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Original Research Article

Artificial Intelligence and Architecture
A Comparative Study of Human-Centered and Machine-Centered Design

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Abstract

Problem statement: Although artificial intelligence (AI) offers unprecedented speed and precision in architectural workflows, fundamental questions remain regarding the role of human creativity and the capacity of AI-generated designs to preserve authenticity and cultural identity.

Research objective: This study conducts a comparative investigation of the aesthetic qualities inherent in human-centered versus machine-centered architectural design.

Research method: Framed as an applied, descriptive-analytical inquiry, the research selected four winning proposals from an Iranian school architecture competition and generated analogous schemes using AI platforms. These eight designs were evaluated by a panel of university faculty, consulting engineers, and both architecture and non-architecture students. Each participant assessed all proposals across five criteria: creativity, harmony, authenticity, attractiveness, and general Concept.

Conclusion: Results reveal that human-generated designs significantly outperform AI-produced schemes on authenticity, while AI designs exhibit a slight advantage in harmony. In terms of visual attractiveness, faculty and consulting engineers favored human designs, whereas non-architecture students showed a marked preference for AI proposals. Overall, the architectural community predominantly judged human-crafted works superior, though the high standard deviations in ratings underscore the subjective nature of aesthetic judgments and the diversity of individual preferences.

The study underscores the indispensable value of human creativity in architecture and positions AI as a complementary tool for enhancing the design process, rather than as a wholesale substitute for human designers.

Keywords: *Architectural Design, AI-Generated Design, Aesthetics, Creativity, Evaluation.*

Introduction

The advent of artificial intelligence (AI)—one of the most remarkable technological achievements of the twenty-first century—has profoundly impacted diverse scientific and artistic disciplines (Momunaliev & Omorkulov, 2024; Thapliyal & Thapliyal, 2024; Ezhilmurugan, & Yashavini, 2024). Architecture, situated at the nexus of art, science, and technology, is now undergoing a fundamental transformation through the integration of AI into both creative and operational workflows. Generative models and platforms such as ChatGPT, generative adversarial networks (GANs), and latent diffusion models (LDMs) have disrupted conventional design methodologies, ushering in new paradigms for conceiving, planning, and executing architectural projects (Lee et al., 2024; Gaier et al., 2024; Ghasemi et al., 2024; Vergunova, 2024). By leveraging machine-learning algorithms and neural networks to analyze vast datasets and simulate human decision-making (Kashyap, 2023), AI systems can produce

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human-like text, offer inventive design suggestions, and even generate entirely novel ideas. In architecture, these capabilities extend far beyond conceptual design to encompass energy optimization, structural simulation, project documentation generation, and adaptive revisions driven by user feedback (Widodo & Susan, 2024; Vergunova, 2024; Onatayo et al., 2024). Furthermore, AI platforms facilitate dynamic, interactive explorations of design alternatives in the early stages, enhancing the quality and depth of outcomes (Williams & Cullen, 2016). Beyond tool sophistication, AI has reshaped design processes, execution methods, analysis techniques, and evaluation protocols, automating tasks such as document production and the optimization of complex schemes (Matter & Gado, 2024; Bolek et al., 2023).

Yet the rise of AI in architecture is not without its challenges (Marburger, 2024; Ellil, 2024; Chi, 2024; Ray, 2023; Gill & Kaur, 2023). Chief among these concerns are potential biases embedded within training datasets—biases of cultural, social, or historical origin—that risk propagating into AI-generated designs (Meyer et al., 2023; Chi, 2024). Additional issues include safeguarding project confidentiality, clarifying intellectual property rights over AI-produced schemes, and avoiding overreliance on automated solutions (Sebastian, 2023; Molla, 2024). Perhaps the most profound question is the impact of AI on human creativity: despite AI's remarkable ability to accelerate and refine architectural workflows, judgment, and originality remain at the core of design practice (Ellil, 2024; Chi, 2024; Marburger, 2024; Gill & Kaur, 2023). Architects must assume the role of informed stewards—critically evaluating AI-derived proposals and making decisions not solely on performance metrics but also on aesthetic and social values (Gill & Kaur, 2023; Petrakova & Simkovic, 2023; Desouki et al., 2023). Although AI can generate architectural concepts, we must ask whether these outputs reflect a genuine understanding of beauty and function or are merely byproducts of data-driven pattern recognition. Can AI ever fully supplant human designers? What are its strengths and limitations in emulating the nuances of human creative thought?

This study undertakes a comparative analysis of design quality as produced by humans versus AI, seeking to answer these pivotal questions and to elucidate the interplay between human ingenuity and artificial intelligence in the architectural design process. The primary aim is to present a balanced perspective on AI's prospective role in the future of architectural innovation.

Literature Review

- **Artificial Intelligence**

Artificial intelligence (AI) constitutes a branch of computer science devoted to replicating human cognitive functions—such as learning, reasoning, and problem-solving—through the use of sophisticated algorithms and machine-learning techniques (Helm et al., 2020). First coined by John McCarthy at the 1956 Dartmouth Conference, the term originally aimed to describe the simulation and extension of human intellect within computational systems (Dong et al., 2020). By ingesting vast volumes of data and detecting underlying patterns, AI systems are capable of making informed decisions and autonomously refining their behavior over time (Cioffi et al., 2020). Beyond routine tasks, modern AI also excels at analyzing user preferences and adapting to changing environmental conditions with remarkable efficiency (Ali Abdel Moley, 2023). As a revolutionary technology, AI has fundamentally reshaped the dynamics of human-machine interaction (Kolomaznik et al., 2024). In the realm of architectural design, AI-driven tools employ data analytics, pattern recognition, and optimization algorithms to accelerate creative ideation and streamline development processes (Chandrasekera et al., 2024).

- **Applications of AI in architecture**

The impact of AI on architecture spans multiple domains. In conceptual design, AI can generate highly realistic, inspirational visualizations to guide architects' creative thinking (Dong Ho & Sung Hak, 2023; Gür et al., 2024; Molla, 2024; Shukla, 2024). When it comes to sustainability, AI models analyze usage profiles and environmental data to propose energy-efficient building configurations (Cortiços et al., 2024; Onatayo et al., 2024). Project management also benefits from AI's resource-planning capabilities and intelligent service allocation, enabling more agile and cost-effective workflows (Rayaprolu, 2024). Furthermore, AI enhances core design processes—automatically optimizing performance criteria, generating space-planning layouts, and supplying innovative conceptual alternatives (Chandrasekera et al., 2024; Del Campo et al., 2020; Momunaliev & Omorkulov, 2024; Thapliyal & Thapliyal, 2024; Ezhilmurugan & Yashavini, 2024). Despite these advances, several challenges persist. The outcomes of AI-driven design can be difficult to control or predict, and its adoption remains uneven across firms (Marino et al., 2024; Magri, 2023). Concerns about authenticity and the intellectual property status of AI-generated works further complicate the landscape, as does AI's current inability to replicate genuinely novel creative insight (Ellil, 2024; Marburger, 2024; Chi, 2024).

- **AI Algorithms in Architecture**

The AI algorithms employed in architectural practice are summarized in Table 1 below.

Theoretical Foundations

- **Aesthetic value assessment in architectural design**

The rapid proliferation of AI in architectural design has given rise to numerous innovative methodologies, yet it also poses significant challenges—chief among them the question of how to objectively evaluate the aesthetic merit of AI-generated designs. Addressing this issue requires a thorough examination of the theories and studies underpinning architectural aesthetics. Aesthetic appraisal in architecture is inherently multifaceted: beyond mere visual form, it encompasses a multisensory experience—including tactile, auditory, and even olfactory dimensions—that contrasts with Enlightenment-era emphases on sight and hearing as the dominant senses.

Critically, aesthetic evaluation can be approached from both subjective and objective perspectives. Subjective approaches acknowledge that individual emotions, memories, and sociocultural needs shape one's perception of beauty. Conversely, objective frameworks trace back to early psychophysical research—such as Fechner's attempts to quantify aesthetic response—and more recent empirical work (Sussman & Ward, 2019; Norman, 2010), which underscores the role of human perceptual mechanisms in forming beauty judgments. This line of inquiry aligns with Christopher Alexander's and Boras's concepts of "quality without a name" and "aesthetic scale," perception (Ingham & Ettlinger, 2023; Boras, 1992), which highlight the importance of rapid, intuitive and demonstrate up to 80–90 percent consistency in design rankings when employing standardized aesthetic scales (Zhang et al., 2023).

Phenomenological theorists such as Merleau-Ponty contend that architectural beauty emerges from the dynamic interplay among subject, object, and context—that is, aesthetic perception arises not

Table 1. AI Algorithms Used in Architecture. Source: Author.

Technology Category	Applications	Examples / Tools	Source
ML-based design tools	Energy-use optimization 2D-to-3D drawing conversion Urban data analysis	Autodesk Forma, BricsCAD BIM, Chaos AI Enhancer	Wang (2024)
Diffusion models	Sketch-to-high-fidelity rendering Rapid design iterations with minor tweaks BIM integration	Stable Diffusion 3.5, FLUX.1, ArchitectureRealMix	Mitchell (2024)
Generative networks (GANs/ VAEs)	Initial conceptual design Photorealistic render generation Schematic-plan optimization	Midjourney, DALL-E 3, ArkDesign.ai	Wang (2024)
Large language models (LLMs)	Technical-document analysis and client-requirement parsing Automated report generation Material-selection support	GPT-4, Gemini, Qwen2.5-Max	Mitchell (2024)

solely from the mind or the material form, but from their union within lived experience. Environmental aesthetics further develops this notion by positing that form, spatial context, and an observer's spatial memory collectively inform aesthetic response. Factors such as lighting, scale, materials, and prior experiences play decisive roles in shaping aesthetic judgment. From a sociocultural standpoint, Bourdieu's theory of cultural capital suggests that aesthetic tastes reflect individuals' social positions and educational backgrounds. Durkheimian perspectives frame beauty as a social phenomenon, produced through collective practices, specialist discourses, and the intergenerational transmission of values. Complementing these views, Arousal Theory maintains that aesthetic experience is optimized when an observer resides in a tension between familiarity and unpredictability—beauty oscillates between the known and the unexpected. Finally, Collective Aesthetics emphasizes the significance of social interaction, arguing that communal dialogues and group dynamics co-construct shared perceptions of architectural beauty.

Evaluating the aesthetic value of AI-generated architectural designs thus requires an integrated perspective that considers perceptual experience, emotional responses, memory, socio-cultural needs, and insights from neuroscience. Among these factors, intuitive human responses and perceptual experience play a central role. Subjective scaling methods have proven useful for assessing architectural imagery produced by AI (Zhang et al., 2023).

Accordingly, the theoretical framework proposed by Chatterjee and Vartanian offers a robust model for evaluating AI-generated architectural designs. This model comprises three primary components perceptual processing, cognitive processing, and emotional response and can be further enriched by incorporating creativity, a critical dimension in AI-driven design (Chatterjee & Vartanian, 2016). Based on this framework, the following four dimensions are proposed for evaluation:

- **Perceptual Processing:** Assessing the authenticity and attractiveness of the designs.
- **Cognitive Processing:** Analyzing the harmony and internal consistency of the architectural proposals.
- **Emotional Response:** Investigating the emotional reactions elicited by the designs.
- **Creativity:** Evaluating the degree of innovation and originality (Zhang et al.,2023).

By quantitatively measuring these dimensions, it becomes possible to analyze participants' emotional responses and aesthetic preferences, thereby assessing the effectiveness of AI in architectural design. This framework captures the intricate interplay among perceptual, cognitive, emotional, and creative dimensions inherent in the architectural experience.

Research Methodology

This study is applied in nature and, based on its methodology and characteristics, falls within the category of descriptive research with a comparative approach. The primary aim is to compare two design paradigms—human-centered and machine-centered across five key dimensions: authenticity, attractiveness, creativity, harmony, and general concept. In doing so, the study also seeks to offer strategies for improving design processes. Given its focus on assessing the strengths and weaknesses of each approach, the research may also be classified as evaluative.

In this study, four architectural designs were randomly selected from submissions to the "Iranian School Iranian Architecture" competition, all of which were situated in a cold, mountainous climate. To create comparable AI-generated designs, the same input parameters used for the human-produced samples based on the official guidelines and specifications for educational complexes provided by the Organization for Development, Renovation, and Equipping of Schools, as well as standardized definitions of site dimensions and climatic conditions were entered into four AI platforms: Midjourney, Leonardo, DALL·E 3, and Stable Diffusion. From a total of sixteen AI-generated designs, four were randomly selected for inclusion in the study.

To facilitate consistent referencing throughout the evaluation process, each selected image was assigned a unique identifier. Additionally, to ensure unbiased assessments and eliminate the potential influence of participants' background knowledge on their judgments, the sequence in which the images were presented was randomized. Selected samples are shown in Figs. 1 & 2.

The selected images were evaluated using a questionnaire distributed among different participant groups. One version of the questionnaire was administered to university faculty members for expert comparison of the designs. A similar version was distributed to 42 practicing architecture consultants. Another version was distributed to 285 architecture students, including fourth-year undergraduates and master's-level students. An additional 115 questionnaires were distributed to non-architecture students, to capture a broader spectrum of aesthetic preferences and emotional responses from the general public. Finally, the AI systems themselves were included in the evaluation. This was done by aggregating average scores from AI models such as CLIP, Spacemaker AI, and ChatGPT, which had not been involved in the generation of the design outputs.

The study employed a mixed-methods research design, combining both quantitative and qualitative approaches. In the quantitative phase, data were collected via questionnaires distributed across the four groups and analyzed using statistical methods. The normality of data distribution for each evaluative dimension was tested using standard normality assessments. For normally distributed data, independent-sample t-tests were used to compare group means. For non-normal distributions, the Mann–Whitney U test—a robust non-parametric alternative—was applied. These choices enhanced the validity of p-values, effect sizes, and the overall robustness of the findings. Following the quantitative analysis, the data were qualitatively interpreted through an interpretive lens, enabling deeper exploration of meaning and uncovering more nuanced dimensions within the findings. The research process is illustrated in Fig. 3.

Fig. 1. Human-designed schemes. Source: Author.

Fig. 2. AI-generated schemes. Source: Author.

Findings

After collecting the questionnaires and organizing the information and data, the questionnaire responses were analyzed. The results are presented below across five components: authenticity, attractiveness, creativity, harmony, and general concept.

- **Authenticity**

As shown in Table 2 and Fig. 4, human-designed schemes were judged significantly more authentic than AI-generated proposals by all respondent groups. University faculty demonstrated the greatest sensitivity, rating human designs 1. 74 points higher on average than

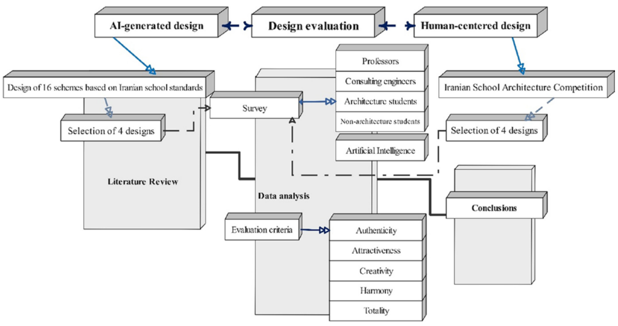

Fig. 3. Research process. Source: Author.

Table 2. Means and standard deviation for each design type on the “Authenticity” criterion. Source: Author.

	Design	Human designs								AI designs							
		First Design		Second Design		Third Design		Fourth Design		First Design		Second Design		Third Design		Fourth Design	
		Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
Authenticity	Professors	8.10	1.68	7.42	2.18	7.26	1.98	7.08	2.15	5.64	1.32	6.05	1.43	5.47	1.86	5.74	1.73
	Consulting Engineers	7.85	1.72	7.06	2.35	7.20	2.60	6.94	1.97	6.11	2.02	6.27	1.81	5.84	1.90	5.79	1.81
	Architecture Students	7.26	2.18	6.89	2.42	6.95	2.14	6.65	2.22	6.79	2.14	6.54	1.95	6.06	1.99	6.12	1.67
	Non-Architecture Students	7.19	2.34	6.78	2.11	7.13	2.28	6.84	2.38	6.28	2.27	6.97	1.48	6.32	1.76	6.18	1.38

AI counterparts ($P= 1.68 \times 10^{-9}$, Cohen’s $d = 0.00031$). Consulting engineers similarly favored human work, with a mean difference of 1.[2] points ($P= 1.86 \times 10^{-9}$, $d = 0.000225$). Architecture students and non-architecture students reported smaller but still significant gaps 0. 56 points ($P= 5.14 \times 10^{-9}$, $d = 0.000198$) and 0. 73 points ($P= 3.12 \times 10^{-9}$, $d = 0.00021$), respectively always in favor of human authorship.

Notably, the standard deviation for human designs was higher—especially among faculty ($SD \approx 2$) indicating greater dispersion in judgments, likely reflecting conceptual complexity and varied creative approaches. In contrast, AI designs yielded tighter consensus ($SD \approx 1.5–2$), suggesting the more standardized, predictable nature of algorithmic outputs. AI-based evaluators also registered a clear authenticity gap, implying that even within their own numerical logic, human authenticity cannot be fully reduced to algorithmic rules.

- **Attractiveness**

Table 3 and Fig. 5 reveal a bifurcated response pattern for visual attractiveness. Faculty and consultants rated human schemes as more attractive—mean scores of 6. 89 and 6. 83 versus 6. 08 and 6. 22 for AI designs whereas architecture and non-architecture students gave higher marks to AI proposals (7. 82 and 7. 90 versus 6. 57 and 6.90). Elevated SDs for AI attractiveness ratings among students (≈ 2.0–2.5) point to greater subjectivity in their assessments.

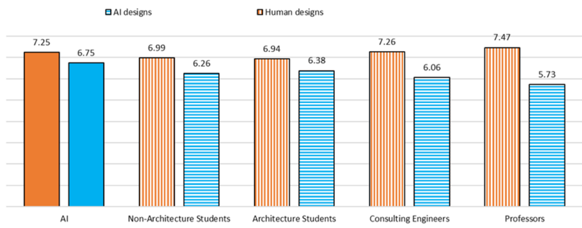

Fig. 4. Authenticity scores by respondent group. Source: Author.

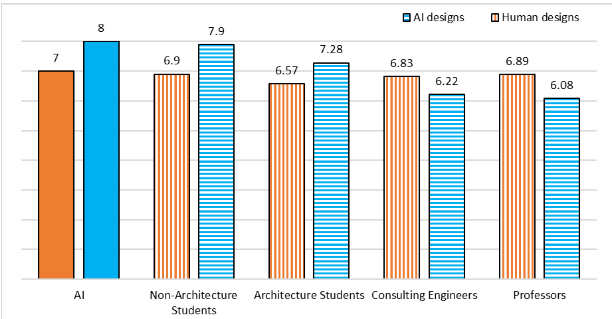

Fig. 5. Attractiveness scores by respondent group. Source: Author.

This divergence suggests that AI’s visual novelt y resonates more strongly with younger or non-specialist audiences, yet fails to satisfy deeper aesthetic criteria valued by experts.

- **Creativity**

According to Table 4 and Fig. 6, faculty and consultants rated human creativity significantly higher (effect sizes $d= 0.000211$ and 0.000197, $P= 2.84 \times 10^{-9}$ and 3.94×10^{-9}, respectively). Architecture students detected no significant creativity difference between the two sources ($P= 0.458$, $d= 0.000545$), while non-

Table 3. Means and standard deviation for each design type on the “Attractiveness” criterion. Source: Author.

Design		Human designs								AI designs							
		First Design		Second Design		Third Design		Fourth Design		First Design		Second Design		Third Design		Fourth Design	
		Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
Attractiveness	Professors	6.54	1.96	6.96	1.84	7.66	1.74	6.41	2.93	6.18	1.31	6.34	1.22	5.96	2.18	5.84	1.37
	Consulting Engineers	6.72	1.81	6.76	1.49	7.11	1.81	6.71	2.14	6.31	1.44	6.72	1.71	6.17	2.24	5.69	1.21
	Architecture Students	6.14	1.36	6.59	1.69	6.92	1.84	6.64	2.12	7.72	2.42	7.36	2.28	7.18	1.99	6.87	2.21
	Non-Architecture Students	6.71	2.12	7.04	2.06	7.12	1.94	6.71	2.62	8.12	2.62	7.95	2.31	8.18	2.12	7.34	2.23

Table 4. Means and standard deviation for each design type on the “Creativity” criterion. Source: Author.

Design		Human designs								AI designs							
		First Design		Second Design		Third Design		Fourth Design		First Design		Second Design		Third Design		Fourth Design	
		Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
Creativity	Professors	7.10	2.31	6.84	2.29	6.98	2.11	6.50	2.16	5.69	1.56	5.55	1.37	6.11	2.28	5.45	2.28
	Consulting Engineers	6.74	1.95	6.91	2.42	6.73	2.01	6.62	2.23	5.93	1.72	5.86	1.41	6.32	2.17	5.71	2.03
	Architecture Students	6.53	1.41	6.78	1.72	6.43	1.74	6.71	2.14	5.23	2.02	6.36	1.69	6.54	2.26	6.41	2.17
	Non-Architecture Students	7.01	2.52	7.09	2.46	7.12	2.14	6.91	2.42	7.52	2.31	7.41	2.12	7.92	2.41	7.12	2.27

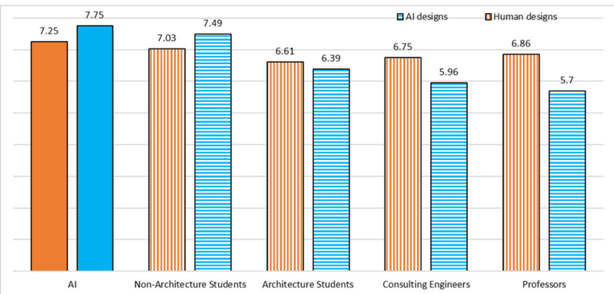

Fig. 6. Creativity scores by respondent group. Source: Author.

architecture students even favored AI designs—mean 7. 49 versus 7. 03 (P= 0.132, d= –0.000831). The lower SD for faculty evaluations of human creativity (≈ 2) indicates consensus around criteria like conceptual coherence and structural innovation. Conversely, the wider SD for AI schemes among students (≈ 2–2.5) likely reflects mixed reactions to the experimental nature of machine-generated ideas.

- **Harmony**

Table 5 and Fig. 7 show that faculty, consultants, and architecture students perceived no significant difference in harmony between human and AI proposals. However, non-architecture students judged AI designs as more harmonious (8. 64 vs. 7.65, P= 7. 46 × 10^{-9}). The higher SD for human designs among faculty (≈ 2.2) suggests that harmony in human work depends more on individual designer skill, whereas AI’s algorithmic consistency produced more uniform evaluations (SD ≈ 1.8–2).

- **General concept**

Faculty, consultants, and architecture students

Table 5. Means and standard deviation for each design type on the "Harmony" criterion. Source: Author.

Design		Human designs								AI designs							
		First Design		Second Design		Third Design		Fourth Design		First Design		Second Design		Third Design		Fourth Design	
		Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
Harmony	Professors	7.15	2.16	6.92	2.12	7.44	2.16	6.13	2.21	7.18	2.24	6.66	2.32	6.95	2.32	6.39	2.12
	Consulting Engineers	7.37	2.21	7.33	2.21	7.61	2.45	6.74	2.01	7.07	2.31	6.93	2.22	7.08	2.12	6.84	2.32
	Architecture Students	7.71	2.41	7.89	2.53	7.91	2.62	7.18	2.31	7.72	2.01	7.91	2.42	7.98	2.54	7.96	2.61
	Non-Architecture Students	8.15	2.01	7.62	2.18	7.41	1.98	7.41	2.05	8.45	2.73	8.71	2.67	8.53	2.63	8.86	2.68

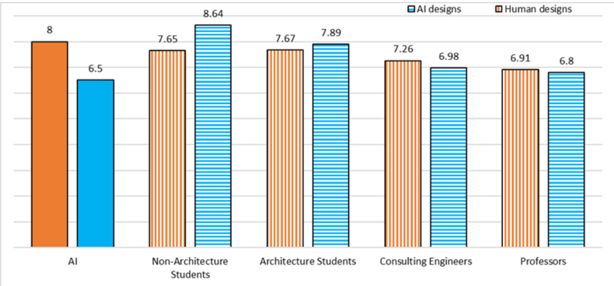

Fig. 7. Harmony scores by respondent group. Source: Author.

deemed human proposals superior to general concepts. In contrast, non-architecture students awarded higher overall scores to AI designs (7. 82 vs. 7.44). Relatively large SDs across all groups (≈ 2–2.5) indicate that holistic judgments remain highly subjective and influenced by individual preferences (see Table 6 and Fig. 8).

Discussion

Authenticity: In architectural discourse, authenticity hinges on conceptual innovation and a meaningful dialogue with context. It reflects not only individual creativity but also the intricate interplay of history, culture, and social needs. Human-generated designs were judged more authentic precisely because they integrate these dimensions, weaving historical narratives and spatial storytelling into their conceptual fabric. By contrast, AI outputs—relying on repetitive patterns and standardized parametric forms—often lack conceptual depth and an organic connection to a project's unique setting.

Our quantitative data reveal that as expertise increases, so does the ability to distinguish between human and machine authenticity. Seasoned professionals (faculty and consultants), drawing on rich long-term memories of design precedents and extensive conceptual networks, can discern subtle layers of authenticity—such as historical references or narrative coherence—that demand a higher cognitive load. This complexity, coupled with divergent theoretical interpretations of each design's conceptual and historical strata, helps explain the wider rating dispersion among experts (SD ≈ 1.3–2.3). Novices and non-specialists, however, tend to base their judgments on first impressions through fast, heuristic processing, resulting in smaller score gaps (≈0.73) and more uniform evaluations of AI-generated work (SD ≈ 0.6–1.0). This contrast underscores that human designs—by virtue of their conceptual richness—elicit diverse cognitive responses, whereas machine outputs channel attention within more predictable boundaries.

Although AI can achieve impressive formal innovations through algorithmic optimization, it remains far from emulating the deep neural networks of human cognition—repositories of collective history and personal experience. Across all participant groups, human designs maintained their lead in perceived authenticity, highlighting AI's fundamental challenge in re-creating the complex, human-centered elements of architectural authorship.

Table 6. Mean and standard deviation for each design type on the "General Concept" criterion. Source: Author.

	Design	**Human designs**								AI designs							
		First Design		**Second Design**		**Third Design**		**Fourth Design**		**First Design**		**Second Design**		**Third Design**		**Fourth Design**	
		Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
General Concept	Professors	7.12	2.38	6.95	2.15	7.40	2.20	6.11	2.16	6.55	2.28	6.32	2.21	6.48	2.45	5.81	2.13
	Consulting Engineers	7.08	2.17	6.99	2.21	7.11	1.97	6.43	2.22	6.45	2.17	6.54	2.37	6.51	2.54	6.03	2.41
	Architecture Students	6.97	2.08	7.05	2.32	7.23	2.41	6.72	2.38	7.08	2.53	6.82	2.43	6.93	2.51	6.11	2.52
	Non-Architecture Students	7.82	2.51	7.15	2.43	7.79	2.52	7.01	2.06	7.85	2.31	7.79	2.62	7.93	2.55	7.69	2.47

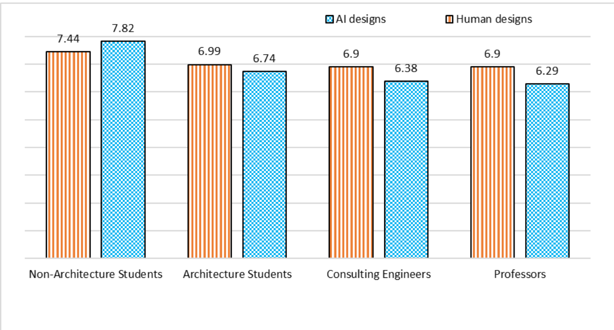

Fig. 8. General Concept scores by respondent group. Source: Author.

Attractiveness: Aesthetic attractiveness in architecture arises from a multilayered interaction between intuitive processing and rational analysis. Our findings show that general audiences (students and non-architects), guided by overt visual cues—such as intricate geometric patterns and striking color palettes—rapidly gravitate toward AI-generated proposals, awarding them an average score of 7.59. This swift preference reflects the engagement of heuristic processing mechanisms, which prioritize surface-level attractiveness. In contrast, experts (faculty and consultants), after their initial visual encounter, probe deeper layers of design integrity. By evaluating the alignment between conceptual coherence and sensory stimulation, they consistently rated human designs as more attractive.

This divergence reveals a paradigm shift among younger, digitally native audiences who equate attractiveness with technological novelty—a phenomenon rooted in the "exposure effect" of cognitive psychology, whereby familiarity blended with apparent innovation fosters a preference for designs that seem both new and recognizable.

Creativity: Architectural creativity resides at the nexus of novel form-making and context-driven problem-solving. Non-specialists (e.g., non-architecture students) equate creativity with the generation of unexpected, unconventional forms; they perceive AI's abstract outputs as emblematic of innovation, driven by the "surprise effect," wherein the brain responds more strongly to unforeseen stimuli. Experts, however, define creativity as multidimensional problem solving—establishing unexpected conceptual linkages grounded in deep contextual knowledge and semantic memory.

In the ideation phase, AI—using generative adversarial networks—demonstrated strong performance by producing statistically novel forms (non-specialists' mean score of 7.49). Yet in the evaluative phase, machine designs faltered, lacking the recursive neural feedback loops and profound functional analyses that underpin expert judgment. This gap amplifies divergences among groups: architecture students, familiar with both formal inventiveness and analytical rigor, perceived no significant difference between human and AI proposals. Faculty, deeply attuned to the full design continuum from concept to execution, registered statistically significant distinctions

($p = 2.84 \times 10^{-9}$), underscoring the enduring importance of conceptual originality. Ultimately, creativity in architecture binds form to context; although AI excels at form generation, it remains distant from grasping architecture's "silent language," rooted in lived experience and collective memory.

Harmony: Gestalt processing describes the mind's propensity to organize visual information according to principles such as proximity, similarity, and continuity. This cognitive bias often leads non-specialists to perceive AI-generated designs—with their simple, predictable structures (e.g., axial symmetry or regular repetition)—as immediately more harmonious.

For non-architect audiences, harmony judgments are mediated by pattern-recognition networks; they remain at a superficial Gestalt level, equating visual order with true harmony. Their higher mean score for AI designs (8.64) reflects the intrinsic attractiveness of standardized structures. Experts, however, move beyond the initial aesthetic impression to engage in structural analysis. Employing integrative cognitive frameworks, they assess relationships among components and the conceptual proportioning of a design. Here, human harmony—born of a designer's nuanced intent—consistently prevailed.

The greater standard deviation in expert ratings (compared to AI assessments) reveals the inherently subjective nature of aesthetic judgment. It highlights how evaluations of harmony are shaped by personal experience, domain knowledge, and individual taste. In other words, Harmony is not an objective property, but a multidimensional phenomenon defined at the intersection of algorithmic regularity and human subjectivity.

General Concept: Experts—by engaging Theory of Mind networks—define general Concept as a design's capacity to meet genuine human needs. Drawing on years of experience with complex projects, they awarded human-generated proposals an average score of 6. 90 for integrity, reflecting their superior responsiveness to functional and psychosocial requirements. Non-experts, relying primarily on Global Processing networks, equate integrity with formal completeness and the absence of discordant elements; thus, they favored AI-generated designs, assigning them an average score of 7.82. Architecture students—averaging 6.99 for human designs—are in transition from a superficial, visually driven understanding toward a deeper, concept-driven appreciation of integrity, gradually learning to evaluate not only form but also the integration of performance and aesthetic criteria. Consulting engineers, employing multi-criteria evaluative frameworks, view integrity as the harmonious confluence of sub-criteria such as authenticity, creativity, and harmony—an outlook shaped by their hands-on experience managing real-world projects.

From a phenomenological standpoint, human designs are imbued with lived experience, memory, and corporeal presence, rendering them both meaningful and aesthetically resonant. Non-architecture students—lacking such cultural capital—tend to equate beauty with formal innovation and thus gravitate toward AI outputs, drawn by novelty and a break from the everyday. AI, reliant on pattern analysis without an understanding of embodied experience, symbolic meaning, or authenticity, quantifies beauty in purely statistical terms, creating what might be called an "evaluation paradox": high scores for appeal coupled with low scores for authenticity. This shortcoming stems from AI's inability to replicate the richly layered networks of the human brain, which carry both cultural and individual histories.

According to Bourdieu's theory of cultural capital, aesthetic preferences mirror social status and educational background. Faculty members are drawn to designs with cultural references and conceptual complexity—nuances often imperceptible to many non-architecture students. Architecture students, still accumulating cultural capital, oscillate between an attraction to technological novelty and an appreciation for human creativity. AI, devoid of such capital, cannot grasp symbolic values or place-based meanings and remains confined to statistical analyses. Within environmental and socio-cultural aesthetics, beauty emerges from the interplay of form, context, memory, and collective discourse. The divergence between faculty and student evaluations thus reflects differences in cultural depth and lived experience.

Drawing on Arousal Theory, true beauty resides at the intersection of familiarity and novelty. While AI designs may captivate at first glance, their lack of deeper meaning prevents sustained engagement, whereas human designs maintain this critical balance. In today's postindustrial, media-saturated milieu—echoing the thoughts of Baudrillard and Lyotard—the boundary between creation and reproduction has blurred, and the appeal of AI to younger generations reflects a postmodern, media-centric aesthetic.

Despite AI's prowess in generating orderly forms, three core challenges impede its full success: (1) an inability to simulate genuine human needs; (2) reliance on historical data, which limits innovation to existing patterns; and (3) a lack of conceptual flexibility for novel contexts. Consequently, human designs—like a complex language requiring mastery of the "grammar" of professional practice—prevail in conceptual depth, while AI outputs, akin to a visual pidgin, are broadly accessible yet devoid of profound semantic layers. This perceptual chasm between humans and machines stems from differences in cognitive processing levels and lived experience.

Ultimately, the true promise lies in combining AI's structural precision in form-making with the profound conceptual insights of human designers—those attuned to cultural and social contexts—thereby creating works that delight the eye and enrich the cultural-natural ecosystem alike.

Conclusion

Today, artificial intelligence stands as a transformative force, reshaping the boundaries of architectural design. Through a comparative analysis of human-centered and AI-driven design paradigms, this study demonstrates that each approach offers distinct advantages and faces unique limitations within the realm of architectural aesthetics.

In terms of creativity, human design is rooted in lived experience, cultural heritage, historical context, and emotional engagement. The ability to intertwine abstract concepts—such as cultural symbolism or biomimetic inspiration—and to embrace risk yields truly original and singular works. Conversely, AI systems mine historical data and existing patterns (for instance, images of successful buildings or user-profile analytics) to generate parametric schemes that, despite their visual novelty, lack cultural depth and human sentiment.

Regarding process efficiency, AI excels at rapidly optimizing thousands of iterations while simultaneously performing technical and environmental analyses. Human design, by contrast, is inherently nonlinear and time-intensive—driven by iterative trial and error—but offers unmatched flexibility when addressing complex, nuanced requirements.

On the criterion of authenticity, human designers set the "gold standard" by forging deep connections with historical, cultural, and environmental contexts. AI outputs, being derivative of past data, struggle to evoke a genuine sense of place or coherent narrative. This disparity is especially clear among experts: a 1.74-point mean gap in authenticity scores and higher standard deviations ($SD \approx 1.3–2.3$) for human designs underscore the experiential and interpretive nature of this metric.

In harmony and attractiveness, AI can simulate physical parameters (light, airflow, structural logic) to produce highly efficient solutions, yet it falters in crafting spaces that inspire phenomenologically. Thus, human design remains the guardian of architectural meaning and experiential richness.

Ultimately, the central tension between these paradigms lies in the trade-off between algorithmic efficiency and intuitive creativity. AI—grounded in standardized data—yields geometrically optimized yet inauthentic forms, while human designers contend with temporal and budgetary constraints. Architectural beauty, however, is inherently multilayered: it emerges only at the intersection of form, meaning, and human experience. Although AI leads in reproducing visual allure, it remains distant from comprehending architecture's "design language"—a language

interwoven with history, biodiversity, and collective aspiration.
Therefore, the future of architecture will not be defined by competition but by a dialogic coexistence of humans and machines. In such a partnership, technology broadens the realm of possibility, while the human designer—acting as the philosopher of form—ensures depth of meaning and authenticity. This intelligent symbiosis, grounded in aesthetic, social, and ethical values, promises a sustainable and innovative horizon for architectural practice.

Suggestions and Strategies

A fundamental challenge in architectural design is the development of AI systems that transcend mere formal pattern analysis to comprehend and encode cultural memory and project context as meaningful data. In this envisioned future, architectural creativity will emerge from the synergistic blending of human and machine capacities rather than from their rivalry.
To bridge the gap between human creativity and AI's computational power, we propose four modes of synergy:
Vertical Integration: Use AI for preliminary tasks (site analysis, concept generation) and transition to human leadership for in-depth conceptual development and contextual alignment.
Scale-Based Division of Labor: Assign large-scale, parametric-optimization projects to AI, while entrusting emblematic or identity-rich commissions to human designers.
Human-Centered Algorithm Training: Enrich machine-learning datasets with cultural, historical, and social information to enhance AI's contextual awareness.
Neuro-Creative Modeling: Leverage advances in neuroscience to simulate the neural networks of expert designers, thereby replicating creative processes within AI frameworks. Realizing these hybrid models requires three strategic initiatives:
Interactive Platforms (Human-in-the-Loop): Create environments where AI-driven production and human judgment seamlessly converge.
Curricular Reform in Architectural Education: Emphasize technological literacy, critical thinking, and the preservation of design authenticity alongside AI tool proficiency.
Cultural-Historical Data Enrichment: Expand AI training corpora with culturally and historically grounded datasets to deepen machine understanding of context, identity, and sense of place.
Given this study's geographic limitation to a cold, mountainous climate, future research should replicate the methodology across diverse climatic regions and with a broader array of AI algorithms, enabling more comprehensive comparative analyses.

Conflict of Interest

No conflict of interest has been declared by the authors.

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