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From Rendering to Decision: A Process-Based Framework of Interior Design Judgement in Human–AI Co-creation

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Abstract

Generative artificial intelligence has transformed the workflow in contemporary design fields. In the realm of interior design, designers are confronted with the challenge of making professional judgments within the AI-assisted design process. Although existing research has recognized the need to incorporate constraints when using AI for design assistance, the operational mechanisms of these constraints remain unclear. This study adopts a qualitative research approach, combining literature review, interviews, and case studies, and through thematic analysis and case analysis, identifies. The key factors in the AI-assisted interior design decision-making process and how they are formed during the design process, thereby establishing a transferable framework for AI-assisted interior design. The research findings indicate that while AI opens up design concepts for designers in the early stages of interior design, it does not alleviate the cognitive load of professional design judgments. The quality of design outcomes depends on whether design constraints are appropriately integrated into the process and whether design judgments are based on evidence-based evaluations.

Keywords: generative AI, interior design judgement, rendering, human–AI co-creation

1. Introduction

Generative artificial intelligence (GenAI) is increasingly optimizing the workflow in the design field. Karadağ and Ozar (2025) finding that AI broadens design possibilities, facilitates iterative ideation, and improves conceptual precision through high-fidelity visualizations. Paananen et al. (2024) also pointed out Generative tools support serendipitous discovery of ideas and an imaginative mindset, enriching the design process. They also mentioned that, image generation could be a meaningful part of the design process when design constraints are carefully considered.

But, when a large number of alternative concept images are presented simultaneously, designers encounter challenges in making their choices. Iyengar and Lepper (2000). Findings from 3 experimental studies starkly challenge this implicit assumption that having more choices is necessarily more intrinsically motivating than having fewer. Meanwhile, during the conceptual design stage, although the "amazing" images generated by AI may make the proposal appear more attractive, they also increase the risk that designers will overlook the feasibility of the design (Bates-Brkljac, 2012). Moreover, because AI can quickly generate concept images that seem highly complete and influence the designers' judgment, they may prematurely assume that a certain direction is already mature enough and thus stop further exploration too early (Crilly, 2015). Therefore, in AI-assisted interior design, the core issue is no longer merely about generating the plans, but rather about making the final decision from among a large number of alternative options. Designers' core competitiveness is shifting from representational skill to design judgment. This means that designers must understand design logic and incorporate constraints such as function, circulation, scale, materials, budget, regulations, and client communication into the key evaluative processes of the workflow.

Existing research indicates that designers currently lack systematic methods for co-creation with large language models (LLMs), and existing frameworks for describing the human-machine co-creation process remain limited (Wang et al., 2025).

This gap is also prevalent in the field of interior design. Due to its strong constraints and high practicality, interior design requires an understanding of how to guide AI-generated outputs by incorporating constraints, as well as how designers can avoid being misled by visually appealing images (Liu et al., 2025). Systematic research in this field remains insufficient.

To address this gap, this study proposes three research questions:

RQ1: In the early stages of interior design involving artificial intelligence, what key judgment factors and decision-making behaviors do designers primarily rely on during the decision-making process?

RQ2: How are decision-making behaviors organized and interrelated during the conceptualization, decision-making, and presentation stages of interior design?

RQ3: How can a transferable framework for AI-human collaborative decision-making be derived based on process-based evidence?

To address these questions, this study employs a qualitative research methodology. Through a literature review and semi-structured interviews, the study identifies the key factors and decision-making behaviors involved in interior design processes based on generative artificial intelligence (GenAI). Additionally, the study analyzes the details of the design processes across 30 case studies, including prompts, iteration logs, and design draft documents. Using thematic analysis, the study reveals how design decision-making behaviors are organized across the conceptualization, decision-making, and presentation phases.

2. Method

This study addresses three research questions through a literature review, interviews, and case studies.

The literature review was used to identify factors influencing design judgments and judgment behaviors, and to clarify their conceptual boundaries (Arksey & O'Malley,2005), thereby providing an analytical framework for Research Question 1. Semi-structured interviews were primarily used to capture designers' reasoning and thought processes while using AI-assisted design tools (Dicicco-Bloom & Crabtree, 2006). Process materials collected through case studies illustrated designers' action paths at each stage and helped explain how design ideation and decision-making were organized (Eisenhardt, 1989). This study employed thematic analysis and case analysis to identify recurring patterns of judgment in both the interviews and the design process (Braun & Clarke, 2022), and to examine whether these patterns were similar across different contexts and what limitations they revealed. Finally, the study aimed to extract core elements that are transferable and replicable.

2.1 Data Collection

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The data for this study were drawn from three sources: literature, interviews, and case process materials. The literature data mainly came from articles published in the past five years on major Chinese and international academic search platforms, including Web of Science, Scopus, Google Scholar, and CNKI. Keywords included: human-machine collaboration design in generative AI, decision-making and design judgments in generative AI, design constraints in generative AI, and interior design using generative AI. A total of 3,528 records were initially identified. After duplicate removal, 1,635 studies remained for title and abstract screening. Among these, 108 articles were retained because they addressed both AI involvement in the interior design process and decision-making mechanisms. Studies focusing solely on algorithmic performance or tool demonstration were subsequently excluded, resulting in a final sample of 34 articles for analysis (Figure 1). These articles were used to identify the conceptual boundaries of judgment factors and judgment actions.

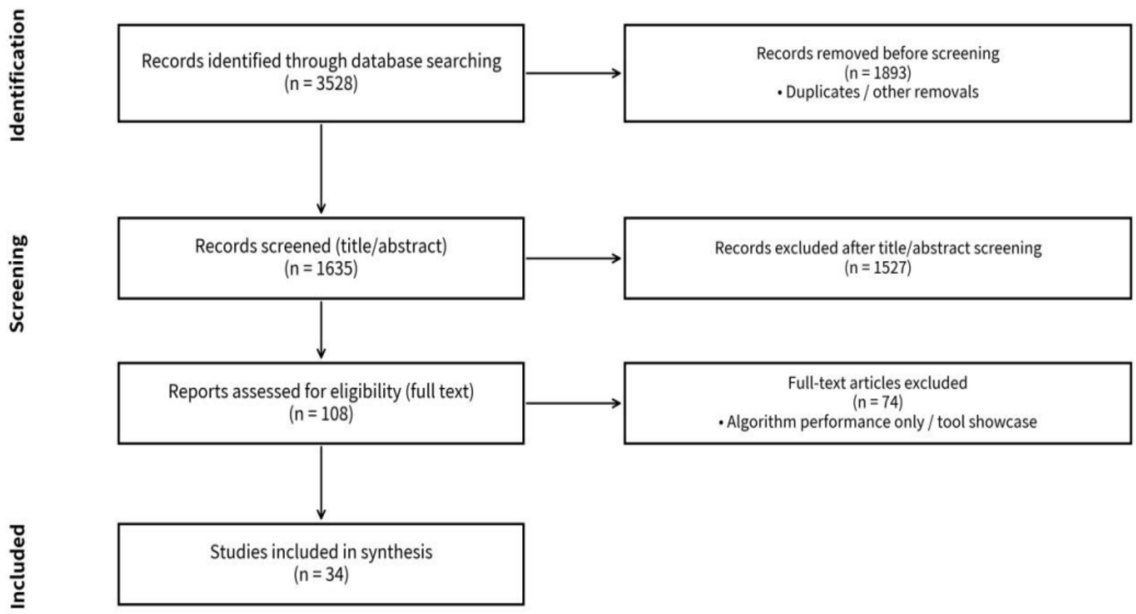

Figure 1. PRISMA flow diagram for database searches (2021-2026)

For the interviews and case materials, this study employed purposive sampling to recruit 30 interior design participants with experience in using GenAI. Each participant was asked to submit a process-material package from one early-stage design case, including the design brief, prompt logs, AI outputs, version evolution records, and key rationales for major design trade-offs, and to complete a structured interview. In addition, a subset of participants was selected through stratified sampling based on experience level (postgraduate students / early-career designers) and case type to participate in stimulated recall in-depth interviews, with the aim of obtaining richer explanations ofthe underlying decision mechanisms.

From an ethical perspective, all interviews and material collection were conducted only after informed consent had been obtained. Participants were clearly informed that they could withdraw from the study at any time without any consequences for their study or work. All materials were anonymized and de-identified through the removal of names, institutions, clients, addresses, brands, and any identifiable images or contractual information; where necessary, drawings and photographs were blurred. All data were stored in encrypted form and used solely for academic research.

2.2 Data Analysis

Based on 34 core articles highly relevant to the research question, this study developed a data extraction table to record descriptions of key factors, processes, and risks related to designers' decision-making at different stages of AI-assisted interior design. In addition, thematic analysis was used to construct an initial coding framework covering design decision factors, behaviors, and conceptual boundaries. Key design reasoning processes were captured through prompt logs, AI outputs, and version history records collected during the case study process. Together with the stimulated recall interview materials, these data were analyzed through three rounds of thematic analysis. Open coding was first used to identify judgment factors and actions. Axial coding then located these factors and actions within the three stages of ideation, decision-making, and representation, while also tracing their sequence and iterative relationships. Finally, selective coding was used to extract typical organizational patterns, failure patterns, and corrective strategies, leading to a revised version of the codebook (v2).

Third, within-case timeline reconstruction and cross-case comparison were conducted across the 30 cases to examine the consistency of judgment-action chains across different experience levels and case types, and to identify transferable core mechanisms and boundary conditions.

Finally, the literature-based and empirical findings were integrated into a human–AI collaborative decision-making framework. The framework was structured around the matrix of three stages × key judgment actions, and was accompanied by a supporting table linking actions, risks, responses, and tool templates. The reliability and auditability of the analysis were strengthened through multi-source evidence triangulation and coder discussion for intercoder consistency.

3. Results

3.1 The Conceptual Boundaries of Judgment Factors and Judgment Actions

Based on the 34 core studies published between 2021 and 2026, this study defines interior design judgment in GenAI contexts as a decision-organizing process centered on constraints, value orientations, evaluation criteria, and reasons/evidence. On this basis, an initial codebook was developed to identify judgment factors and judgment actions. The literature consistently suggests that, because GenAI greatly expands the range of candidate proposals, the focus of interior design research should shift from the ability to generate images to how to select, explain, and verify design options.

In Literature12 (L12), Vissers-Similon and Dounas (2024) describe “spatial interpretation moments” as the turning points at which AI-generated two-dimensional images are translated into genuine three-dimensional spatial design concepts. At this point, the designer will continue to interpret and verify the AI-generated results based on the design constraints. In L23, Liu et al. (2025) also pointed out that the output generated by the AI should evaluate generative AI tools in terms of creativity, aesthetics, practicality, and feasibility, offering empirically grounded insights for interior design pedagogy. This shift is also evident in Case C01. As the design goals became clearer, functional requirements and flow planning took precedence over style and atmosphere, becoming the main focus of the design process.

3.2 Key Judgment Factors and Judgment Actions

This study is based on existing theoretical foundations and, through thematic analysis, the interview data and case process data were refined into an initial coding framework. The data included prompt records, AI-generated outputs, version evolution records, and the designers' explanations for their choices at key nodes.. These materials ultimately contributed to the development of Codebook v2, which is better suited to interior design research and identifies the key factors related to design decision-making. The findings suggest that although generative AI has made image production faster, design direction, rules, and judgment remain the designer's primary responsibilities. Decision rationales showed a strong constraint-driven orientation: hard constraints—such as function, circulation, scale, budget, regulations, and communicative acceptability—served as the primary basis for decision-making, while softer factors, such as style and narrative, were usually weighed only after hard constraints had been satisfied.

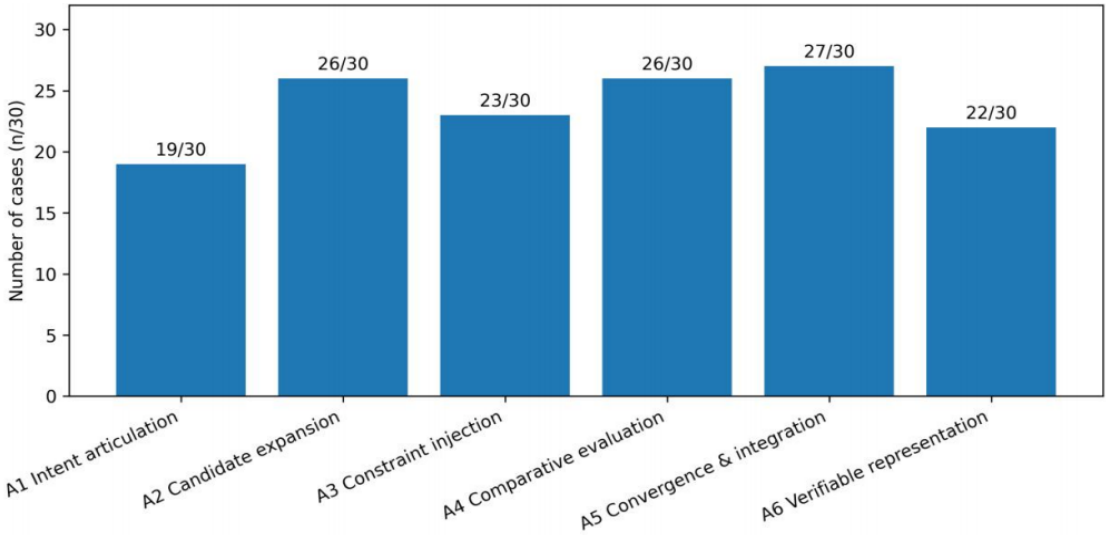

Figure 2. Coverage of judgement actions across cases (n=30)

Further stratified comparison showed that early-career designers were more consistent in front-loading constraints and checking implementation feasibility (E: A3 = 15/17, A6 = 13/17), whereas the corresponding levels were lower among postgraduate students (S: A3 = 8/13, A6 = 9/13). This suggests that practical experience more often leads to the sustained execution of constraint injection and validation actions.

Among the representative cases, C16 exemplified an organizational pattern of "constraints first, then generation," supported by an evaluation table (A3 + A4), whereas C17 demonstrated the critical role of A6 through representational transparency and the explicit annotation of validation evidence. Overall, GenAI does not automatically improve design quality. Rather, differences in quality depend more on whether constraints are effectively embedded and whether evaluation and reasoning are grounded in evidence. These differences are reflected precisely in the judgment factors and judgment actions identified above, as well as in their varying levels of coverage across cases.

3.3 Three-Stage Organizational Mechanism and Typical Pathways

The 30 cases were mapped across three stages: ideation, decision-making, and representation.

This mapping showed that judgment activities and related risks appeared most often in the decision-making stage. Among the 30 cases, 15 were centered in decision-making, while 8 were centered in ideation and 7 were centered in representation. This pattern shows that, after GenAI is introduced, the key point in the design process is not the generation stage itself. It is the stage where designers choose among options and move toward a workable decision. At this stage, designers screen alternatives, balance constraints, and compare options in a more standard way.C02 is a clear example. In the early stage, the generated images were very strong visually, so they created an anchoring effect. But when the case moved into the decision-making stage, the evaluation process changed. The design was reviewed through a required comparison of at least three options and a check against a list of constraints. This process changed the original design direction.

Cross-case analysis of the 30 cases identified three main pathway types: the alternating negotiation pathway (A, 14/30), the generation-driven pathway (G, 9/30), and the constraint-driven pathway (C, 7/30) (Table 1). The comparison also showed clear differences between participant groups. Early-career designers were mostly found in the alternating negotiation pathway, with 11 of 17 cases in this type. Their full distribution was A = 11, C = 4, and G = 2. Postgraduate students were more often found in the generation-driven pathway, with 7 of 13 cases in this type. Their full distribution was G = 7, A = 3, and C = 3. This pattern shows that early-career designers more often reached convergence through repeated rounds of negotiation between generation, constraint, and evaluation. Postgraduate students more often relied on broad generation in the early stage and then moved to later filtering and revision. C03 is an example of the constraint-driven pathway. When the generated outputs became too similar, the participant added more specific constraints to the prompts, such as layout type, material contrast, and lighting strategy. This helped create clearer differences between the alternatives and supported later evaluation and selection.

At the risk level, the four risk types appeared at different rates in the sample (Table 2). Homogenization was the most common, appearing in 22 of the 30 cases. Constraint drift came next, appearing in 19 cases. Visual anchoring appeared in 16 cases. Buildability illusion was the least common of the four, appearing in 14 cases. Stratified differences were particularly evident in the tendencies to be misled by images and to misjudge buildability. The incidence of visual anchoring was higher among postgraduate students (S: 10/13, 77%) than among early-career designers (E: 6/17, 35%). A similar pattern appeared for buildability illusion (S: 9/13, 69% vs. E: 5/17, 29%). By contrast, homogenization was slightly more common among early-career designers (E: 13/17, 76% vs. S: 9/13, 69%), suggesting that under iteration rhythms closer to real-world projects, stylistic convergence in generated outputs is more likely to become a persistent problem. In this regard, the differentiated constraint injection illustrated in C03 represents a typical corrective strategy against homogenization, whereas the forced comparative evaluation plus constraint checking demonstrated in C02 provides an effective pathway for counteracting visual anchoring.

Overall, these findings collectively indicate that, after the introduction of GenAI, the core challenge in linking the three stages is not whether enough alternatives are generated, but whether constraints and evaluation can be effectively organized during the decision-making stage, and whether buildability checks can be completed during the representation stage, so as to prevent highly realistic generated outputs from amplifying anchoring and misjudgment risks. Cases were more likely to reach stable convergence and build a clear decision path when they added constraints early, set standards for comparison, and included validation in the representation stage.C02 also shows that after being attracted by a high-quality AI-generated image, the participant was able to deliberately set aside their immediate impressions, discipline themselves to compare multiple alternatives, and check them against design constraints, thereby avoiding excessive deviation from the design trajectory. C03 further demonstrates that when designers actively introduce different constraints, the AI-generated results become more clearly differentiated. These cases suggest that, through the use of constraints, designers can shift the design process from anchoring to recalibration, and from homogenization to more differentiated exploration.

Table 1. Distribution of the three stages × pathway types (I/D/R and G/C/A)

Stage \ Path	**A**	**C**	**G**
I	5	1	2
D	5	3	7
R	4	3	0

Note: I = ideation; D = decision; R = representation; A = alternating negotiation; C = constraint-driven; G = generation-driven.

Table 2. Judgment actions and risks (Overall n = 30 and Stratified Comparison: S vs. E)

Item	**Overall n/30**	**E n/17**	**S n/13**	**E%**	**S%**
A1 Externalizing Intent	19/30	13/17	6/13	76%	46%
A2 Expanding Alternatives	26/30	15/17	11/13	88%	85%
A3 Injecting Constraints	23/30	15/17	8/13	88%	62%
A4 Comparative Evaluation	26/30	15/17	11/13	88%	85%
A5 Converging and Integrating	27/30	16/17	11/13	94%	85%
A6 Representational Validation / Transparency	22/30	13/17	9/13	76%	69%
Risk: Visual Anchoring	16/30	6/17	10/13	35%	77%
Risk: Homogenization	22/30	13/17	9/13	76%	69%

Risk: Constraint Drift	19/30	10/17	9/13	59%	69%
Risk: Buildability Illusion	14/30	5/17	9/13	29%	69%

Note: E = early-career designers (n = 17); S = postgraduate students (n = 13). The frequencies of both judgment actions (A1 –A6) and risks were based on coding of process materials from the 30 cases.

3.4 A Transferable Human–AI Collaborative Decision-Making Framework and

The study, based on data analysis of the literature, interviews, and case process materials, proposed a human–AI collaborative decision-making framework for interior design. The framework consists of three stages: design conception, decision-making, and representation.

Across these three stages, six types of key decision actions (A1–A6) were identified. A2 and A5 appeared most frequently in the sample, occurring in 26 out of 30 and 27 out of 30 cases, respectively. A3 and A6 occur relatively infrequently, appearing in 23 and 22 of the 30 cases, respectively. A3 and A6 typically mark key turning points in the AI-assisted design process, helping to transform design proposals into decisions that can actually be implemented.

This framework also incorporates the four common types of risks associated with AI-assisted design: homogeneity (22/30), constraint drift (19/30), visual anchoring (16/30), and constructibility illusion (14/30). Each risk is accompanied by a corresponding corrective strategy.

In Case C02, when the participants were confronted with the images generated by AI, they actively reintroduced the real-world design constraints into the evaluation process and compared multiple options to avoid being limited by a single choice. The combined effect of "constraint injection" and "comparative evaluation" helped mitigate the participants' anchoring effect, enabling the designers to gradually converge from the divergent design possibilities to the solutions. A similar pattern was also observed in Case C17. When presenting the final solution, the participants explained how the key constraints during the AI-assisted performance stage were addressed. For instance, they explained why the proposed solution was reasonable in terms of scale, budget, and regulations, which elements were provided as references by AI, and which parts were the actual decisions verified and confirmed by the designers. This indicates that transparency can reduce the risk of the solution being unimplementable.

Furthermore, this study also proposed three specific practical tools: a constraint condition checklist, a candidate solution evaluation form, and a transparency guidance guide. The constraint condition checklist is designed to identify the most critical practical design conditions - such as functional requirements, flow patterns, scale, budget, and regulatory requirements - in order to help prevent the omission of key constraints during the design process. The candidate solution evaluation form is used to compare different solutions and record the reasons for the selection, thereby reducing the influence of anchoring effect on designers. Transparency focuses on the final presentation stage, emphasizing that this process should not only prioritize the visual appeal of the renderings, but also examine why the plan is valid and what evidence supports the plan. Finally, by integrating the framework, risks and tools, the researchers transformed the design judgments in human-machine collaboration into a replicable decision-making method.

4. Discussion

The research has found that although AI can reduce the time required for creating concept diagrams and renderings, it does not decrease the time spent by designers on evaluating design proposals. Especially when the design constraints are not properly understood, generative AI not only fails to provide effective support but may even hinder the progress of the design process.

The case study identified three decision-making patterns: generating alternative options, comparing and evaluating, and converging and integrating. This further indicates that AI-assisted design does not produce the final solution in one step, but rather requires the continuous introduction of constraints at different stages of the process. The concept of generating alternative solutions refers to using AI to generate various spatial layouts, style directions and material combinations, allowing the design thinking to initially diverge in a broad manner; subsequently, through a comparison and evaluation matrix, professional judgments are made on different alternative solutions; finally, a feasible design decision is gradually narrowed down. Therefore, the value of AI-assisted design does not lie in replacing the judgment of designers, but in quickly generating alternative solutions, supporting comparisons and validations, and helping designers complete the professional decision-making process of "generation - comparison - convergence" more efficiently.

The research also found that people with different design experiences would adopt different approaches when using AI for design assistance. These methods can be classified into three categories: generation-driven, constraint-driven, and alternating negotiation-based. Participants who adopt the generation-driven approach tend to generate a large number of design proposals first, and then gradually filter them out in the later stages. This approach relies more on the AI's ability to quickly generate visual results. In contrast, participants who adopt the constraint-driven approach will incorporate realistic constraints such as functional requirements, budget, and scale as inputs for AI-assisted design from the very beginning. While participants who adopt the alternating negotiation approach will continuously modify these constraints as the generation and evaluation of the plan proceed simultaneously.

The data shows that designers at the early stage of AI-assisted design practice tend to adopt the alternating negotiation approach, while graduate students are more likely to use the generation-driven approach. This indicates that the key to proficient use of AI is not mainly about technical operational skills, but rather whether one has a design process guided by sound judgment. People with practical experience usually have a better understanding of when to introduce real-world constraints, how to organize multiple rounds of comparison and evaluation, and when to stop generating more design proposals.

The common failure patterns of AI-assisted interior design identified in this study include homogenization, constraint drift, visual anchoring, and the illusion of constructability. AI-assisted generative models are better at producing standardized aesthetic patterns drawn from large-scale data, while often overlooking personalized needs, which leads to homogenization. Without the introduction of aesthetic constraints, the results of multiple rounds of iteration tend to become increasingly similar. Constraint drift refers to the gradual weakening of the original boundary conditions after participants go through multiple rounds of prompting. Meanwhile, the polished and visually impressive images generated by AI may lead designers to judge a scheme as reasonable on a visual level while overlooking its actual feasibility in practice. For graduate students with relatively limited practical experience, the illusion of constructability is more likely to affect their judgment. This also suggests that, in educational settings, there is often insufficient training based on real projects, while the production of design renderings is instead treated as an important indicator of competence.

This study makes contributions to both design theory and design practice. Its theoretical contribution lies in integrating design judgment in AI-assisted design into observable actions and explaining how these actions unfold across the three stages of design ideation, decision-making, and presentation. Furthermore, this framework also summarizes the behavioral risks associated with AI-assisted design and the corresponding mitigation strategies. And three supporting tools are provided - "Constraint Checklist", "Candidate Solution Evaluation Form" and "Transparency Reminder Form" (Appendices A, B, C), so that the framework can be applicable in other design fields.

This study also has several limitations. Firstly, the case study mainly focuses on the early stage of AI-assisted interior design. Therefore, future research can further explore the subsequent stages, such as the detailed construction, budgeting, and procurement of the subsequent design process, as well as other practical issues. Secondly, the data of this study mainly come from qualitative data. Although the triangular verification method was adopted to enhance the effectiveness and reliability of the approach, the limited sample size may still lead to observation bias.

Finally, to reduce bias, future research should include designers with varying levels of proficiency in artificial intelligence, including those who are just beginning to engage with AI. This will help to gain a more comprehensive understanding of the challenges faced by the entire industry. Future research can further employ various experimental methods to validate this framework.

5. Conclusion

This study explores how the judgment behaviors of designers are formed during the early stage of interior design when AI is used for assistance in design. The research aims to establish a universally applicable framework for collaborative decision-making between interior designers and users. The research employed qualitative methods, through literature review, interviews and case studies, and utilized thematic analysis to identify the key elements and key actions in AI-assisted interior design decision-making. The research reveals that the judgment process can be classified into six core actions, which are mapped into the structure of three stages: conception, decision-making, and performance.

The case study also revealed three organizational paths adopted by the participants when using AI for interior design: the generation-driven type, the constraint-driven type, and the alternating negotiation type. The research further transformed the framework into three supportive assessment tools, aiming to facilitate the introduction of constraints, evidence-based evaluation, and verifiable performance. Future research can further test the applicability of this framework in a wider range of disciplines.

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The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Data sharing statement

No additional data are available.