine sets of AI visual regeneration protocols were repeatedly evaluated by 360 participants each, resulting in a total of 3240 Level 1 evaluation records. Data integrity, missing values, and variable ranges are checked first. In SPSS, the random intercept zero model is then estimated using restricted maximum likelihood (REML), and the participant ID is specified as the clustering variable. Intraclass correlation coefficients (*ICC*(1)) for perceived cultural authenticity (PCA), affective comfort of public space (AC), perceived realism (PR), perceived trust in visual representation (PT), and scheme support (SUP) were calculated to assess the extent of intra-participant clustering in repeated assessments.

Given that assessment records are nested among participants, a two-level confirmatory factor analysis (MCFA) was performed using robust maximum likelihood (MLR) in Mplus 9.1. The measurement model focused primarily on the within level, whereas the between level was used to separate relatively stable between-participant differences [71]. Initial five-factor MCFA inspection showed localized residual associations among the constructs' first items (PCA1, AC1, PR1, PT1, SUP1). We therefore specified an exploratory within-participant shared-variance factor. Its loadings were restricted to these five items. Correlations with the substantive factors were fixed to zero. This post hoc specification aimed to accommodate localized residual covariance. It was not intended to identify a specific item-position effect or correct all sources of common method bias [72]. We separately examined the measurement specification's sensitivity to the equality constraint on these five loadings. Measurement quality was evaluated using standardized factor loadings, Cronbach's α, composite reliability (CR), average variance extracted (AVE), the Fornell–Larcker criterion [73], and the heterotrait–monotrait ratio (HTMT) [74], with Cronbach's α calculated from the within-participant covariance structure [75]. Model fit for the MCFA and subsequent structural models was evaluated using robust χ^2, CFI, TLI, RMSEA, SRMRwithin, and SRMRbetween. After support was established for the overall measurement structure, a repeated-measures CFA accounting for within-participant dependence was conducted to test configural, loading, and intercept invariance of the five constructs across the three scheme conditions, thereby assessing measurement comparability across schemes.

On this basis, multilevel structural equation modeling (MSEM) was used to estimate the theory-specified associations among psychological evaluations and scheme support at the within-participant level. The directions of the paths among these concurrently

measured constructs reflect the S–O–R-based model specification rather than empirically established temporal or causal relationships. Scheme type was then introduced as a within-level exogenous variable to construct the full extended S–O–R model. Using the industrial heritage exhibition-oriented scheme (S1) as the reference category, the associations of scheme type with PCA, AC, and PR were examined, while the direct paths from scheme type to SUP were estimated simultaneously, conditional on the mediating variables, to separate the specific indirect effects from the remaining direct associations. Both the core structural model and the full S–O–R model retained the measurement specification established in the final MCFA. Because the substantive hypotheses focused on the within-participant level, item variances and covariances at the between-level were freely estimated to separate relatively stable between-participant differences and to avoid imposing additional structural constraints on between-level measurement relationships that were not a substantive focus of the study. The structural models were estimated using MLR, and within-level coefficients of determination (R^2) were reported for the relevant endogenous variables. To assess whether the structural estimates depended on the inclusion of the exploratory first-item shared-variance factor, the full S–O–R model was also re-estimated without this factor. The analytic sample, measurement specification for the five substantive constructs, scheme coding, 13 structural paths, within- and between-level model specifications, missing-data handling, and MLR estimator were held constant. Indirect effects and prespecified between-scheme contrasts were tested using a 5000-replication two-level cluster bootstrap, with participants serving as the resampling clusters. Participants were resampled with replacement at the cluster level, with all nine original repeated evaluation records retained within each selected participant cluster. The bootstrap auxiliary models used the same analytic sample, variable definitions, missing-data handling, within/between structure, measurement constraints, and structural parameterization as their corresponding MLR main models; the reference category for scheme type in the full S–O–R model was also kept unchanged. The bootstrap auxiliary models were estimated using maximum likelihood (ML), and 95% bias-corrected bootstrap confidence intervals were reported; an effect was considered statistically supported when its confidence interval did not include zero. Model fit and standardized structural paths were reported from the MLR main models.

Finally, observed composite scores calculated as the mean of the items for each construct were used as the analysis variables, and separate 3 × 3 repeated-measures analyses of variance (ANOVAs) were conducted for PCA, AC, PR, PT, and SUP, with Scene and Scheme specified as two within-subject factors. Sphericity was assessed using Mauchly's test, with Greenhouse–Geisser-corrected results considered where appropriate. For significant main effects of the scheme, Bonferroni-adjusted pairwise comparisons among the three scheme types were conducted within each construct, and partial eta squared (partial η^2) was reported as the effect size.

4. Data Analysis and Results

4.1. Participants and Sample

The main survey was administered via the Wenjuanxing platform, and a total of 451 responses were collected. After data collection, responses were screened according to the prespecified IP-location and duplicate-submission criteria, yielding a final analytic sample of 360 participants, corresponding to 79.8% of the collected submissions. The final sample comprised 210 male participants (58.3%) and 150 female participants (41.7%), with participants aged 18–50 years accounting for 78.1% of the sample. The demographic characteristics of the participants are summarized in Table 2.

Table 2. Sociodemographic characteristics of the participants (N = 360).

Characteristic	Category	*n*	%
Gender	Male	210	58.3
	Female	150	41.7
Age	18–25 years	89	24.7
	26–30 years	37	10.3
	31–40 years	83	23.1
	41–50 years	72	20.0
	51–60 years	28	7.8
	>60 years	51	14.2
Education level	High school/technical secondary school	108	30.0
	Junior college	110	30.6
	Bachelor's degree	96	26.7
	Master's degree or above	46	12.8
Location	Shenyang	360	100.0
Total		360	100.0

4.2. Assessment of the Multilevel Data Structure

Sample completeness, missing values, and the repeated-measures data structure were first examined. None of the 16 scale items in the final modeling dataset contained missing values, and observed responses spanned the full 1–7 scale. Item-level skewness ranged from −0.182 to −0.013 and kurtosis from −0.367 to 0.016; the proportions of responses at the minimum score of 1 ranged from approximately 0.03% to 0.71%, whereas those at the maximum score of 7 ranged from approximately 5.49% to 7.07%. No pronounced concentration at one end of the scale or severe distributional departures was observed. Because each participant evaluated nine sets of AI-visualized stimuli, the Level-1 evaluation records were nested within participants. Random-intercept null models were therefore fitted using linear mixed models in SPSS, with ParticipantID specified as the clustering variable and restricted maximum likelihood (REML) used to estimate the participant-level random-intercept variance and within-participant residual variance separately for each core construct. Based on these two variance components, the intraclass correlation coefficient (*ICC*(1)) was calculated to assess the degree of clustering of repeated evaluations within participants.

In this study, *ICC*(1) was calculated from the participant-level random-intercept variance, τ_{00}, and the within-participant residual variance, σ^2, obtained from the random-intercept null model, as follows:

$$ICC(1) = \frac{\tau_{00}}{\tau_{00} + \sigma^2}$$

The variance decomposition results from the random-intercept null models are presented in Table 3. The *ICC*(1) values for PCA, AC, PR, PT, and SUP ranged from 0.311 to 0.328, indicating that approximately 31.1–32.8% of the total variance in the construct scores was attributable to relatively stable differences between participants, whereas the remaining variance arose primarily from within-participant variation across evaluations of different stimuli. These results indicate non-negligible correlations among repeated evaluations within participants and therefore support the need to explicitly account for the hierarchical structure of the data in the subsequent measurement and structural model analyses. The participant-level variance and residual variance for each of the five constructs, including PCA, were estimated from the corresponding SPSS random-intercept null models.

Table 3. Variance Components and *ICC*(1) of the Random-Intercept Null Models for the Core Constructs.

Construct	Participant-Level Variance	Within-Level Residual Variance	*ICC*(1)
Perceived Cultural Authenticity (PCA)	0.326	0.692	0.320
Affective Comfort of Public Space (AC)	0.312	0.691	0.311
Perceived Realism (PR)	0.329	0.716	0.315
Perceived Trust in Visual Representation (PT)	0.311	0.643	0.326
Scheme Support (SUP)	0.304	0.624	0.328

4.3. Measurement Model Assessment

4.3.1. Assessment of Model Reliability and Validity

After confirming intra-participant correlations in repeated measures data, a multilevel confirmatory factor analysis (MCFA) was performed to examine the five reflective constructs of perceived cultural authenticity, affective comfort of public space, perceived realism, perceived trust in visual representation, and scheme support, with parameters estimated using robust maximum likelihood (MLR). Because the study focused on within-participant differences in evaluations across regeneration schemes, the substantive measurement assessment was conducted at the within level, whereas item variances and covariances were freely estimated at the between level to account for differences between participants [75,76]. The baseline five-factor model successfully converged but still exhibited a local mismatch with robust $\chi^2(94) = 1690.944$, CFI = 0.950, TLI = 0.872, RMSEA = 0.072, SRMRwithin = 0.034, and SRMRbetween = 0.011. Local diagnostics suggested residual associations among PCA1, AC1, PR1, PT1, and SUP1, all of which appeared first in their respective questionnaire blocks. Item location effects provide a possible explanation for this pattern [77], although phraseological features, local item context, or unmodeled propensity to substantive responses cannot be ruled out. Since all participants received the same item order and no independent method marker was included, the source of this residual covariance could not be determined from the current data. Therefore, the additional factor was used to account for the observed residual covariance, rather than to establish an item-position effect.

After the first-item shared-variance factor was added and the loadings of the five first-position items on this factor were freely estimated, model fit improved substantially: robust $\chi^2(89) = 217.556$, CFI = 0.996, TLI = 0.989, RMSEA = 0.021, SRMRwithin = 0.013, and SRMRbetween = 0.004. Previous methodological research has distinguished between equal and unequal specifications of method effects and has evaluated equality constraints by comparing equal-loading and freely estimated loading models [78,79]. Accordingly, the unstandardized loadings of the five first-position items on this factor were constrained to equality. This constraint did not produce a significant deterioration in model fit ($\Delta\chi^2$MLR(4) = 6.64, p = 0.156); therefore, the equal-loading first-item shared-variance specification was retained as the final MCFA measurement model. The final model showed a good fit, with robust $\chi^2(93) = 223.377$, $p < 0.001$, CFI = 0.996, TLI = 0.989, RMSEA = 0.021, SRMRwithin = 0.013, and SRMRbetween = 0.005. Standardized factor loadings, Cronbach's α, composite reliability (CR), and average variance extracted (AVE) for each construct are presented in Table 4. At the within-level, standardized loadings on the theoretical factors ranged from 0.693 to 0.831, whereas loadings of the five first-position items on the shared-variance factor ranged from 0.357 to 0.390 and were all statistically significant.

As a sensitivity analysis, the within-level variances and covariances of the five substantive factors were fixed to the estimates obtained from the baseline model without the shared-variance factor to examine whether the results associated with this factor depended on re-estimation of the substantive-factor correlation structure. The restricted model continued to show a good fit: robust $\chi^2(108) = 224.740$, CFI = 0.996, TLI = 0.992, RMSEA = 0.018, SRMRwithin = 0.019, and SRMRbetween = 0.012. When more restrictive

tau-equivalent loading constraints were imposed, the model still showed a good absolute fit (robust $\chi^2(119) = 321.496$, CFI = 0.994, TLI = 0.987, RMSEA = 0.023, SRMRwithin = 0.029, and SRMRbetween = 0.028), but fit deteriorated significantly relative to the preceding, less restrictive constrained model ($\Delta\chi^2$MLR(11) = 82.29, $p < 0.001$). These results indicate that the restrictive assumption of equal loadings within constructs was not supported; therefore, the final model retained a congeneric measurement specification in which the loadings of the theoretical items were freely estimated [80]. All subsequent reliability and validity assessments and structural model analyses were based on the final MCFA model, in which the theoretical item loadings were freely estimated while the equal-loading first-item shared-variance factor was retained.

Table 4. Reliability and Convergent Validity of the Measurement Model.

Construct	Item	Standardized Loading	Cronbach's α	CR	AVE
PCA	PCA1	0.711	0.804	0.811	0.589
	PCA2	0.805			
	PCA3	0.784			
AC	AC1	0.693	0.847	0.852	0.590
	AC2	0.795			
	AC3	0.831			
	AC4	0.747			
PR	PR1	0.697	0.809	0.813	0.593
	PR2	0.784			
	PR3	0.824			
PT	PT1	0.734	0.803	0.804	0.577
	PT2	0.770			
	PT3	0.775			
SUP	SUP1	0.701	0.796	0.809	0.586
	SUP2	0.816			
	SUP3	0.775			

After the final MCFA measurement structure had been established, internal consistency and convergent validity at the within level were further assessed. Within-level Cronbach's α was calculated using the within-participant covariance matrix decomposed in Mplus, thereby avoiding the conflation of stable between-participant differences with within-participant variation in repeated evaluations. Cronbach's α values for the five constructs ranged from 0.796 to 0.847, while composite reliability (CR) values ranged from 0.804 to 0.852; all exceeded 0.700. Average variance extracted (AVE) values ranged from 0.577 to 0.593, all exceeding 0.500. In the final MCFA model, the standardized within-level factor loadings of the five theoretical constructs ranged from 0.693 to 0.831. Overall, the constructs demonstrated good internal consistency and convergent validity.

Discriminant validity at the within level was further assessed using the Fornell–Larcker criterion and the heterotrait–monotrait ratio (HTMT), with the results presented in Tables 5 and 6, respectively. The square roots of AVE for the constructs ranged from 0.760 to 0.770 and were all greater than the absolute values of their within-level correlations with the other constructs, thus satisfying the Fornell–Larcker criterion. HTMT values between the constructs ranged from 0.043 to 0.770, all below the more stringent threshold of 0.850. The strongest association was observed between perceived realism and perceived trust in visual representation (r = 0.742, HTMT = 0.770), but this association still satisfied both criteria for discriminant validity. Therefore, the five theoretical constructs demonstrated good discriminant validity at the within level.

Table 5. Fornell–Larcker Assessment of Discriminant Validity at the Within Level.

Construct	PCA	AC	PR	PT	SUP
PCA	0.768				
AC	−0.112	0.768			
PR	0.188	0.143	0.770		
PT	0.588	0.013	0.742	0.760	
SUP	0.479	0.449	0.502	0.720	0.765

Table 6. HTMT Assessment of Discriminant Validity at the Within Level.

Construct	PCA	AC	PR	PT	SUP
PCA	—				
AC	0.116	—			
PR	0.205	0.161	—		
PT	0.615	0.043	0.770	—	
SUP	0.506	0.471	0.530	0.754	—

4.3.2. Measurement Invariance Across Scheme Conditions

After support was established for the overall measurement structure, reliability, and validity, measurement invariance of the five constructs across the S1, S2, and S3 conditions was further examined to assess the comparability of measurement parameters across scheme conditions [81]. Because the three scheme types were repeatedly evaluated by the same participants, a joint five-construct measurement model was estimated separately for scenes O1, O2, and O3 using repeated-measures CFA that accounted for within-participant dependence. The models allowed correlations among the latent factors across scheme conditions and correlated residuals for the same items across schemes, while retaining the previously specified control for shared variance among the first-position items. Configural, loading, and intercept invariance were tested sequentially. Consistent with the primary measurement model, the 7-point Likert items were treated as approximately continuous variables and estimated using MLR; accordingly, the intercept-invariance models constrained the corresponding item intercepts rather than thresholds. Measurement invariance was evaluated jointly on the basis of the MLR-scaled χ^2 difference test and changes in CFI, RMSEA, and SRMR [82]. The model comparison results for each scene are presented in Table 7.

Table 7. Model Comparisons for Measurement Invariance Across Scheme Conditions.

Scene	Model Comparison	$\Delta\chi^2$MLR(df), *p*	ΔCFI	ΔRMSEA	ΔSRMR
O1	Configural → Loading	39.817 (22), $p = 0.011$	−0.002	0.001	0.006
	Loading → Intercept	33.266 (22), $p = 0.058$	−0.001	0.000	0.001
O2	Configural → Loading	31.989 (22), $p = 0.078$	0.000	0.000	0.005
	Loading → Intercept	41.432 (22), $p = 0.007$	−0.002	0.001	0.000
O3	Configural → Loading	41.393 (22), $p = 0.007$	−0.002	0.001	0.004
	Loading → Intercept	25.637 (22), $p = 0.268$	0.000	0.000	0.001

Note: ΔCFI, ΔRMSEA, and ΔSRMR were calculated relative to the preceding level of invariance. $\Delta\chi^2$MLR denotes the robust nested-model difference test calculated using the MLR scaling correction factor.

The configural invariance models showed good fit in all three scenes, with CFI values ranging from 0.981 to 0.986, TLI from 0.977 to 0.983, RMSEA from 0.022 to 0.026, and SRMR from 0.033 to 0.034. After equality constraints were imposed on the factor loadings, the absolute change in CFI (|ΔCFI|) did not exceed 0.002 in any scene, while ΔRMSEA did not exceed 0.001 and ΔSRMR did not exceed 0.006. After equality constraints were additionally imposed on the item intercepts, the corresponding changes did not exceed

0.002, 0.001, and 0.001, respectively. The MLR-scaled χ^2 difference tests, however, rejected the equality of factor loadings in O1 ($p = 0.011$) and O3 ($p = 0.007$) and the equality of item intercepts in O2 ($p = 0.007$). Thus, the small changes in approximate fit indices were accompanied by evidence against exact parameter equality in selected comparisons. Taken together, the results are consistent with approximate measurement comparability across the three scheme conditions within the examined scenes, but do not establish exact loading and intercept invariance for all five constructs. Consequently, comparisons of scheme-related evaluations should be interpreted cautiously, as item-level noninvariance could influence part of the estimated differences. Because the tests constrained all five constructs jointly, they do not identify which items or constructs contribute to the detected departures from exact invariance.

4.4. Structural Equation Modeling and Path Analysis

4.4.1. Core Psychological Structural Model

Building on the preceding measurement model assessment, multilevel structural equation modeling (MSEM) was further used to examine the core structural relationships among the five constructs. The model retained the measurement specification of the final MCFA, with the structural paths estimated at the within level. The core psychological structural model showed good overall fit: robust $\chi^2(95) = 244.560$, $p < 0.001$, CFI = 0.995, TLI = 0.988, RMSEA = 0.022, SRMRwithin = 0.015, and SRMRbetween = 0.005. Within-level path estimates are presented in Table 8. Perceived cultural authenticity showed a significant positive association with perceived trust in visual representation ($\beta = 0.467$, $p < 0.001$), and perceived realism likewise showed a significant positive association with perceived trust in visual representation ($\beta = 0.645$, $p < 0.001$). Perceived trust in visual representation was positively associated with scheme support ($\beta = 0.588$, $p < 0.001$). In addition, perceived cultural authenticity ($\beta = 0.188$, $p < 0.001$) and the affective comfort of public space ($\beta = 0.456$, $p < 0.001$) both showed significant positive associations with scheme support. The model accounted for 74.6% and 71.6% of the within-level variance in perceived trust in visual representation and scheme support, respectively.

Table 8. Within-Level Path Estimates of the Core Psychological Structural Model.

Structural Path	B	SE	Standardized Direct Effect (β)	z	*p*
PCA → PT	0.443	0.019	0.467	23.103	<0.001
PR → PT	0.658	0.022	0.645	29.893	<0.001
PT → SUP	0.581	0.024	0.588	24.386	<0.001
PCA → SUP	0.176	0.020	0.188	9.000	<0.001
AC → SUP	0.440	0.018	0.456	23.824	<0.001

Note: B denotes the unstandardized within-level path coefficient; β denotes the STDYX-standardized path coefficient; SE, z, and *p* values are based on robust MLR estimation. The R^2 values for PT and SUP were 0.746 and 0.716, respectively.

The results of the subsequent indirect-association tests are presented in Table 9. Perceived cultural authenticity showed a significant positive indirect association with scheme support through perceived trust in visual representation, with a standardized indirect association of 0.275 and an unstandardized indirect association of 0.257; the 95% bias-corrected bootstrap confidence interval was [0.227, 0.290]. The indirect association between perceived realism and scheme support through perceived trust in visual representation was also significant, with a standardized indirect association of 0.379 and an unstandardized indirect association of 0.382; the 95% bias-corrected bootstrap confidence interval was

[0.346, 0.421]. Neither confidence interval included zero. Accordingly, H3–H9 were all supported.

Table 9. Indirect-Association Tests for the Core Psychological Structural Model.

Indirect Path	Standardized Indirect Effect β_{ind}	B	Bootstrap SE (B)	95% BC Bootstrap CI (B)
PCA → PT → SUP	0.275	0.257	0.016	[0.227, 0.290]
PR → PT → SUP	0.379	0.382	0.019	[0.346, 0.421]

Note: Indirect effects were tested using 5000 participant-level cluster bootstrap replications, all of which were successfully completed. The 95% CIs are bias-corrected bootstrap confidence intervals. β_ind denotes the product of the standardized coefficients of the component paths, whereas the bootstrap confidence intervals correspond to the unstandardized indirect effect (B).

4.4.2. Full Extended S–O–R Model

To further examine the relationships among regeneration scheme type, public psychological evaluations, and Scheme Support, scheme type (Scheme) was incorporated into the multilevel structural equation model as a within-level exogenous variable representing the experimental condition, building on the core psychological structural model. Because all 360 participants evaluated nine sets of stimuli, yielding 3240 Level-1 evaluation records, ParticipantID was specified as the clustering variable, and within-participant variation in evaluations across different stimuli was modeled at the Within level. S1 was specified as the reference category, with D2 and D3 representing the contrasts of S2 versus S1 and S3 versus S1, respectively. At the within level, the model retained the measurement specification of the final MCFA, including the five substantive constructs and the equal-loading first-item shared-variance factor. At the between-level, item variances and covariances were freely estimated, consistent with the final MCFA and core MSEM, to separate relatively stable between-participant differences. The structural model was estimated using MLR. The interpretation of the ensuing scheme contrasts is subject to the measurement-invariance qualifications described in Section 4.3.2.

The model demonstrated good overall fit: robust $\chi^2(119) = 298.421$, $p < 0.001$, CFI = 0.995, TLI = 0.988, RMSEA = 0.022, SRMRwithin = 0.014, and SRMRbetween = 0.005. At the within-level, the relationships among the core psychological variables remained stable after scheme type was incorporated into the model. Perceived cultural authenticity (β = 0.462, $p < 0.001$) and perceived realism (β = 0.646, $p < 0.001$) were both positively associated with perceived trust in visual representation. Perceived cultural authenticity (β = 0.214, $p < 0.001$), affective comfort of public space (β = 0.460, $p < 0.001$), and perceived trust in visual representation (β = 0.580, $p < 0.001$) were all positively associated with scheme support. The model explained 74.3% and 73.0% of the within-level variance in perceived trust in visual representation and scheme support, respectively.

Different scheme types exhibited distinct patterns of association with the psychological evaluations. With S1 as the reference category, both S2 and S3 showed significantly lower perceived cultural authenticity (β = −0.395 and −0.505, respectively; both $p < 0.001$), whereas both showed significantly higher affective comfort of public space (β = 0.171 and 0.546, respectively; both $p < 0.001$). By contrast, neither S2 nor S3 differed significantly from S1 in perceived realism (β = 0.007, $p = 0.735$; β = 0.010, $p = 0.650$). After controlling for the psychological evaluation variables included in the model, S2 relative to S1 retained a significant positive conditional direct association with scheme support (β = 0.120, $p < 0.001$), whereas the conditional direct association for S3 relative to S1 was not significant (β = 0.011, $p = 0.612$). The model explained 21.2% and 23.4% of the within-level variance in perceived cultural authenticity and affective comfort of public space, respectively,

whereas the explained variance in perceived realism was close to zero. The full structural paths and coefficients of determination are presented in Table 10.

Table 10. Within-Level Standardized Path Estimates and Explained Variance in the Full Extended S–O–R Model.

Path	β	SE	*p*
Panel A. Scheme conditions and psychological evaluations			
S2 (vs. S1) → PCA	−0.395	0.020	<0.001
S3 (vs. S1) → PCA	−0.505	0.020	<0.001
S2 (vs. S1) → AC	0.171	0.020	<0.001
S3 (vs. S1) → AC	0.546	0.019	<0.001
S2 (vs. S1) → PR	0.007	0.022	0.735
S3 (vs. S1) → PR	0.010	0.022	0.650
Panel B. Psychological structural paths			
PCA → PT	0.462	0.017	<0.001
PR → PT	0.646	0.015	<0.001
PCA → SUP	0.214	0.023	<0.001
AC → SUP	0.460	0.018	<0.001
PT → SUP	0.580	0.019	<0.001
Panel C. Conditional direct effects on SUP			
S2 (vs. S1) → SUP	0.120	0.017	<0.001
S3 (vs. S1) → SUP	0.011	0.022	0.612
Panel D. Within-Level Explained Variance			
Endogenous Latent Variable	**R^2**	**SE**	***p***
PCA	0.212	0.015	<0.001
AC	0.234	0.015	<0.001
PR	0.000	0.000	0.812
PT	0.743	0.019	<0.001
SUP	0.730	0.019	<0.001

Note: β denotes the within-level STDYX-standardized estimate from the primary MLR model. S1 is the reference condition for the categorical Scheme variable; S2 (vs. S1) and S3 (vs. S1) correspond to the dummy-variable coefficients D2 and D3, respectively. The Scheme → SUP coefficient represents the conditional direct effect after controlling for the psychological evaluation variables included in the model and should not be interpreted as the unadjusted raw mean difference in SUP between schemes. R^2 represents the proportion of within-level variance explained in the corresponding latent variable.

Two specification sensitivity analyses were conducted for the full S–O–R model. First, the retained model with the equal-loading first-item shared-variance factor (M1) was compared with an otherwise equivalent model omitting this factor (M0). Second, the equality constraint on the first-item factor loadings was released while the remaining model specifications were held constant. Both models converged successfully. However, M0 showed poorer overall fit (robust $\chi^2(120) = 1687.439$, CFI = 0.952, TLI = 0.892, RMSEA = 0.063, SRMRwithin = 0.031, and SRMRbetween = 0.011) than M1 (robust $\chi^2(119) = 298.421$, CFI = 0.995, TLI = 0.988, RMSEA = 0.022, SRMRwithin = 0.014, and SRMRbetween = 0.005). Despite the differences in global fit, the five core psychological paths exhibited relatively small changes in their STDYX-standardized estimates. The coefficients for PCA predicting PT, PR predicting PT, PCA predicting SUP, AC predicting SUP, and PT predicting SUP changed from 0.472, 0.655, 0.210, 0.459, and 0.590 in M0 to 0.462, 0.646, 0.214, 0.460, and 0.580 in M1, respectively. All five paths remained positive and statistically significant in both models (all $p < 0.001$). Across all 13 structural paths, the maximum absolute

change in the reported standardized coefficients was 0.010, with no changes in path direction or statistical significance classification. Complete coefficient comparisons are provided in Supplementary Table S1. These results indicate limited sensitivity of the principal path estimates to this particular specification change. Nevertheless, the poorer fit of M0 limits the interpretation of this comparison and does not establish general robustness across alternative measurement models.

The model with freely estimated first-item loadings continued to show a good fit (robust $\chi^2(115) = 293.339$, CFI = 0.995, TLI = 0.987, RMSEA = 0.022, SRMRwithin = 0.014, and SRMRbetween = 0.005) and did not yield a significant improvement in fit relative to the equal-loading model ($\Delta\chi^2$MLR(4) = 5.73, $p = 0.220$). In this equal-versus-free loading comparison, the five core structural paths retained their directions and statistical significance, and their standardized coefficients differed by no more than 0.001. These results indicate that the main structural findings were not materially affected by the equal-loading specification for the first-item shared-variance factor.

The primary equal-loading model was then used to estimate three prespecified pairwise scheme contrasts—S1−S2, S1−S3, and S3−S2—to assess pairwise differences among the scheme conditions and their specific indirect associations with SUP. The auxiliary inferential model was estimated using ML, and a two-level cluster bootstrap with 5000 replications was implemented using participants as the clustering unit. Ninety-five percent bias-corrected bootstrap confidence intervals were reported, and all 5000 bootstrap replications were successfully completed. This auxiliary model was used solely for interval inference concerning the prespecified contrasts and derived effects; model fit and standardized structural paths were based on the results of the primary MLR model described above.

The planned contrasts further confirmed the directions of the differences among the three schemes in perceived cultural authenticity and affective comfort of public space. For perceived cultural authenticity, S1 was significantly higher than S2 (B = 0.639, 95% BC CI [0.568, 0.705]) and S3 (B = 0.817, 95% BC CI [0.746, 0.887]), while S3 was significantly lower than S2 (B = −0.179, 95% BC CI [−0.244, −0.114]), yielding the overall ordering S1 > S2 > S3. For affective comfort of public space, S1 was significantly lower than S2 (B = −0.269, 95% BC CI [−0.336, −0.207]) and S3 (B = −0.859, 95% BC CI [−0.932, −0.786]), while S3 was significantly higher than S2 (B = 0.590, 95% BC CI [0.524, 0.656]), yielding the overall ordering S3 > S2 > S1. By contrast, the 95% bias-corrected bootstrap confidence intervals for all three pairwise comparisons of perceived realism included zero, providing no statistical support for significant differences in perceived realism across schemes.

For the S1−S2 contrast, the specific indirect estimate through perceived cultural authenticity (PCA) was positive (B = +0.130, 95% BC CI [0.101, 0.162]), as was the sequential indirect estimate through PCA and perceived trust in visual representation (PT) (B = +0.162, 95% BC CI [0.139, 0.187]). In contrast, the indirect estimate through affective comfort of public space (AC) was negative (B = −0.121, 95% BC CI [−0.153, −0.092]). All three confidence intervals excluded zero, indicating statistically supported indirect pathways with opposing signs. The indirect estimate through perceived realism (PR) and PT was not statistically supported (B = −0.004, 95% BC CI [−0.029, 0.020]).

For S1−S3, the specific indirect estimate through PCA (B = +0.166, 95% BC CI [0.130, 0.207]) and the sequential indirect estimate through PCA and PT (B = +0.208, 95% BC CI [0.181, 0.236]) were both positive. By contrast, the indirect estimate through AC was negative (B = −0.386, 95% BC CI [−0.434, −0.343]); all three confidence intervals excluded zero. The two positive PCA-related point estimates summed to +0.374, nearly offsetting the negative AC estimate of −0.386. This numerical comparison is descriptive and does not constitute a separate statistical test of differences between pathways. The indirect estimate through PR and PT was not statistically supported (B = −0.006, 95% BC CI [−0.030, 0.019]).

For S3−S2, the specific indirect estimate through PCA (B = −0.036, 95% BC CI [−0.054, −0.023]) and the sequential indirect estimate through PCA and PT (B = −0.045, 95% BC CI [−0.064, −0.029]) were both negative, whereas the indirect estimate through AC was positive (B = +0.265, 95% BC CI [0.231, 0.304]). All three confidence intervals excluded zero. The indirect estimate through PR and PT was not statistically supported (B = +0.001, 95% BC CI [−0.025, 0.027]). These oppositely signed specific indirect estimates yielded a positive total indirect estimate, as reported in Panel C of Table 11.

Table 11. Prespecified Pairwise Comparisons and Indirect Effect Tests for the Three Regeneration Schemes.

Panel A. Pre-specified pairwise scheme comparisons				
Construct	**Scheme Comparison**	**B**	**95% BC CI (B)**	**Result**
PCA	S1−S2	0.639	[0.568, 0.705]	Significant
	S1−S3	0.817	[0.746, 0.887]	Significant
	S3−S2	−0.179	[−0.244, −0.114]	Significant
AC	S1−S2	−0.269	[−0.336, −0.207]	Significant
	S1−S3	−0.859	[−0.932, −0.786]	Significant
	S3−S2	0.590	[0.524, 0.656]	Significant
PR	S1−S2	−0.011	[−0.077, 0.052]	Not Significant
	S1−S3	−0.015	[−0.080, 0.049]	Not Significant
	S3−S2	0.004	[−0.066, 0.072]	Not Significant
Panel B. Specific indirect effects				
Scheme Comparison	**Specific Indirect Pathway**	**B**	**95% BC CI (B)**	**Result**
S1−S2	Scheme → PCA → SUP	0.130	[0.101, 0.162]	Significant
	Scheme → PCA → PT → SUP	0.162	[0.139, 0.187]	Significant
	Scheme → AC → SUP	−0.121	[−0.153, −0.092]	Significant
	Scheme → PR → PT → SUP	−0.004	[−0.029, 0.020]	Not Significant
S1−S3	Scheme → PCA → SUP	0.166	[0.130, 0.207]	Significant
	Scheme → PCA → PT → SUP	0.208	[0.181, 0.236]	Significant
	Scheme → AC → SUP	−0.386	[−0.434, −0.343]	Significant
	Scheme → PR → PT → SUP	−0.006	[−0.030, 0.019]	Not Significant
S3−S2	Scheme → PCA → SUP	−0.036	[−0.054, −0.023]	Significant
	Scheme → PCA → PT → SUP	−0.045	[−0.064, −0.029]	Significant
	Scheme → AC → SUP	0.265	[0.231, 0.304]	Significant
	Scheme → PR → PT → SUP	0.001	[−0.025, 0.027]	Not Significant
Panel C. Direct, total indirect, and total effects				
Scheme Comparison	**Effect Type**	**B**	**95% BC CI (B)**	**Result**
S1−S2	Direct effect	−0.185	[−0.236, −0.133]	Significant
	Total indirect effect	0.167	[0.104, 0.227]	Significant
	Total effect	−0.018	[−0.081, 0.042]	Not Significant
S1−S3	Direct effect	−0.017	[−0.086, 0.052]	Not Significant
	Total indirect effect	−0.018	[−0.091, 0.049]	Not Significant
	Total effect	−0.035	[−0.099, 0.030]	Not Significant
S3−S2	Direct effect	−0.167	[−0.223, −0.112]	Significant
	Total indirect effect	0.185	[0.124, 0.244]	Significant
	Total effect	0.017	[−0.043, 0.078]	Not Significant

Note: B denotes an unstandardized pairwise contrast on the MSEM latent-variable scale (Panel A) or an unstandardized derived effect (Panels B and C). Contrasts were calculated as S1−S2, S1−S3, or S3−S2; the sign of B therefore follows the specified subtraction order. The 95% bias-corrected confidence intervals (BC CIs) were obtained from 5000 participant-level cluster bootstrap replications of the ML auxiliary model. An interval excluding zero was taken as statistical support for the

corresponding model-based estimate. The total indirect effect is the sum of the four specific indirect effects, and the total effect equals the conditional direct effect plus the total indirect effect. Overall model fit and standardized paths were obtained from the primary MLR model. The estimated indirect effects should not be interpreted as evidence of causal mediation.

Although several specific indirect effects were statistically supported, the total effects were not statistically significant for any of the three scheme comparisons. For S1−S2, the total indirect effect was positive (B = +0.167, 95% BC CI [0.104, 0.227]), whereas the conditional direct effect was negative (B = −0.185, 95% BC CI [−0.236, −0.133]); both confidence intervals excluded zero. These opposing estimates yielded a nonsignificant total effect (B = −0.018, 95% BC CI [−0.081, 0.042]). A similar pattern emerged for S3−S2: the positive total indirect effect (B = +0.185, 95% BC CI [0.124, 0.244]) and negative conditional direct effect (B = −0.167, 95% BC CI [−0.223, −0.112]) both had confidence intervals excluding zero, whereas the total effect was not statistically significant (B = +0.017, 95% BC CI [−0.043, 0.078]).

The S1−S3 contrast showed a different pattern in the model-based decomposition. The two positive PCA-related specific indirect estimates (B = +0.166 and +0.208), the negative AC-related estimate (B = −0.386), and the near-zero PR-related estimate (B = −0.006) summed to a total indirect estimate that was not statistically significant (B = −0.018, 95% BC CI [−0.091, 0.049]). The total effect was also not statistically significant (B = −0.035, 95% BC CI [−0.099, 0.030]). Thus, the three contrasts had different effect decompositions despite nonsignificant total effects. These nonsignificant findings should not be interpreted as evidence of equivalence in scheme support or as negating the statistically supported specific indirect effects.

Overall, S1 was characterized primarily by a relative advantage in perceived cultural authenticity, whereas S3 was characterized primarily by a relative advantage in affective comfort of public space. The three schemes did not differ significantly in perceived realism, and none of the corresponding specific indirect effects through perceived realism and perceived trust in visual representation received statistical support. According to the prespecified correspondence between the hypotheses and these pathways, H10 and H12 were supported, whereas H11 was not supported.

4.5. Comparative Analysis of the Three Regeneration Schemes

Based on the preceding assessment of measurement comparability, separate 3 × 3 two-way repeated-measures analyses of variance (ANOVAs) were conducted for the five constructs to compare the three AI-visualized regeneration schemes and examine whether scheme differences varied across spatial scenes, with Scene (O1, O2, O3) and Scheme (S1, S2, S3) specified as two within-subject factors. Mauchly's tests did not indicate significant departures from sphericity for the Scene, Scheme, or Scene × Scheme effects for any of the five constructs (all $p > 0.05$); therefore, the primary analyses used degrees of freedom based on the sphericity assumption. The Greenhouse–Geisser correction did not alter the statistical significance conclusions for any of the effects. For significant main effects of the scheme, Bonferroni-adjusted pairwise comparisons among the three schemes were subsequently conducted. Descriptive statistics for each scheme and the main effects of the scheme are presented in Table 12.

Table 12. Comparative Results for the Three Types of AI-Visualized Regeneration Schemes.

Variable	S1 M ± SD	S2 M ± SD	S3 M ± SD	Scheme Main Effect F(2, 718)	*p*	ηp²	Bonferroni Comparison
PCA	5.25 ± 0.71	4.64 ± 0.74	4.46 ± 0.74	307.538	<0.001	0.461	S1 > S2 > S3
AC	4.38 ± 0.74	4.65 ± 0.70	5.26 ± 0.72	371.346	<0.001	0.508	S3 > S2 > S1
PR	4.79 ± 0.74	4.80 ± 0.75	4.81 ± 0.77	0.207	0.813	0.001	n.s.

PT	5.06 ± 0.69	4.78 ± 0.70	4.72 ± 0.77	56.149	<0.001	0.135	S1 > S2; S1 > S3; S2 vs. S3, n.s.
SUP	4.83 ± 0.68	4.85 ± 0.70	4.87 ± 0.74	0.741	0.477	0.002	n.s.

Note: M and SD were calculated from each participant's observed composite scores for the same scheme type across the three scenes. F, *p*, and ηp^2 correspond to the main effect of Scheme; for constructs with a significant Scheme main effect, the final column summarizes the Bonferroni-adjusted pairwise comparisons among the three schemes.

A significant main effect of the scheme was observed for PCA, F(2, 718) = 307.538, $p < 0.001$, $\eta p^2 = 0.461$. Neither the main effect of Scene nor the Scene × Scheme interaction was significant, F(2, 718) = 0.526, $p = 0.591$, $\eta p^2 = 0.001$, and F(4, 1436) = 1.261, $p = 0.283$, $\eta p^2 = 0.003$, respectively. The industrial heritage exhibition-oriented scheme had the highest PCA score (M = 5.25, SD = 0.71), followed by the public activity-oriented scheme (M = 4.64, SD = 0.74) and the shaded relaxation-oriented scheme (M = 4.46, SD = 0.74). Bonferroni-adjusted pairwise comparisons showed that S1 was significantly higher than S2 (MD = 0.614, 95% CI [0.535, 0.692], $p < 0.001$) and S3 (MD = 0.788, 95% CI [0.707, 0.869], $p < 0.001$). The complete set of pairwise comparisons also showed that S2 was significantly higher than S3, providing full pairwise support for the overall ordering S1 > S2 > S3. Accordingly, H1, H1a, and H1b were all supported.

The main effect of Scheme on AC was also significant, F(2, 718) = 371.346, $p < 0.001$, $\eta p^2 = 0.508$, whereas neither the main effect of Scene (F(2, 718) = 2.179, $p = 0.114$, $\eta p^2 = 0.006$) nor the Scene × Scheme interaction (F(4, 1436) = 0.198, $p = 0.939$, $\eta p^2 = 0.001$) was significant. The shaded relaxation-oriented scheme had the highest AC score (M = 5.26, SD = 0.72), followed by the public activity-oriented scheme (M = 4.65, SD = 0.70), with the industrial heritage exhibition-oriented scheme showing the lowest score (M = 4.38, SD = 0.74). Bonferroni-adjusted pairwise comparisons further showed that S3 was significantly higher than S1 (MD = 0.875, 95% CI [0.794, 0.956], $p < 0.001$) and S2 (MD = 0.609, 95% CI [0.532, 0.686], $p < 0.001$). The complete set of pairwise comparisons also showed that S2 was significantly higher than S1, providing full pairwise support for the overall ordering S3 > S2 > S1. Accordingly, H2, H2a, and H2b were all supported.

For the remaining evaluation variables, the main effects of the scheme were not significant for either PR or SUP: for PR, F(2, 718) = 0.207, $p = 0.813$, $\eta p^2 = 0.001$; for SUP, F(2, 718) = 0.741, $p = 0.477$, $\eta p^2 = 0.002$. By contrast, the main effect of Scheme on PT was significant, F(2, 718) = 56.149, $p < 0.001$, $\eta p^2 = 0.135$. The industrial heritage exhibition-oriented scheme had the highest PT score (M = 5.06, SD = 0.69), which was significantly higher than those of the public activity-oriented scheme (M = 4.78, SD = 0.70; MD = 0.278, 95% CI [0.198, 0.357], $p < 0.001$) and the shaded relaxation-oriented scheme (M = 4.72, SD = 0.77; MD = 0.339, 95% CI [0.256, 0.422], $p < 0.001$). The difference between S2 and S3 was not significant (MD = 0.061, 95% CI [−0.022, 0.144], $p = 0.238$). The main effects of Scene were not significant for PR, PT, or SUP, and no significant Scene × Scheme interaction was observed for any of the five constructs. Overall, significant differences among the three scheme types were observed primarily in perceived cultural authenticity, the affective comfort of public space, and perceived trust in visual representation, whereas no significant between-scheme differences were observed in perceived realism or scheme support.

5. Discussion

5.1. Perceived Cultural Authenticity and Affective Comfort of Public Space: Differentiated Evaluations of AI-Visualized Regeneration

The industrial heritage exhibition-oriented scheme showed a clear advantage in perceived cultural authenticity, whereas the shaded relaxation-oriented scheme showed a clear advantage in affective comfort of public space. This differentiation is consistent with

the two evaluation logics described by the heritage authenticity perspective and the environmental emotional quality framework. Authenticity evaluation is not the same as judging visual realism; Rather, it is more concerned with whether heritage and its cultural significance are preserved and remain identifiable [36,83]. Environmental evaluation also includes emotional meanings different from cognitive meanings, and pleasant and relaxed represent characteristic descriptors of environmental emotional quality [84]. Therefore, the two scheme types highlight two distinct evaluation bases, respectively: the continuity of cultural meaning and the emotional experience of future spaces.

The advantages of schemes oriented to industrial heritage exhibitions in perceived cultural authenticity can be understood from the semantic continuity between the AI-generated schemes and the existing cultural referents of the heritage site. The judgment of the authenticity of heritage is clearly dependent on the environment, and the maintenance of the authenticity and integrity of different heritage sites needs to be understood according to their specific value and site characteristics [85].

Cultural codes such as structural relationships and symbolic colors also play an important role in the cultural fidelity of heritage imagery [86]. Therefore, the advantages of schemes oriented towards industrial heritage exhibitions are better explained by a higher subjective evaluation of cultural semantic continuity rather than a verification of the objective historical fidelity of the schemes. From this perspective, heritage authenticity provides a foundation for understanding how the public assesses the connection between generative representations of future programmes and the existing cultural identity of heritage sites.

The advantage of shaded relaxation-oriented schemes in affective comfort of public space is consistent with the relationship between natural environment cues and positive affective responses described by the theory of environmental affective quality and Ulrich's psychological evolutionary theory of stress recovery [87]. People often have more positive feelings and lower stress responses in natural places that they perceive to be safe. The relaxation-oriented shading scheme includes continuous vegetation and shade, which is the most direct signal of calm and safety, while the quiet resting space reinforces the feeling of comfort and relaxation. Together, these elements act as environmental emotional cues. The public's evaluation of urban greening schemes generated by artificial intelligence is not only determined by the quantity of greening, but by the form of greening and the configuration of spatial functions [12]. In this study, the shaded relaxation-oriented scheme achieved higher scores in terms of emotional comfort, consistent with theoretical expectations. These ratings reflect the public's subjective evaluation of the emotional quality of the future environment shown in the images. These findings suggest that AI-generated images may support preliminary evaluations of anticipated affective comfort in proposed public spaces.

5.2. Perceived Realism and Perceived Cultural Authenticity: Two Correlates of Perceived Trust in Visual Representation

Perceived realism and perceived cultural authenticity were positively associated with perceived trust in visual representation. The standardized path coefficient was numerically larger for perceived realism. In the estimated structural model, perceived trust in visual representation was also positively associated with scheme support. Trust in automation has been linked to reliance under uncertainty [56]. Empirical work has also examined trust when people decide whether to rely on automated aids [88]. Work on automation has further distinguished patterns of use, including misuse and disuse [89]. Research on automation has addressed trust, reliance, and patterns of use, providing useful context for the present discussion. What perceived trust in visual representation captures is different: the credibility participants attributed to an AI-generated image as a depiction of a regeneration proposal that had not yet been built. It does not measure trust in the GenAI system itself. Accordingly, the positive association between representational trust and scheme support should not be interpreted as evidence of reliance on the GenAI system. Instead, the findings indicate that perceived realism and cultural authenticity are distinct correlates of representational trust, which is positively associated with support for the depicted scheme.

Perceived realism did not differ significantly across the three selected schemes. Perceived trust in visual representation was significantly higher for the industrial heritage exhibition-oriented scheme than for either of the other two schemes, whereas the difference between the public activity-oriented and shaded relaxation-oriented schemes was not statistically significant. Because comparable realism was also a stimulus-screening criterion, the absence of detected scheme differences in perceived realism should be interpreted within the selected stimulus set. Although perceived realism was positively associated with perceived trust in visual representation, the scheme comparisons provided no statistical evidence that differences in perceived realism accounted for the observed differences in trust. In the context of AI-generated video, a significant positive association between perceived realism and perceived trust has already been observed [26]. In AI-generated urban images, visual realism and representational fidelity of urban visual identity are also considered at the same time, while landmarks with cultural and historical significance show more obvious representational limitations; When the generated images fail to accurately convey the actual character or identity of a city, their value for planning and design may be limited [38]. The present findings link these two views. In contrast, perceived cultural authenticity was positively associated with representational trust and differed significantly across schemes. Thus, for industrial heritage with prominent historical references and site identities, the credibility of an AI-generated representation may depend not only on general visual realism, but also on whether the representation culturally anchors the identity of a particular heritage site.

The results distinguish the strength of psychological associations from the ability of evaluated attributes to differentiate regeneration schemes. Although perceived realism showed significant positive indirect associations with scheme support through perceived trust in visual representation in the core structural model, there were no significant differences between selected schemes, and the corresponding scheme-specific indirect associations were not statistically supported. Perceived cultural authenticity shows different patterns. Its ratings differed significantly across schemes. The scheme-related indirect associations through PCA, both with and without PT, were statistically supported. However, its standardized path coefficient predicting perceived trust in visual representation was smaller than that of perceived realism. These findings suggest that strong structural associations between psychological constructs do not necessarily mean that the same constructs explain the differences between scheme conditions.

5.3. Attribute Differentiation and Overall Support: Multi-Attribute Evaluation of AI-Visualized Schemes

The three AI visualization regeneration schemes showed clear differences in perceived cultural authenticity and affective comfort of public spaces, but these attribute-level differences were not accompanied by significant differences in overall scheme support. This divergence requires consideration of how the assessment of specific attributes relates to the broader judgment of regeneration recommendations. Constructive preference studies have shown that the contribution of attribute information to evaluative judgment may depend on the evaluation task and the way the information is processed [90,91]. Therefore, cultural continuity and anticipated experiences of public space may constitute different but co-related considerations in industrial heritage regeneration without necessarily determining overall scheme support.

The multi-attribute approach to public preferences provides another way to explain this pattern. Choice-based studies of industrial heritage reuse and urban regeneration show that one needs to consider several attributes [92,93]. Respondents may assign different importance to each attribute. These differences in priorities offer a possible explanation. Even when cultural-authenticity and affective-comfort evaluations differ across schemes, these differences need not translate into significant differences in overall scheme support. The way we measure scheme support is also important here. Respondents rated each proposal's acceptance, willingness to support its implementation, and willingness to recommend. They do not need to choose one proposal over others. Overall scheme support may reflect respondents' acceptance of each regeneration proposal. This support may not reveal how respondents rank proposals based on specific attributes.

The scheme comparison results provide a further perspective on the difference between attribute-level assessment and overall support. In a comparison between an industrial heritage exhibition-oriented scheme and a shaded relaxation-oriented scheme, indirect association through perceived cultural authenticity and sequential indirect association through perceived cultural authenticity and perceived trust in visual representation operate in the opposite direction to indirect association through affective comfort of public space. In contrast, comparisons involving the public activity-oriented scheme (S2) showed opposite directions between net indirect associations and the remaining conditional direct associations. These contrasting patterns suggest that the lack of significant differences in overall scheme support is accompanied by different configurations of model estimation associations. While these connections do not establish a conscious trade-off between cultural authenticity and emotional comfort, they underscore the distinction between the overall endorsement of regenerative proposals and the specific cultural and empirical assessments associated with such endorsement.

5.4. Theoretical Implications for Evaluating AI Representations of Future Spaces

This study helps theoretically in providing two analytical functions of psychological evaluations in S–O–R: (1) mapping associations with trust and scheme support, and (2) identifying differences in evaluations across the selected scheme conditions. Previous work has focused on, for example, whether visualizations of GenAI applications for the design of cities are desirable [10], stakeholder preferences for alternative scenarios depicting AI-generated public space [12], and realism and urban identity in AI-generated cityscapes [38]. One study compared support for different scenarios for reconverting industrial heritage using AIGC-supported assessments [14]. Related work compared designer intent with public perceptions of industrial heritage regeneration using multimodal social media data [94] and generative visualizations for participatory planning workshops [95]. Our findings add another perspective to this research. The strength of an evaluative construct's structural associations may not match its ability to distinguish the selected

visualized schemes. Visual realism and overall support alone may not adequately describe public evaluations of AI-visualized regeneration proposals. Public perceptions of representational credibility and professional assessments of design validity provide different but complementary forms of evidence. Representational trust reflects how credible a visualized proposal appears to viewers, whereas architectural accuracy, heritage conservation compatibility, and technical feasibility concern, respectively, its correspondence with documented site conditions, the appropriateness of the proposed interventions for heritage values and conservation requirements, and their potential for implementation. Public evaluations capture how viewers perceive the proposed schemes. Professional assessments, by contrast, examine architectural accuracy, heritage conservation compatibility, and technical feasibility.

5.5. Practical Implications for AI-Assisted Industrial Heritage Regeneration

The findings suggest that the application of visual GenAI in industrial heritage regeneration should not be guided by visual effects alone. Instead, on the basis of early site investigation and heritage value identification, buildings, material traces, spatial relationships and cultural symbols bearing historical significance and site identity are included as constraints in the generation and screening process, so as to avoid replacing important heritage information with generic landscape language. Once outputs are produced, their spatial-visual plausibility and the effectiveness of cultural representation should be evaluated separately. The former focuses on whether building scale, perspective relationships, materials, and environmental elements appear visually plausible, whereas the latter concerns whether industrial heritage features, historical spatial relationships, and cultural cues remain clearly recognizable. Visual realism does not necessarily imply accurate cultural representation, and adequate representation of cultural elements cannot substitute for an assessment of spatial plausibility. Accordingly, the quality of AI-generated outputs is better evaluated through an integrated consideration of both visual credibility and cultural continuity.

The contrasting evaluations of the regeneration schemes provide a potential design implication for industrial heritage regeneration. Participants reported higher perceived cultural authenticity with the exhibition-oriented scheme and higher affective comfort of public space with the shaded relaxation-oriented scheme. This contrast suggests that the legibility of heritage and the anticipated everyday spatial experience deserve to be considered together when developing future alternatives to regeneration. One possible design approach is to use preserved industrial features and historical spatial relationships as references when introducing environmental improvements and public events, and subsequently re-evaluate whether the revised proposal maintains identifiable heritage features while improving perceived spatial comfort. In this case, a public evaluation of AI visualization alternatives can provide diagnostic feedback for iterative design improvements. However, the present findings do not demonstrate that such an integrated approach results in greater public support, better environmental performance, or more efficient use of public space.

Our findings suggest that the use of visual GenAI in industrial heritage regeneration should leverage public perception and professional design evaluation. Both provide complementary sources of information. This is especially important when AI-generated images show a non-professional audience how space may change. Explaining what exists, what is envisioned, and the design details that have been validated by professionals can help viewers understand the status of each proposal. With these distinctions, visual GenAI may help communicate and compare alternative regenerative directions. Designers can utilize public feedback and professional evaluation when refining these proposals.

5.6. Research Limitations and Directions for Future Research

We take Fengtian factory in Shenyang as our research background. We mainly surveyed people aged 18 and above from the general public in Shenyang. All participants were provided with the same site information and photographs of the existing conditions before evaluating the regeneration schemes. The proposals involve a factory with its own industrial history and local culture, a context that may influence the perspective of the participants. Historic buildings and other structures still standing in the factory may also shape participants' views. Our data is only from the Fengtian facility, and we have not checked these relationships at other facilities. Testing this outside of the Fengtian factory means looking at several cities, different types of industrial heritage, and different regeneration settings. Future studies may include several cities and a range of industrial heritage sites. In addition to local residents and general visitors, these studies may also involve design professionals, heritage managers, and other stakeholders. At different sites, researchers can examine whether the assessment factors of these groups differ from each other. These variations may be related to field conditions as well as the experience of different groups in judging regeneration recommendations displayed through AI-generated images.

In addition to case-specific considerations, a fixed presentation order may also affect comparisons between schemes. All participants saw the visual information in the same order when evaluating the regeneration proposal. Even if procedures are consistent between participants, sequential effects are still possible. Within each scene, S1, S2, and S3 were always presented in the same order. Therefore, scheme-related differences cannot be fully separated from potential effects of presentation position, familiarity, fatigue, or sequential comparison. Even if the scene × scheme interaction is not significant, we cannot rule out these possible effects. Using current data, we cannot independently determine the direction or magnitude of any such effects. These findings reflect how the public evaluated regeneration proposals under the standardized presentation conditions of this study. They should not be construed as estimates of scheme differences independent of the order of presentation. One approach for future research is to maintain scene-based evaluation procedure, balance the sequence of schemes within scenes, and change the sequence of scenes among participants.

Better control of presentation order does not eliminate the limitation of sampling only a small number of visual stimuli. These limitations still affect how we interpret scheme differences. Using common cue criteria, we generate multiple image candidates and ask experts to screen them for comparability. Nonetheless, each "scene × scheme" condition is represented by only one selected AI-generated image. For the same conditions, we were unable to estimate the variation between surrogate images. Nor can we attribute the observed differences solely to the expected regeneration strategy. Some observed differences can also reflect accidental changes in lighting, composition, or other image details. Our results describe how participants evaluated selected AI-visualized regeneration schemes under the conditions of this study. We cannot assume that the results are applicable to other visual representations of the same regeneration strategy.

We systematically compared public assessments of selected regeneration proposals in three scenes, yielding empirical evidence. Future work could test the consistency of patterns observed for each scheme in different visual representations. This can be achieved by independently generating multiple images for each strategy using different prompts, generation batches, and generation models. Future studies could complement expert screening with an independent recognition task to examine how consistently participants distinguish S2 from S3 without scheme labels. When a sufficiently large number of stimuli is available, participants and stimuli could be treated simultaneously as random sources of variation in cross-classified or other appropriate multilevel models, thereby

further distinguishing individual-level variation, stimulus-level variation, and differences attributable to design strategies.

In addition to these experimental-design considerations, interpretation of the relationships among the variables in this study should remain confined to the level of statistical association. The repeated-measures design and multilevel structural equation modeling account for the non-independence of multiple evaluations provided by the same participant and allow the analysis to focus on changes in evaluations as participants encounter different visual stimuli. However, perceived cultural authenticity, affective comfort of public space, perceived realism, perceived trust in visual representation, and scheme support were all measured by self-report items after participants viewed each visualized scheme. Therefore, important structural pathways and indirect effects alone cannot establish a chronological order or causal direction in these psychological assessments. Future research could independently manipulate cultural cues, levels of visual realism, or elements of environmental experience, and combine these manipulations with temporally separated measures, longitudinal designs, or multi-stage experiments to more rigorously test the directionality of current relational constructs. The associated measurement limits also warrant caution. The exploratory first-item shared-variance factor accommodated the local residual covariance, but did not identify its source because of the fixed order of items and the lack of independent methodological markers. Ignoring this factor greatly deteriorates the overall fit of the complete S–O–R model, although the change in direct structural path estimation is relatively small. Therefore, the reported association should be interpreted according to this exploratory measurement specification and not as a result of demonstrating robustness in alternative measurement models. Furthermore, small changes in approximate fit indices coexisted with statistically significant robust χ^2 difference tests in selected measurement-invariance comparisons. Therefore, comparisons across scheme conditions should be interpreted as supported by approximate measurement comparability rather than exact loading and intercept invariance for all constructs. Future studies could balance item sequences, include appropriate methodological markers, and investigate item-level invariance using pre-specified criteria.

Even if future research further strengthens experimental control and causal identification, the AI visualization medium itself means that the current research addresses a form of future spatial evaluation based on visual representations. Static images facilitate the standardization of viewpoints and the control of visual conditions, but they cannot fully represent movement through real industrial heritage public spaces, embodied scale, sound, or experiences accumulated through continued use. Correspondingly, scheme support reflects self-reported attitudes developed in response to hypothetical future schemes and cannot be directly equated with actual choice, engagement, or long-term use behaviors in real regenerative decision-making. Future studies can compare assessments of static images, interactive AI-generated environments, virtual reality, and live environments while incorporating actual scheme selection, behavioral observations, and spatial usage data.

6. Conclusions

Using the outdoor public space of the Fengtian Factory as the research context, this study examined the relationships among three AI-visualized regeneration schemes, public psychological evaluations, and scheme support through repeated evaluations. Under the stimulus conditions used in this study, the industrial heritage exhibition-oriented scheme showed a clear advantage in perceived cultural authenticity, whereas the shaded relaxation-oriented scheme showed a clear advantage in the affective comfort of public space, suggesting that the selected schemes were evaluated differently in terms of

perceived heritage cultural continuity and anticipated affective experience of public space. Perceived realism, by contrast, did not differ significantly across the three schemes.

The structural analysis further showed that perceived cultural authenticity and perceived realism were positively associated with perceived trust in visual representation, while perceived trust in visual representation, perceived cultural authenticity, and affective comfort of public space were positively associated with Scheme Support. Both perceived cultural authenticity and perceived realism showed significant indirect associations with scheme support through perceived trust in visual representation. However, perceived realism did not differ significantly across schemes, and the indirect associations between scheme type and scheme support through perceived realism and perceived trust in visual representation were not statistically supported. By contrast, differences in perceived cultural authenticity and affective comfort of public space across schemes corresponded to specific indirect associations with support in opposite directions. Thus, although ratings differed across the three scheme conditions on several psychological dimensions, overall scheme support did not differ significantly. For S2 and S3, these results reflect evaluations of the selected images, while participants' recognition of their intended design differences warrants further examination.

These findings suggest that evaluating AI-visualized industrial heritage regeneration schemes should not focus solely on visual realism or the isolated advantage of a particular regeneration strategy. Instead, evaluation should consider heritage cultural continuity, future public-space experience, and the credibility of AI-generated visual representations together. In future applications, visual GenAI may serve not only as a tool for generating design renderings but also as a medium for comparing alternative schemes and facilitating public feedback. Evaluating cultural authenticity, affective comfort, and representational trust together may help identify opportunities for improving public-space proposals while retaining recognizable industrial heritage characteristics.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/buildings16224522/s1. Table S1: Sensitivity of Structural Path Estimates to the Inclusion of the Exploratory First-Item Shared-Variance Factor.

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described in the Materials and Methods section. The specific version of the image-generation model was not separately displayed in the user interface at the time of use. The authors reviewed all AI-assisted outputs and take full responsibility for the content of this publication.

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