

Artificial Intelligence and Interior Design: From Efficiency Tool to Collaborative Paradigm

Manish Sharma *¹

Abstract

Precision oncology requires advanced computational methods to analyze complex genomic data and predict Artificial intelligence is penetrating the field of interior design at an unprecedented pace. Based on empirical studies published in the past two years, this article systematically examines AI's impact on interior design workflows, design thinking, user satisfaction, and professional identity. The analysis shows that AI is remarkably effective in concept generation efficiency and design option diversity, but contributes limitedly to user-centeredness and deep design thinking. Designer intervention is the key to bridging the gap between AI's technical capabilities and users' emotional needs, with intervened schemes receiving substantially higher user preference. AI collaboration is driving a shift in the designer's role from "creative producer" to "knowledge manager and critical evaluator," with professional identity reconstruction as the core mechanism. Current challenges include the absence of emotional understanding, ethical risks, and the need to cultivate critical use capabilities in design education. The article concludes by proposing a phased integration framework that positions AI as a phase-aware collaborative partner rather than a universal replacement for human design judgment.

Keywords

Artificial intelligence; interior design; human-AI collaboration; professional identity reconstruction; design workflow

¹ Independent Researcher, India

INTRODUCTION

Interior design is a complex discipline that integrates aesthetics, engineering, and ergonomics, with a workflow spanning multiple collaborative stages from client consultation to construction supervision. The traditional design process, however, has long been constrained by a linear and labor-intensive structure: hand-drawn sketches, three-dimensional modeling, and photorealistic rendering are extremely time-consuming, limiting the depth of scheme iteration and the breadth of creative exploration within a given time frame. This efficiency bottleneck has become increasingly pronounced under the dual pressures of compressed project cycles and growing demand for client customization.

The rise of generative artificial intelligence offers a breakthrough for this predicament. Technologies represented by large language models and text-to-image diffusion models are reshaping the cognitive approach and operational paradigm of interior design. A 2025 industry survey showed that 82% of interior designers already use AI tools in their daily work, with visualization applications accounting for the highest proportion (62%), followed by concept ideation (58%). At the same time, 70% of designers

believe AI can enhance creativity, but more than half (52%) simultaneously worry that AI may lead to a loss of originality, and 42% express concern about ethical issues such as plagiarism and bias. This "embrace and vigilance" attitude reflects the deep tension of a technological transition period.

Academic discussion of the relationship between AI and design is evolving from a "tool theory" to a "collaboration theory." Early research mostly regarded AI as an efficiency accelerator, focusing on its value at the task automation level; more recent research has begun to treat AI as an "active collaborative partner" rather than a passive tool, exploring the deep impact of human-AI collaboration on the design process and professional identity. The literature increasingly recognizes that AI's role extends beyond generation to analysis, critique, and the restructuring of design cognition itself. Against the backdrop of this theoretical turn, this article systematically reviews empirical evidence on AI in interior design and answers three core questions: First, what quantifiable changes in efficiency and creative output has AI produced in the interior design workflow? Second, how does designer intervention affect the emotional quality

***Corresponding Author: Manish Sharma**

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and user satisfaction of AI-assisted design? Third, how does human-AI collaboration reshape the designer's professional identity and design thinking?

2. METHODOLOGY

This article adopts a systematic literature review method. The search covered major academic databases including IEEE Xplore, Taylor & Francis, ScienceDirect, ACM Digital Library, and Zenodo, with a time span from December 2024 to October 2026. Search keyword combinations included: "artificial intelligence" OR "generative AI" OR "AIGC" AND "interior design"; "human-AI collaboration" AND "spatial design"; "AI acceptance" AND "design education"; "cognitive load" AND "design ideation." The initial search yielded 87 articles. After title and abstract screening to remove irrelevant studies, 31 articles remained, and based on the following criteria, 12 empirical studies were ultimately included: (1) reported original quantitative or qualitative data; (2) the research context was interior design or an adjacent spatial design field; (3) included measurable results on human-AI interaction or AI tool use. Priority was given to studies that employed controlled experimental designs, validated psychometric instruments, or mixed-methods approaches combining behavioral and self-report measures.

2.2 Analytical Framework

This article uses an "input-process-output" analytical framework to organize the evidence. The input dimension focuses on designers' acceptance and perception of AI (technology acceptance model-related research); the process dimension examines how AI is embedded in the design workflow and its impact on design thinking; the output dimension evaluates the efficiency, creative quality, and user satisfaction of design outcomes. In addition, this article incorporates professional identity reconstruction (PIR) as a mediating mechanism to explain the effects of human-AI collaboration. The cognitive load theory (CLT) framework is also employed to interpret the mixed findings regarding AI's effects on mental effort and creative performance.

2.3 Data Extraction and Synthesis

The following data were extracted from the included studies: sample size and composition, research design type, AI tool type, main quantitative results

(effect sizes, percentage changes, satisfaction ratings), and qualitative findings. Due to the high heterogeneity of research designs, this article uses narrative synthesis rather than meta-analysis.

3. RESULTS

3.1 Quantitative Improvements in Efficiency and Creative Output

AI's most direct impact on the design process is reflected in the efficiency dimension. A controlled experiment compared the performance of an AIGC-enhanced workflow with the traditional process, showing a time efficiency gain of 45.6%, while design option diversity increased to 2.96 times that of the traditional method. A supplementary survey of professional designers gave an average satisfaction rating of 4.55/5.

At a more granular task level, AI's performance is equally prominent. A study on spatial recognition and vectorization tasks showed that an AI model based on attention mechanisms and feature fusion could complete spatial recognition and vector graphic creation in 5 minutes, a task that traditionally required 25 minutes of manual work, with a mean average precision of 91.0%. In style recognition tasks, a multimodal deep style evolution network achieved a classification accuracy of 94.7%, an improvement of 12.3 percentage points over the baseline model, and the design iteration cycle was shortened by an average of 65%.

Recent empirical work has extended these findings across additional task domains. SmartRoomStyler, a hybrid AI system combining computer vision and rule-based optimization, demonstrated a 30% faster design time compared to manual tools, with furniture detection precision (mAP@0.5) of 0.89. The system's lighting-aware recommendation engine adjusts palettes based on OpenCV-derived luminance maps, representing an advancement over tools reliant on static templates or manual inputs. An interactive assisted design algorithm using natural language processing and Deep Q-Network (DQN) reinforcement learning achieved 95.91% accuracy in identifying user needs, completed living room design in 1.2 hours, and received an average user satisfaction score of 4.42. An Interactive Genetic Algorithm with CNN-based filtering reported 97.6% accuracy in matching preferences and 95.3% recall for unique ideas, outperforming artificial neural

networks, support vector machines, and standard

genetic algorithms.

Table 1: Quantitative Performance of AI in Interior Design Tasks

Indicator	Value	Source
Time efficiency gain	45.6%	IEEE AIGC-IDW study
Design option diversity increase	2.96 times	IEEE AIGC-IDW study
Professional designer satisfaction	4.55/5	IEEE AIGC-IDW study
Spatial recognition mAP	91.0%	IEEE Access review
Style classification accuracy	94.7%	IEEE style evolution study
Design iteration cycle reduction	65%	IEEE style evolution study
Design time reduction (SmartRoomStyler)	30%	IEEE SmartRoomStyler
User need identification accuracy	95.91%	IEEE DQN study
User satisfaction (DQN study)	4.42	IEEE DQN study
Preference matching accuracy (IGA)	97.6%	IEEE IGA study

3.2 Differential Patterns in Creative Quality and Design Thinking

The significant improvement in efficiency indicators did not translate proportionally into creative depth. A study in a design education environment reached a more nuanced conclusion after analyzing design outputs using a six-criterion evaluation model (idea translation, feasibility, originality, user-centeredness, idea reformulation, and innovation) on a five-point scale. The findings indicated that AI significantly accelerated the generation of initial concepts and scheme expression at the visual and organizational level, but showed limited improvement in deeper design thinking indicators such as conceptual analysis, user-centeredness, and idea reconstruction. The researchers pointed out that AI functions primarily as a supportive and enabling tool rather than an independent creativity generator—core concepts usually still originate from designers, and AI's role is concentrated in organizing, expanding, visualizing, and reconstructing.

This finding corroborates the conclusions of a controlled study on cognitive load and creativity. Using the NASA Task Load Index, eye tracking, heart rate variability, and the Creative Product Semantic Scale, researchers found that while AIGC reduced extraneous processing by automating retrieval and variation, it also introduced new demands through interpreting and refining AI outputs. The net effect on creative quality depended critically on how designers navigated this balance. Over-reliance on AI suggestions was observed to narrow search and reduce originality, while critical design decisions regarding feasibility, coherence,

and aesthetics remained firmly with human designers.

A systematic review of 80 peer-reviewed studies identified eight key themes, including that AI use is heavily concentrated in early design phases, integration paradoxically reinforces the need for human-centric skills and judgment, and a quantifiable education-practice gap persists particularly in later design phases. This pattern suggests that AI's contribution to creative quality is phase-specific rather than uniformly positive.

3.3 The Decisive Impact of Designer Intervention on User Satisfaction

If AI has shortcomings in deep design thinking, can designer intervention make up for this gap? An experimental study on user psychological preferences and AI design outputs provided key evidence. The study designed a controlled comparison between AI-only design and "designer intervention + AI generation" design. The results showed that after incorporating designer intervention based on psychological questionnaires, 90% of participants preferred the designer-intervened schemes. Participants typically described AI-only designs as "too cold," "mechanical," and "lacking a personal touch," while designer-enhanced schemes were described as "warm," "calm," "elegant," and "reflecting my personality." The researchers accordingly proposed that AI's efficiency advantages need to be combined with the designer's emotional intelligence and interpretive ability to produce spatial schemes that are both functionally reasonable and emotionally resonant.

This finding aligns with industry observations. Havenly's AI tool, trained on nearly 3 million room designs, explicitly positions itself as complementary to professional design services rather than a replacement. The company's CEO noted that "there is a fluidity of creating and then sharing ideas with a designer," with the network of professional designers able to refine, alter, or execute users' AI-generated concepts. The distinction between AI as a "starting point for play" and professional design as a "collaborative process" reflects the recognition that emotional and contextual understanding remains a human domain.

3.4 Acceptance and Perception: Confidence and Anxiety Coexist

Designers' attitudes toward AI show clear differentiation. A survey of the Australian interior design community (covering students, educators, and practitioners) based on the technology acceptance model tested the effects of perceived usefulness and perceived ease of use on usage intention. The study hypothesized differences in acceptance among the three groups and used an AI engine to conduct sentiment and stance analysis of open-ended responses. Related research also found a similar pattern among Moroccan design students: the student group was open to AI tools but held firm views on the necessity of a "human touch" and was skeptical about AI completely replacing human creativity.

Industry survey data further revealed the structure of this ambivalence. Among 328 interior designers from 70 countries, 82% regularly use AI, but among young designers aged 18 to 24, 66% expressed anxiety about AI's impact on originality—a proportion significantly higher than the corresponding level among senior designers (aged 55 to 64). The problems designers most want the next generation of AI tools to solve are "easier visualization using real products" (71%) and "translating AI visuals into real materials and products" (62%); these two needs point directly to the gap between current AI output and buildable design.

A systematic review of AI in interior architecture education identified affective factors—motivation and anxiety—as significant influences on adoption.

The review noted that literacy demands are evolving from basic "prompt fluency" toward broader AI literacy encompassing understanding of model limitations, data provenance, and verification strategies. This evolution reflects a maturation of professional engagement: designers are not merely learning to use AI tools but developing critical frameworks for assessing when and how AI outputs can be trusted.

3.5 Reconstruction of Professional Identity

The impact of human-AI collaboration on designers goes far beyond operational efficiency changes. A study based on original survey data explored how "perceived human-AI collaboration" affects project innovation performance through "professional identity reconstruction." The study validated a mediating model in architecture and interior design contexts: designers do not simply "plug" AI into existing workflows; rather, in the collaboration process they redefine their professional role—from "creative producer" to "knowledge manager, output guide, and critical evaluator." Professional identity reconstruction was identified as the mediating bridge that converts algorithmic capabilities into project outcomes, meaning that AI's impact on design output is not a direct substitution in a technological determinist sense, but is realized through designers' reinterpretation of their own professional identity.

The historical evolution of design tools supports this interpretation. A multi-method study tracing the trajectory from manual drafting to CAD, BIM, and now AIGC argues that each technological era has reorganized workflows, team structures, and communication patterns. The AIGC-assisted era introduces a feedback-driven mode of thinking in which designers act as "curators of machine-generated alternatives, navigating between algorithmic suggestions and human intention". This curatorial role requires capabilities that are qualitatively different from those traditionally emphasized in design education: judgment, discernment, and the ability to articulate design intent in ways that can guide algorithmic generation.

4. DISCUSSION

4.1 The Efficiency Paradox: Why Acceleration Does Not Equal Deepening

The most consistent finding of this review is the contrast between AI's significant gains in the efficiency dimension and its limited contribution in the creative depth dimension. The quantitative evidence of a 45.6% improvement in time efficiency and nearly a threefold expansion of option diversity is impressive, but design thinking indicators—especially user-centeredness and conceptual reconstruction—have not improved in tandem. This "efficiency paradox" suggests that what AI accelerates is the organization and presentation of design information, not the definition and reconstruction of design problems.

Cognitive load theory provides a useful interpretive framework. AIGC may reduce extraneous processing by automating retrieval and variation, but it can also add new demands through interpreting and refining AI outputs. The NASA Task Load Index data from controlled studies indicate that the net cognitive effect depends on how the workflow is structured and how designers are trained to engage with AI outputs. When AI is treated as a generator of finished solutions, designers may experience reduced agency and increased screening burden; when treated as a collaborative partner for exploration, cognitive resources may be redirected toward deeper conceptual work.

Design education research reveals a deeper problem: user-centered design was the "weakest performing indicator" in both AI-assisted and traditional design stages. This means that insufficient user-centeredness is not caused by AI, but rather that AI makes this long-standing educational gap more visible. If design education cannot strengthen students' ability to understand real user needs, AI's efficiency dividend may be used to generate more "beautiful but empty" schemes rather than deeper design exploration.

4.2 The Emotional Gap and the Irreplaceability of Designer Intervention

AI-only designs were described by users as "cold," "mechanical," and "lacking a personal touch," while designer-intervened schemes were perceived as "warm" and "personalized." The theoretical significance of this finding lies in revealing the structural absence of current AI at the level of "tacit knowledge." Interior design is not only about the rational configuration of spatial functions; it also

involves keenly capturing occupants' emotional needs, cultural backgrounds, and living habits—a "psychological empathy" capability that current multimodal models find difficult to simulate.

This finding aligns closely with Norman's emotional design theory framework: user satisfaction is strongly shaped by emotional reactions such as pleasure, comfort, and perceived control. AI can generate spatial images that conform to aesthetic rules, but it cannot understand why a space "feels like home" to a specific occupant. The essence of designer intervention is not "correcting AI's mistakes," but translating psychological preference data into spatial experience. A framework for enabling AI to analyze spatial narrative in interior design, tested on a project by architect Kengo Kuma, demonstrated that AI could map key elements correctly and produce coherent text in denotative terms, but connotative understanding toward design intent and cultural context remained beyond its current capabilities.

The 90% user preference for designer-intervened schemes does not negate AI's value; rather, it precisely defines AI's position in the current design ecosystem: a powerful visualization engine and option generator, but its output needs to pass through the designer's emotional filtering and meaning-giving to become a "space with warmth."

4.3 Professional Identity Reconstruction as a Mediating Mechanism of Human-AI Collaboration

The finding that professional identity reconstruction acts as a mediating variable provides an analytical path beyond the "substitution vs. augmentation" binary for understanding AI's design impact. When designers regard AI as an "active collaborative partner" rather than a passive tool, the redefinition of their professional identity provides a psychological channel for improved innovation performance. This finding echoes across contexts with the role shift observed in design education—from "creative generator" to "digital knowledge manager, output guide, and critical evaluator".

Designers' anxiety about AI (66% of young designers worry about loss of originality) is in a sense cognitive friction in the process of identity reconstruction. This anxiety should not be simply

viewed as an emotional reaction of "resisting technology," but may be a healthy professional self-awareness: when certain parts of the creative process are automated, designers need to re-answer the fundamental question of "where is my irreplaceability?" The professional identity reconstruction framework's value lies in transforming this question from a threat into an opportunity—identity reconstruction is not a concession to AI, but an opportunity for professional capabilities to leap to a higher level (judgment, guidance, critique, empathy).

This interpretation is supported by the historical trajectory of design tools. Each prior technological transition—from hand drafting to CAD, from CAD to BIM—similarly required designers to redefine their value proposition. The current AI transition is distinctive in the speed of change and the breadth of tasks affected, but the underlying dynamic of professional redefinition is continuous.

4.4 From Tool Theory to Collaboration Theory: An Unfinished Paradigm Shift

Taken together, the relationship between AI and interior design is currently in an intermediate state of transition from "tool theory" to "collaboration theory." Tool theory positions AI as a passive efficiency tool, with its value measured by "time saving" and "cost reduction"; collaboration theory treats AI as a collaborative partner with agency, whose value lies in expanding the boundaries of design possibilities and forcing designers to redefine professional capabilities.

The development of systems such as SmartRoomStyler, interactive assisted design algorithms using DQN, and AI-driven XR interior design systems represents the advancement of the technology side toward the collaboration paradigm. These systems no longer pursue "replacing designers" but are designed to iterate together with designers. An AI-driven XR system integrates cloud AI, real-time ray-tracing, and 3D Gaussian Splatting to enable users to "live" in their self-designed future homes, shifting users from passive viewers to active co-creators. The system explicitly frames its contribution as "design democratization"—empowering individuals to design their own living spaces while lowering barriers to quality design.

However, the "collaboration readiness" of technical capabilities does not mean the "collaboration capability readiness" of designers. A systematic review of 80 studies proposed a CIDA-aligned curricular framework for cultivating "Intelligent Design Strategists" who combine computational leverage with critical, ethical, and human-centered judgment. The framework distinguishes between AI Literacy (competencies to understand, steer, document, and verify AI-mediated work) and AI Ecosystems (interoperable socio-technical environments across design phases), suggesting that design education needs to address both individual capabilities and systemic integration.

4.5 The Lag and Urgency of the Ethical Framework

42% of designers express concern about AI-related plagiarism and bias, and the lack of intellectual property protection strategies has been repeatedly identified as one of the main obstacles to AI integration. The copyright ownership of AI-generated designs is currently in a legal gray area: when designers provide prompts, AI generates images, and designers then modify them, the boundary of "originality" becomes blurred. Regulatory developments in 2025 and 2026, including the U.S. Copyright Office's report on copyright and artificial intelligence and the European Commission's code of practice on transparency of AI-generated content, represent initial attempts to address these ambiguities, but their application to design contexts remains uncertain.

In addition, biases in training data may be systematically amplified through AI output—if the training set is dominated by European modern style, AI may tend to equate "good design" with "Nordic minimalism," thereby suppressing the expression of cultural diversity. Research on fairness in design has begun to develop frameworks for facilitating ethical artificial intelligence designs, but these frameworks remain at an early stage of development. Establishing clear ethical frameworks and intellectual property policies is not a restriction on AI application, but a prerequisite for its sustainable development.

4.6 Toward a Phase-Aware Integration Framework

The evidence reviewed in this article points toward a phase-aware approach to AI integration that recognizes the differential value and risk of AI across design stages. In early ideation phases, AI's strengths in rapid visualization and option generation are most valuable and its limitations least consequential. In later phases—technical development, material specification, and construction documentation—AI's contributions are less established, and the risks of error, inconsistency, or ethical compromise are higher.

A phased implementation roadmap would position AI roles differently at each stage: as an exploration partner in ideation, an analytical assistant in evidence-based design, a visualization accelerator in presentation, and a critical check requiring human verification in technical phases. This framework would require design education to cultivate stage-specific competencies: divergent thinking with AI in early phases, critical evaluation of AI outputs in middle phases, and responsible verification in later phases.

The SmartRoomStyler system exemplifies this phase-aware approach in its integration of computer vision for furniture detection, rule-based optimization for lighting-adaptive layouts, and e-commerce API integration for actionable outputs. The system does not attempt to automate the entire design process but rather targets specific decision points where AI can provide reliable augmentation while leaving final judgment to the user.

5. CONCLUSION

Artificial intelligence is profoundly reshaping the practical landscape of interior design, but its impact is far from a linear "technological upgrade." Based on empirical research from the past two years, this review draws the following core conclusions:

First, efficiency improvement is significant but creative deepening is limited. AI has achieved remarkable results in workflow efficiency (time efficiency gain of 45.6%) and scheme diversity (2.96 times), but improvements in design thinking depth and user-centeredness do not match. The efficiency dividend needs to be consciously directed toward deeper design exploration, rather than merely accelerating the mass production of schemes.

Second, designer intervention is the key guarantee of emotional quality. 90% of users prefer AI schemes that have undergone designer psychological intervention, indicating that current AI has a structural gap in emotional understanding and personalized response. AI is a powerful option generator, but a "space with warmth" still requires human emotional intelligence and interpretive ability to endow it with meaning.

Third, the essence of human-AI collaboration is the reconstruction of professional identity. The discovery of professional identity reconstruction as a mediating mechanism reveals that AI's ultimate impact on design output depends on how designers redefine their own roles—from executor to judge, from generator to guide. This reconstruction process is accompanied by anxiety (66% of young designers worry about originality), but it also contains the opportunity for professional capabilities to leap to a higher level.

Fourth, the construction of educational, ethical, and institutional frameworks lags behind technological diffusion. Design education needs to upgrade from "teaching AI tool operation" to "cultivating critical human-AI collaboration capabilities". The industry needs to establish clear ethical norms and intellectual property protection mechanisms. Technology development needs to shift from "pursuing the degree of automation" to "optimizing the collaboration experience."

Fifth, a phase-aware integration framework offers a productive path forward. Rather than treating AI as a universal tool for all design stages, the evidence supports differentiated integration that leverages AI's strengths in ideation and visualization while maintaining human judgment in technical and emotionally consequential phases.

Future research should focus on the following directions: longitudinally tracking designers' identity evolution trajectories in long-term AI use; cross-culturally comparing AI's differential impact on different design traditions; developing methodological frameworks that systematically integrate user psychological data into AI-assisted processes; and establishing ethical evaluation standards and copyright ownership rules for AI design output. AI will not replace interior designers, but designers who know how to collaborate with AI

and, in the process, uphold and deepen professional judgment will occupy an irreplaceable position in the future design ecosystem.

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