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Approaches to Employing Generative Artificial Intelligence in Interior Design Processes: A Proposed AI-Assisted Interior Design Workflow (AI-IDWF)

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Abstract

Generative artificial intelligence is increasingly used to support interior design activities, yet the growing number of platforms and the variability of their capabilities make tool selection a practical and research challenge. This study develops a proposed AI-assisted interior design workflow through a comparative evaluation of generative tools across different design processes. A controlled comparative case study was conducted on a 30 m² contemporary residential living room. The architectural floor plan, functional requirements, design identity, palette, materials, and reference information were kept as consistent as possible across comparable tests. The study examined planning and programming, ideation, visual development and visualization, furniture asset extraction, image-to-3D generation, 3D-model-to-photorealistic rendering, and technical documentation. Outputs were evaluated using task-specific criteria on a five-point scale, while technical drawings were assessed qualitatively because dimensional or representational errors can invalidate construction documents. Results showed that no single platform achieved the best performance across all tasks. ChatGPT performed best in planning, sketch-to-render, multi-view generation, and overall furniture asset extraction; DALL·E ranked highest in ideation; Gemini performed best in visual development and 3D-model-to-photorealistic rendering; and Hi3D.ai ranked highest in image-to-3D generation. Technical documentation remained the least reliable area and required human verification and reconstruction in CAD/BIM environments. The findings support a multi-tool workflow in which task-specific tool selection is combined with human validation gates before outputs are transferred to subsequent processes.

Keywords

Generative Artificial Intelligence, Interior Design Processes, AI-Assisted Design, Design Workflow, AI-IDWF.

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Introduction:

Generative artificial intelligence (GenAI) has advanced rapidly, and text, image, and multimodal models can now support an expanding range of design tasks, from requirements analysis and alternative generation to visual development and the creation of preliminary three-dimensional digital assets. Latent diffusion models improved the efficiency and quality of image synthesis while enabling more flexible conditional guidance (Rombach et al., 2022). Visual conditioning approaches such as ControlNet subsequently allowed generation to be guided by structural information including edges, depth maps, and semantic segmentation (Zhang et al., 2023).

In interior design, applications have expanded from generating design proposals from textual descriptions (Chen et al., 2023), to controllable panoramic scene generation with improved spatial and stylistic consistency (Yang et al., 2025), and to developing visual design outputs from texture-free indoor three-dimensional models (Shao et al., 2024). This breadth of application indicates a shift from treating generative AI as an image-making mechanism toward using it across multiple operations within a design workflow.

Nevertheless, the value of a generated output depends on its role within the design process. An image that is useful for exploring an aesthetic direction is not necessarily suitable as a

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construction document, and a visually convincing model may contain inconsistent spatial relationships or non-buildable dimensions. Generative AI in interior design should therefore be evaluated not only by visual realism, but also through task-relevant criteria such as functional correctness, spatial consistency, preservation of design intent, representational accuracy, and the usability of an output as input to the next operation. This perspective also reinforces human-AI collaboration, in which system capabilities and limitations are made visible and the user retains responsibility for review, correction, and final decisions (Amershi et al., 2019).

Accordingly, this research treats the interior design workflow as an interconnected system of decisions and outputs rather than a sequence of isolated images. The workflow begins with understanding users, constraints, and the design program; proceeds through ideation and visual development; and extends to digital asset generation and technical information. The study compares multiple generative tools within one controlled design case, tracks changes in their performance across selected interior design processes, identifies the best-fit tool or combination of tools for each task, and uses the findings to formulate a proposed AI-assisted interior design workflow.

Research problem:

The research problem lies in the limited availability of clear methodologies that connect generative AI tools within a sequential design workflow while identifying the most appropriate tool for each interior design process and maintaining continuity and consistency as outputs move from one operation to the next.

Research objective:

The research aims to formulate a proposed workflow for interior design processes assisted by generative AI, based on a comparative evaluation of the performance of tools used in selected design operations.

Research significance:

Provide a methodological framework for studying the role of generative AI in interior design processes.

Develop a workflow that can be applied and replicated in comparable interior design projects.

Identify processes in which generative AI can effectively support the designer and those in which it should not be relied upon independently.

Reduce time spent on random trial-and-error across generative platforms.

Research hypotheses:

The efficiency of generative AI tools varies according to the design process and the task required.

No single tool achieves the best performance across all interior design processes.

The need for human intervention increases as the workflow moves from ideation and visual generation toward technical drawings and documentation.

Research Methodology:

The study combines two complementary approaches. The descriptive-analytical approach is used to examine the theoretical background of generative AI, interior design processes, and the principal ways in which generative tools can be employed within those processes. The comparative applied approach uses a single interior design project with inputs and design requirements kept as consistent as possible, then compares and evaluates outputs according to task-specific criteria in order to identify the most appropriate tool or combination of tools for each operation.

Research scope and limitations:

Application scope

The applied study is limited to one contemporary residential living room designed for a family of four. The room area is 30 m², with internal dimensions of 6.00 × 5.00 m and a clear height of 3.00 m. The same design case was used throughout the tests to support direct comparison between tool outputs.

Technical scope

The study is limited to the generative AI tools and platforms actually tested: ChatGPT, Gemini, Microsoft Copilot, DALL·E, Ideogram, Whisk, Leonardo AI, Krea AI, Stable Fast 3D, Hi3D.ai, and Tripo3D.ai. Tools were selected for each task according to their available capabilities; not every tool was applied to every process because their functional scopes differ.

Temporal scope

The results reflect the capabilities and versions available during the testing period. Because generative AI platforms are updated rapidly, their performance and output characteristics may change over time.

Theoretical framework:

Concept of generative artificial intelligence

Generative artificial intelligence refers to a class of AI techniques capable of creating new content from patterns and relationships learned from data. Outputs may include text, images, drawings, multimodal content, and digital models. In contrast

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with many conventional AI applications that focus primarily on classification, prediction, or data analysis, generative systems are characterized by their ability to produce new alternatives in response to user inputs. A recent review of 179 studies examined generative AI in built-environment design, including interior design, and highlighted the breadth of applications, mechanisms of use, and evaluation approaches (Zhang & Zhang, 2025).

Several model families have shaped the current generation of generative systems. Generative adversarial networks introduced an adversarial framework for data generation (Goodfellow et al., 2014), while the Transformer architecture transformed language processing through the attention mechanism and became foundational to many contemporary language models (Vaswani et al., 2017). Latent diffusion models further advanced high-quality image generation and conditional control using text and other guidance inputs (Rombach et al., 2022). The present research does not examine the mathematical formulation of these architectures; instead, it focuses on how their outputs can be employed within interior design processes and how tool performance changes with task requirements.

Interior design processes

Interior design is an integrated process concerned with organizing and shaping interior environments to satisfy functional, human, aesthetic, and technical requirements. It extends beyond the final visual image and includes interconnected operations such as understanding project and user requirements, analyzing space and constraints, developing the program and concept, generating alternatives, refining the design solution, selecting materials, colors, lighting, and furniture, producing visual representations, and preparing technical documentation for implementation (Ching & Binggeli, 2018).

The design process is iterative rather than strictly linear: designers move repeatedly between generation, evaluation, and modification as requirements and problems emerge. Contemporary digital environments also involve multiple forms of representation, including text, two-dimensional drawings, sketches, images, and three-dimensional models. This multimodal context creates a suitable environment for integrating generative AI tools across different parts of the design workflow (Jang et al., 2025).

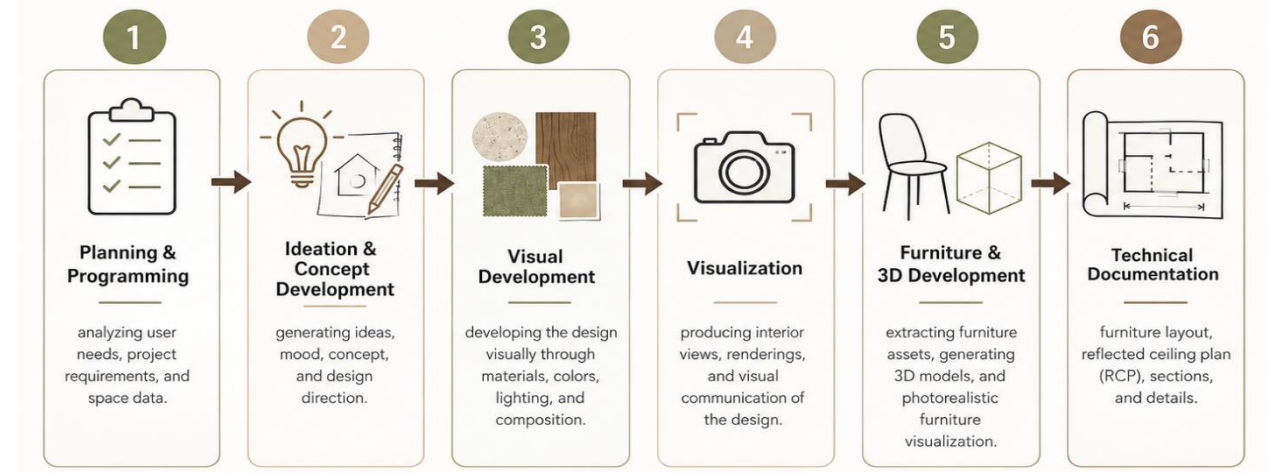


Figure 1. Simplified interior design processes used to frame the study.

Generative AI in interior design processes

The development of generative tools has introduced new forms of interaction between designers and digital environments, allowing text, images, sketches, and visual references to function as inputs for generating or developing design content. Research in architecture shows that generative AI applications extend beyond image generation to multiple tasks associated with design processes, data forms, and evaluation methods. Jang et al. reviewed 161 studies and found that generative AI applications remain concentrated in early design processes, while later-stage applications are less extensively investigated (Jang et al., 2025).

In interior design, generative interaction may include text-to-text support for requirements analysis and programming, text-to-image generation for ideation and visualization, image-to-image transformation for visual development, sketch-to-render translation, image-to-3D model generation, and visual development based on digital models. Chen et al. demonstrated the use of diffusion models to generate interior design proposals associated with specific functions and styles from textual descriptions, with subsequent result modification and refinement (Chen et al., 2023).

The value of these tools lies in accelerating alternative exploration, supporting visual communication of design intent, and connecting different forms of input and output within a digital workflow. However, visual quality alone is not a

sufficient indicator of successful use. Certain design tasks require preservation of spatial composition, proportions, element geometry, functional relationships, or technical information. Recent reviews similarly identify control, accuracy, and evaluation methodology as central issues when integrating generative AI in built-environment design (Zhang & Zhang, 2025; Jang et al., 2025). The designer therefore remains responsible for defining inputs, constraints, and references, evaluating generated outputs, and redirecting the tool when required.

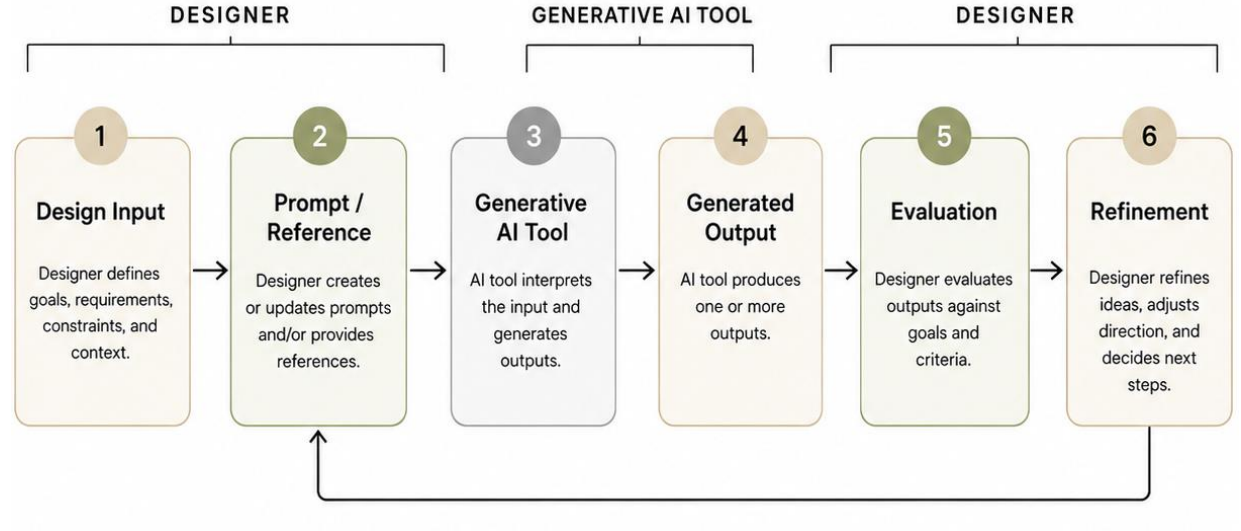


Figure 2. Iterative interaction between the designer and a generative AI tool.

Comparative evaluation and development of a proposed workflow

Generative AI tools used in design do not provide the same level of performance across all tasks. Input type, required output, and the necessary level of geometric or visual control differ substantially among planning, ideation, visualization, three-dimensional model generation, and technical documentation. The tools themselves also differ in architecture, available functions, and their response to prompts and references; therefore, it is inappropriate to assume that one platform provides the optimal solution across all interior design processes.

Recent research supports comparing models and tools according to task-specific evaluation criteria. Jang et al. identified comparative evaluation as the most frequently used assessment approach in the studies they reviewed (Jang et al., 2025), while Zhang and Zhang emphasized measurement, comparison, and benchmarking as means of understanding both the effectiveness and limitations of generative AI in design contexts (Zhang & Zhang, 2025). The present study therefore tests multiple tools within a unified design case, keeps inputs as consistent as possible, and evaluates outputs using criteria linked to each task, with the goal of identifying best-fit tools and formulating a proposed workflow.

Comparative applied framework

A comparative case study was conducted using a contemporary residential living room to test selected generative AI tools across multiple interior design processes. Project data, design inputs, and references were held as constant as possible within each comparison, while comparable tools were given the same core requirements so that differences in outputs could be associated primarily with tool capabilities.

Tools were selected for each operation according to task characteristics and platform capabilities. Outputs were then evaluated using criteria defined for each task on a five-point rating scale, where higher scores indicate stronger fulfillment of the criterion. Scores are used for descriptive comparison within each task rather than for statistical comparison across tasks with different criteria. Technical documentation was evaluated qualitatively because individual dimensional, sectional, or symbolic errors may invalidate a construction drawing even when its visual appearance is convincing.

Design case

The applied study used one fixed contemporary residential living room. Table 1 summarizes the project data and design constraints that were maintained across the comparative tests.

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Table 1. Fixed design specifications of the case study

Item	Specification
Space type	Contemporary residential living room for a family of four
Area and dimensions	30 m²; 6.00 × 5.00 m; clear height 3.00 m
Openings	0.90 m door; 2.40 m window according to the architectural plan
Functions	Family seating, television viewing, storage, reading/conversation, clear circulation
Design identity	Calm contemporary character with simple lines and a balance of comfort and clarity
Color palette	Beige, white, natural walnut, light gray, and olive green
Materials	Wood, stone, glass, metal, and neutral textiles
Constraints	Preserve opening locations, maintain circulation, and keep furniture proportional to the room

Based on these specifications, the architectural plan shown in Figure 3 was adopted as the fixed geometric reference. It defined room dimensions, wall locations, and architectural openings and was reused whenever a task required spatial or geometric information.

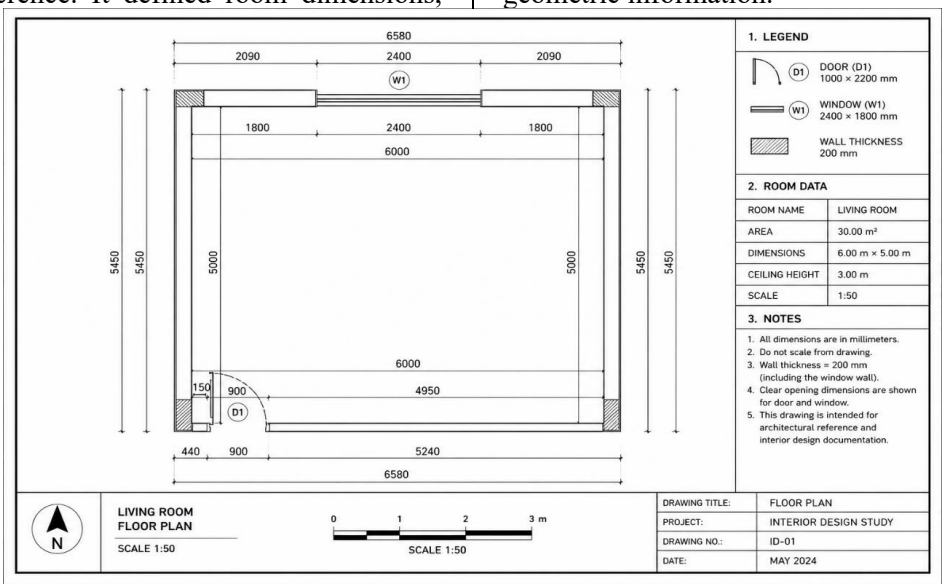


Figure 3. Approved architectural floor plan of the design case.

Design processes and evaluated tools

The applied study was organized into four principal interior design processes containing sequential sub-tasks. Generative AI tools were selected according to the nature of each task and the capabilities of each platform, as summarized in Table 2.

Table 2. Matrix of design processes, tasks, and evaluated tools

Process	Task	Evaluated tools
Planning and programming	Analyze program, constraints, and plan	ChatGPT; Gemini
Ideation	Planning and visual alternatives; concept boards	ChatGPT; Gemini; DALL·E; Copilot; Ideogram
Visualization and visual development	Visual development of the approved image	Gemini; Copilot; DALL·E
Visualization and visual development	Sketch-to-render	ChatGPT; Gemini; Whisk
Visualization and visual development	New view of the same interior	ChatGPT; Copilot; Gemini
Visualization and visual development	Furniture asset extraction	ChatGPT; Gemini; Whisk; Leonardo AI; Krea AI
Visualization and visual development	Image-to-3D model generation	Stable Fast 3D; Hi3D.ai; Tripo3D.ai
Visualization and visual development	3D model-to-photorealistic render	Gemini; ChatGPT; Copilot
Technical documentation	Furniture layout, RCP, sections, details	ChatGPT; Gemini; Copilot

Comparison control and prompt structure

Comparison inputs were controlled as far as practicable. These included the architectural plan, functional program, design identity, colors, materials, visual references, and required output type. Prompts followed a common structure composed of role definition, design context, fixed constraints, task, preservation requirements, and output specifications. Detailed prompt content changed according to task type, while the core requirements remained consistent when tools were compared on the same task.

General prompt structure: Role Definition → Design Context → Fixed Constraints → Task → Preservation Requirements → Output Specifications.

Implementation sequence and traceability

Tasks were implemented sequentially, beginning with project analysis and planning, followed by ideation and selection of a design direction, visual development, additional interior views, furniture asset extraction, image-to-3D conversion, photorealistic rendering, and technical documentation tests. At the end of each task, inputs, outputs, and evaluation results were documented. The highest-rated acceptable output was used as the reference for the next relevant task only after human review. This human validation step was intended to verify fitness, design continuity, and reference consistency before errors could propagate through subsequent operations.

Comparative results:

Planning and design programming

ChatGPT and Gemini were tested for analyzing project data and the architectural plan, organizing requirements, constraints, and functional relationships, and formulating initial guidance for furniture, materials, colors, and lighting. Ten criteria were used: data analysis, plan interpretation, completeness of the functional program, spatial relationship logic, circulation, furniture layout guidance, design brief formulation, recognition of constraints, color/material/lighting direction, and usability of the output in the following ideation process.

The two tools performed similarly at a high level, with ChatGPT achieving a slightly higher mean score of 4.90/5 than Gemini at 4.80/5. ChatGPT provided a more complete functional program and organized its output in a form that was somewhat easier to use in the next task. Gemini was close in overall performance but showed a minor reduction in program completeness. The results indicate that language models can effectively transform project data into organized design inputs, while designer review remains necessary to verify plan interpretation and spatial conclusions.

Table 3. Comparative evaluation of planning and design programming

Tool	Total	Mean / 5	Rank
ChatGPT	49/50	4.90	1
Gemini	48/50	4.80	2

Ideation and concept generation:

Five generative tools—ChatGPT, Gemini, DALL·E, Copilot, and Ideogram—were tested to produce an integrated design direction from the same design brief. Outputs were expected to include a proposed functional layout, interior perspectives, color and material palettes, and furniture references. Thirteen criteria were used, including layout accuracy, plan-perspective consistency, concept clarity, style appropriateness, color and material quality, alternative diversity, and overall visual presentation.

DALL·E achieved the highest mean score at 4.85/5, providing the strongest balance between visual presentation and consistency between two-dimensional and three-dimensional representations. Gemini ranked second at 4.69/5 and performed particularly well in layout clarity and storage treatment. ChatGPT scored 4.38/5 and produced a rich concept board, although some relationships between seating and television zones were less accurate. Copilot scored 4.15/5; its layout was acceptable, but some perspectives did not fully correspond to the plan. Ideogram ranked fifth at 3.62/5, offering useful visual variation but lower board completeness and greater variation between alternatives.

Table 4. Comparative evaluation of ideation outputs

Tool	Total / 65	Mean / 5	Rank
DALL·E	63	4.85	1
Gemini	61	4.69	2
ChatGPT	57	4.38	3
Copilot	54	4.15	4
Ideogram	47	3.62	5

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Figure 4. Comparison of ideation outputs generated under a unified design brief.

The comparison demonstrates that visual quality or alternative diversity alone is insufficient for selecting a design output. Consistency between the plan and perspective and preservation of spatial relationships are decisive for whether an output can move into the following development process. DALL·E was therefore adopted as the reference design direction after human verification of its suitability for the case study.

Visualization and visual development:

This process included a series of representation and transformation tasks: visual development of the approved design, sketch-to-render translation, generation of additional views of the same interior, furniture asset extraction, image-to-3D model generation, and photorealistic rendering from an untextured three-dimensional model. The results demonstrate substantial variation in tool performance depending on the input-output transformation required.

Visual development of the approved design:

Gemini, Copilot, and DALL·E were tested for improving realism, materials, and lighting while preserving the general composition of the approved image. Gemini achieved the highest score at 4.90/5, maintaining spatial relationships and built-in elements more consistently while improving visual quality. Copilot ranked second at 4.40/5 with good lighting and material treatment but limited changes. DALL·E scored 3.90/5; despite an attractive output, more noticeable changes appeared in perspective and composition. The results indicate that successful visual development should improve an approved reference rather than redesign it.

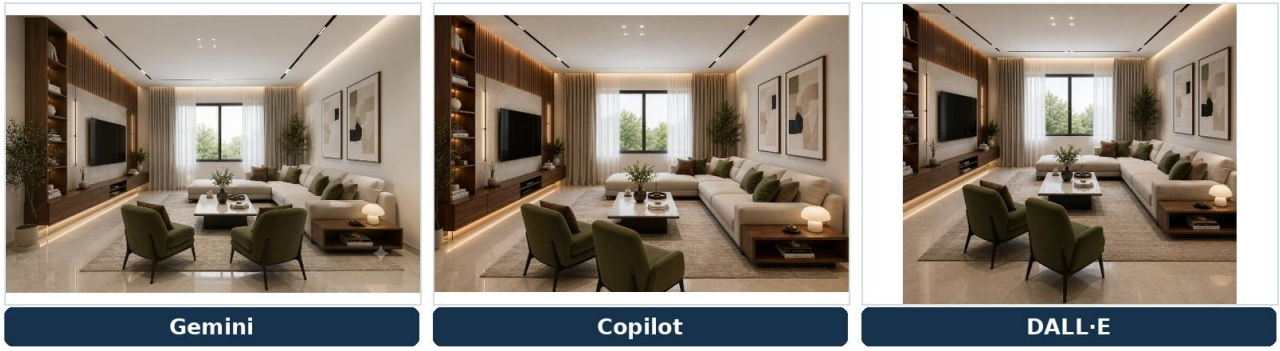


Figure 5. Visual development comparison using Gemini, Copilot, and DALL·E.

Sketch-to-render:

This task tested the ability of the tools to translate a hand sketch into a realistic interior image while preserving furniture distribution, architectural elements, and overall design identity. ChatGPT achieved the highest mean score of 4.69/5 and preserved the general sketch structure while producing a coherent realistic interpretation. Gemini scored 3.88/5; it preserved the main functions but reinterpreted some details. Whisk scored 3.81/5 and provided balanced material treatment, but with a noticeable camera-angle shift and changes to some elements.

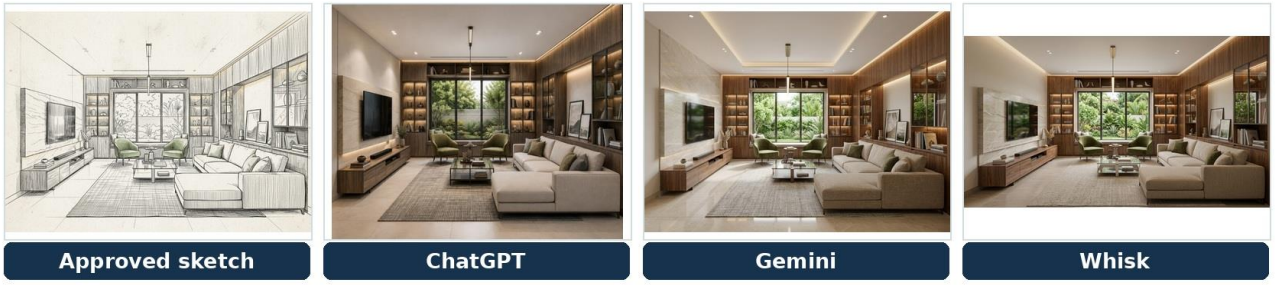


Figure 6. Approved sketch and sketch-to-render outputs generated by ChatGPT, Gemini, and Whisk.

Multi-view interior generation

This task evaluated the ability to represent the same approved interior from a different camera position using both the architectural plan and the approved reference view. ChatGPT achieved the best result at 4.80/5, generating a new view while maintaining the general identity of the room, with a minor inconsistency in the orientation of the pendant light. Copilot ranked second at 3.40/5, followed by Gemini at 3.20/5; both outputs tended to regenerate a similar scene rather than convincingly re-photograph the same room from a new position. These results confirm that photorealism alone is not sufficient for evaluating multi-view consistency.

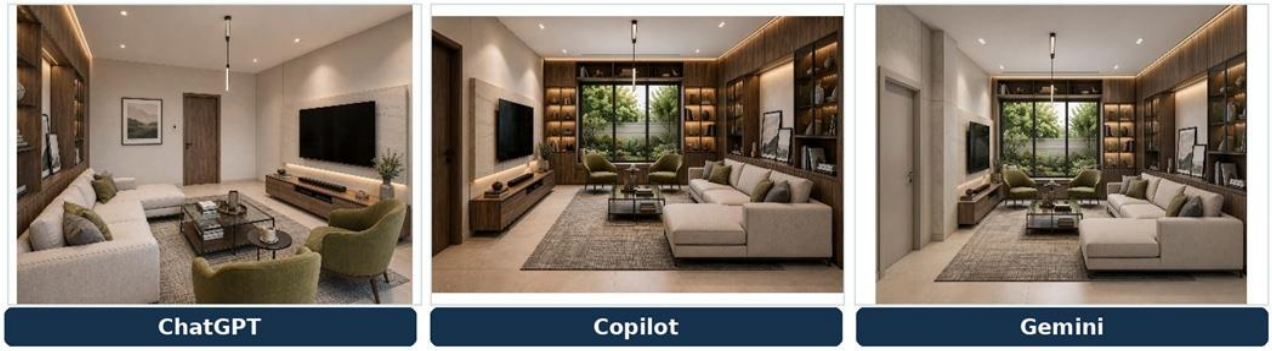


Figure 7. Comparison of generated new views of the same interior.

Table 5. Results of visual development and representation-conversion tasks

Task	Tool	Mean / 5	Rank
Visual development	Gemini	4.90	1
Visual development	Copilot	4.40	2
Visual development	DALL·E	3.90	3
Sketch-to-render	ChatGPT	4.69	1
Sketch-to-render	Gemini	3.88	2
Sketch-to-render	Whisk	3.81	3
Multi-view generation	ChatGPT	4.80	1
Multi-view generation	Copilot	3.40	2
Multi-view generation	Gemini	3.20	3

Because the criteria and the number of criteria differ from one task to another, the scores in Table 5 are used for comparison within each task and not for direct statistical comparison across tasks.

Furniture asset extraction

The approved final render was used as the reference for extracting the principal furniture elements into a furniture asset sheet. ChatGPT achieved the highest overall board score at 4.90 /5, while Gemini scored 3.57/5. Item-level review, however, showed that individual pieces could be represented more accurately by different tools; the television console was closer to the reference in the Gemini output, and some supplementary trials produced a more accurate coffee table. Leonardo AI and Krea AI showed greater deviations and were not included in the final selected board. This finding supports selective item-level extraction from more than one tool rather than exclusive reliance on a single platform.

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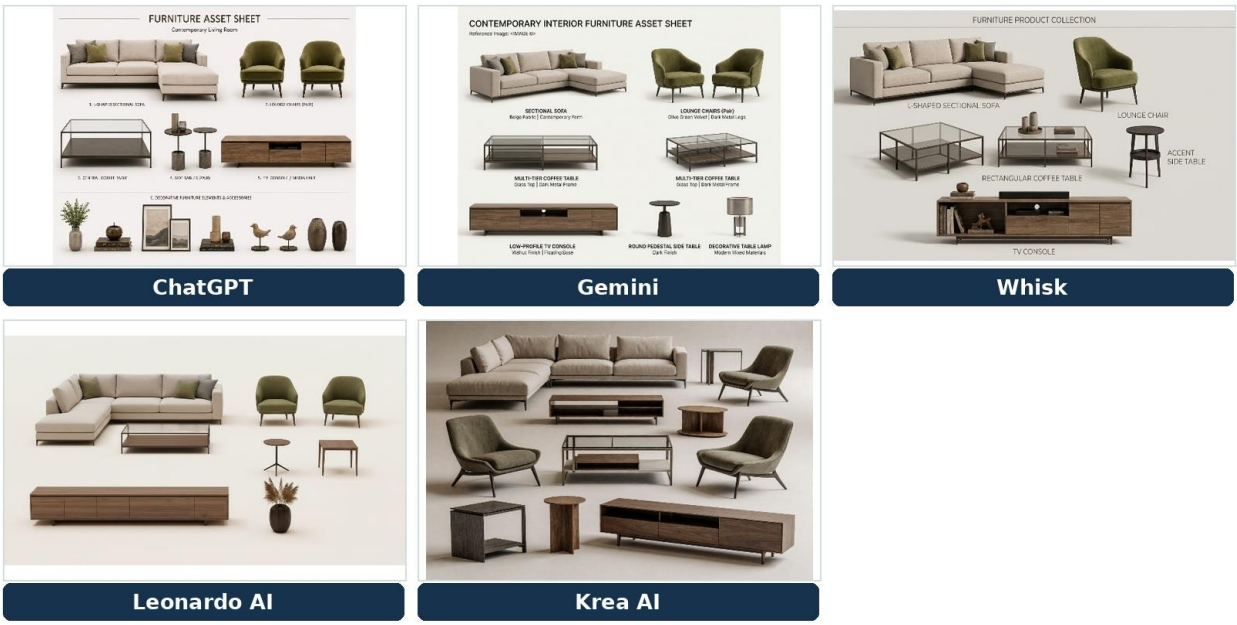


Figure 8. Furniture asset extraction boards and supplementary tool trials.

Image-to-3D model generation

Stable Fast 3D, Hi3D.ai, and Tripo3D.ai were tested using the extracted sectional sofa image. Hi3D.ai achieved the highest mean score at 4.13/5, performing best in proportions, overall form, curvature, model completeness, and mesh quality. Tripo3D.ai ranked second at 2.13/5, followed by Stable Fast 3D at 1.88/5. All three tools scored relatively low in preserving materials and textures, indicating that generated models require cleaning and retexturing before professional use.

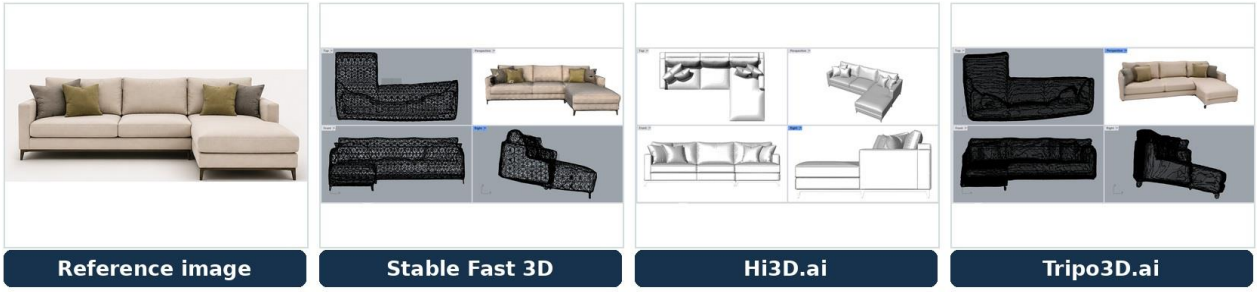


Figure 9. Reference image and comparison of image-to-3D model generation results.

3D model-to-photorealistic render

An untextured three-dimensional model was used as the geometric reference together with a visual reference for materials, colors, and textures. Gemini achieved the highest score at 4.90/5, showing strong preservation of model geometry and high visual fidelity in transferring the intended materials and colors. ChatGPT scored 4.40/5, producing a realistic result with limited changes to form or detail. Copilot scored 3.40/5 because of greater deviation from the geometric reference. The results indicate that a composite workflow- using one tool for geometry generation and another for photorealistic rendering- can be more effective than expecting one platform to provide an end-to-end solution.



Figure 10. Untextured three-dimensional model and photorealistic rendering outputs from Gemini, ChatGPT, and Copilot.

Table 6. Results of asset extraction and three-dimensional transformation tasks

Task	Tool	Total	Mean / 5	Rank
Furniture extraction	ChatGPT	34/35	4.90	1
Furniture extraction	Gemini	25/35	3.57	2
Image-to-3D	Hi3D.ai	33/40	4.13	1
Image-to-3D	Tripo3D.ai	17/40	2.13	2
Image-to-3D	Stable Fast 3D	15/40	1.88	3
3D model-to-render	Gemini	49/50	4.90	1
3D model-to-render	ChatGPT	44/50	4.40	2
3D model-to-render	Copilot	34/50	3.40	3

Across the visualization and visual development process, no single tool was superior in every task. Gemini performed best in visual development and 3D-model-to-photorealistic rendering; ChatGPT performed best in sketch-to-render, multi-view generation, and overall furniture asset extraction; and Hi3D.ai performed best in image-to-3D generation. The process therefore benefits from task-specific tool selection rather than the use of one platform throughout.

Technical documentation generation

ChatGPT, Gemini, and Copilot were tested on four technical documentation tasks: furniture layout, reflected ceiling plan (RCP), interior sections, and construction details. Evaluation in this process differed from visual-generation tasks because visual plausibility is insufficient for judging a technical document. Technical usability depends on dimensional accuracy, geometric relationships, section cuts, symbols, levels, and consistency with the approved plan and design. The evaluation therefore relied primarily on qualitative analysis of errors and the potential technical use of each output.

For the furniture layout, Gemini provided the strongest relative result among the three tools in terms of clarity and technical representation, although the output still required review and adjustment before any construction use. In the reflected ceiling plan, none of the tested tools achieved sufficient reliability in lighting-grid representation, relationships, and symbols to be considered a dependable technical document.

More substantial errors appeared in the interior sections. Gemini produced an inaccurate spatial representation; Copilot generated two sections that were too similar despite different cut locations; and ChatGPT produced three-dimensional sectional views and introduced elements not present in the approved reference. In construction details, ChatGPT provided the strongest relative output, but it remained closer to an illustrative representation than to a measurable, construction-ready detail. Within the tested tools and design case, the findings demonstrate a clear gap between generating a document that appears technically plausible and producing a technically accurate document suitable for implementation.

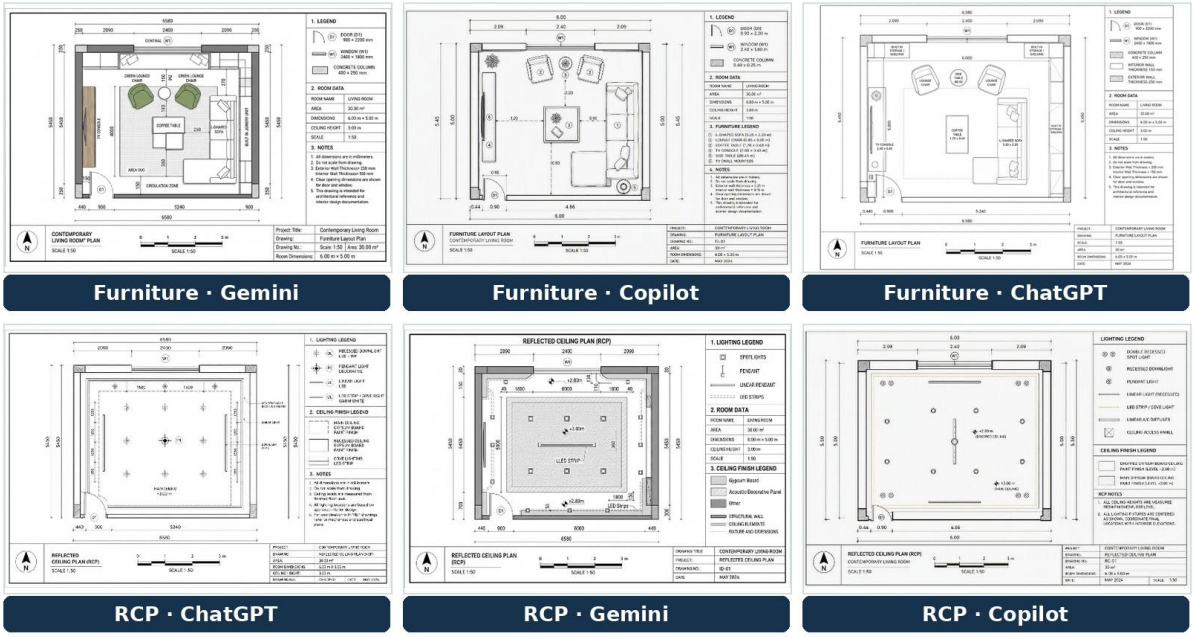


Figure 11. Comparison of furniture-layout and reflected-ceiling-plan outputs.

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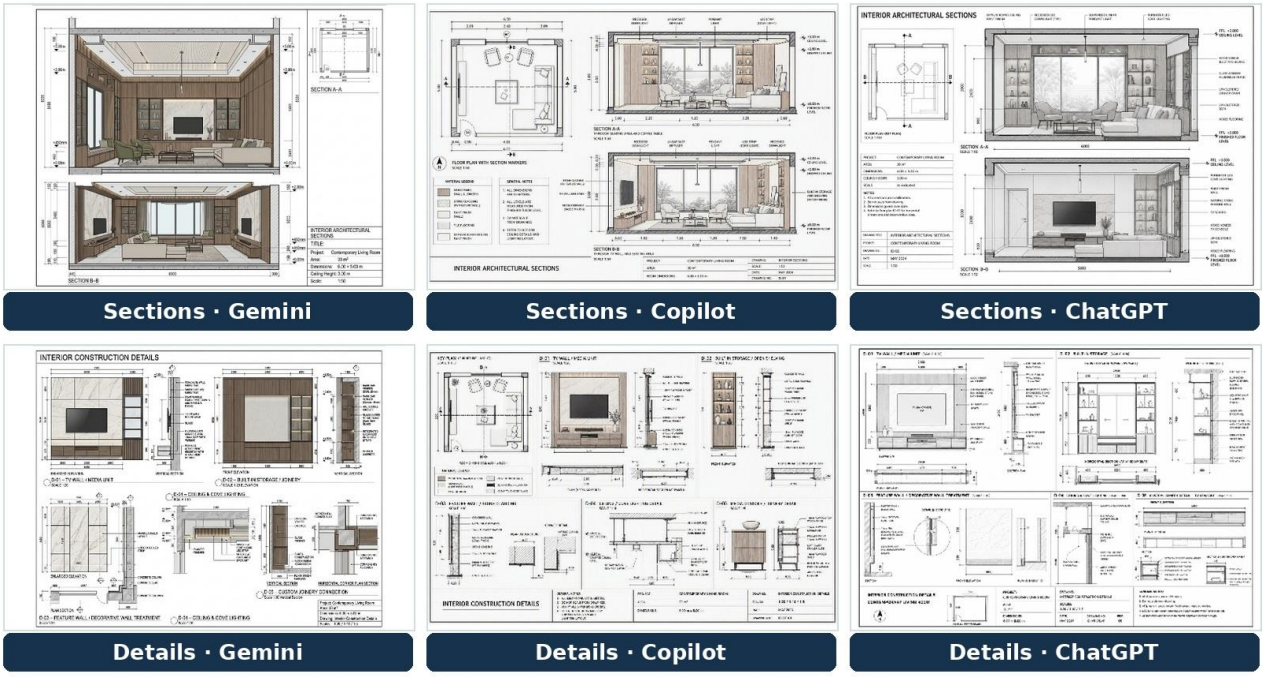


Figure 12. Comparison of interior-section and construction-detail outputs.

Table 7. Qualitative evaluation of technical documentation outputs

Task	ChatGPT	Gemini	Copilot	Proposed use level
Furniture layout	Readable distribution with some errors and unstable relationships	Best relative result; still requires review and adjustment	Deviations in furniture elements and dimensions	Preliminary draft requiring technical review
RCP	Unreliable symbols and relationships	Inaccurate grid and data	Distribution inconsistent with reference	Not suitable for construction reliance
Interior sections	3D representation and additions inconsistent with reference	Inaccurate spatial representation	Two sections too similar despite different cuts	Rebuild in CAD/BIM
Construction details	Best relative result, but not directly reliable	Inaccurate details	Insufficiently documented assemblies	Preliminary visual reference only

Overall, the tested tools could provide preliminary or exploratory outputs for some technical-drawing tasks, but their ability to preserve engineering accuracy and construction information remained limited. Gemini was relatively strongest for the furniture layout and ChatGPT for details, while none of the tested tools produced a satisfactory RCP or interior section. Human review and reconstruction in CAD/BIM environments therefore remain necessary before technical use.

Technical-use control: within the results of this study, any generated output containing dimensions, symbols, section lines, levels, or construction layers should not be treated as a final construction document before professional review, verification, and adjustment in a specialized CAD/BIM environment.

Overall comparative results and best-fit tool selection

The applied study revealed clear performance differences among generative tools according to the design task. No single platform achieved the highest performance across all operations. Some tools were stronger in text-based and analytical work, while others performed better in ideation, visual preservation, representation conversion, or three-dimensional generation.

Best-fit tools were therefore identified according to output quality, compliance with task requirements, and the potential for the output to be used in the following operation. When the tested tools did not achieve a level suitable for direct reliance—particularly in technical documentation—the appropriate level of use was specified instead of designating a tool as a final solution.

Table 8. Best-fit tools according to the applied study

Process	Task	Best-fit tool(s)	Main observation
Planning and programming	Project analysis and program formulation	ChatGPT	Strongest organization of outputs into a usable design brief
Ideation	Design-direction generation	DALL·E	Best balance between visual quality and 2D–3D consistency
Visualization and visual development	Visual development	Gemini	Best improvement while preserving composition
Visualization and visual development	Sketch-to-render	ChatGPT	Highest preservation of the sketch structure
Visualization and visual development	Multi-view generation	ChatGPT	Best new view of the same interior
Visualization and visual development	Furniture asset extraction	ChatGPT + selective use of other tools	Asset accuracy varies by furniture item
Visualization and visual development	Image-to-3D	Hi3D.ai	Best form and proportion; limited material preservation
Visualization and visual development	3D model-to-photorealistic render	Gemini	Best geometry preservation and visual material transfer
Technical documentation	Furniture layout	Gemini- exploratory use	Best relative result; requires adjustment
Technical documentation	RCP	No reliable tool identified	Outputs not technically reliable
Technical documentation	Sections	No reliable tool identified	Requires reconstruction in CAD/BIM
Technical documentation	Details	ChatGPT- preliminary visual reference	Best relative result; not a final construction document

The overall comparison indicates that generative AI efficiency in interior design is more strongly related to the task than to the platform itself. The most appropriate approach is therefore a multi-tool workflow in which the best-fit tool is selected for each operation and human verification is performed before the output is approved and transferred to the next task. The level of direct reliance on generative AI decreases as the workflow moves from conceptual and visual tasks toward operations requiring high engineering and construction accuracy.

Proposed AI-assisted interior design workflow (AI-IDWF)

Based on the comparative evaluation, the proposed AI-assisted interior design workflow links each design operation with the tool or combination of tools that performed most appropriately in the tested case. The workflow transfers an approved output from one task to the next only after human validation, supporting continuity of the design concept and reducing the propagation of errors. It also explicitly limits reliance on generative outputs in technical tasks that require high geometric and construction accuracy.

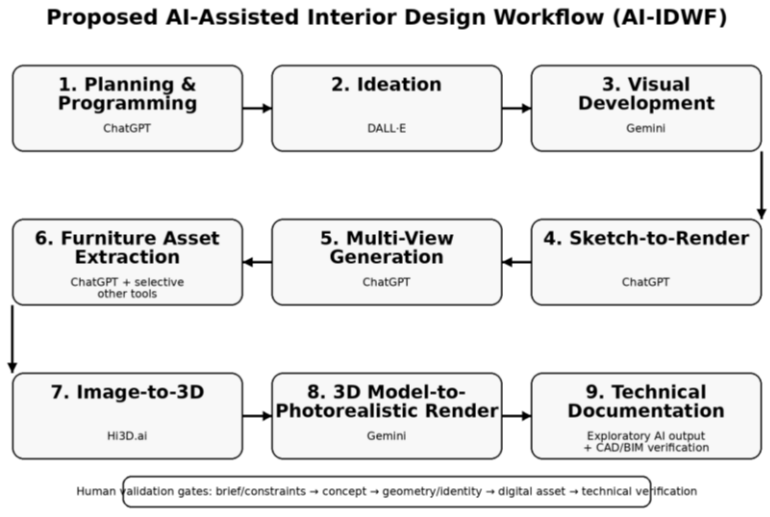


Figure 13. Proposed AI-assisted interior design workflow (AI-IDWF) and human validation gates.

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Proposed levels of professional use

The comparative results also support classifying the role of generative AI according to the level of professional reliance that is appropriate for each type of task. Table 9 summarizes four proposed levels, from direct support to exploratory use only, together with the corresponding responsibility of the designer.

Table 9. Proposed levels of professional use of generative AI in interior design processes

Level	Task type	Role of generative AI	Role of the designer
A-Direct support	Brief analysis, constraint organization, ideation variation	Accelerate analysis and expand alternatives	Audit, select, and make the design decision
B-Conditional development	Rendering, sketch-to-render, multi-view generation, visual material transfer	Produce developable visual outputs	Compare against references and correct deviations
C- Preliminary digital asset	Furniture extraction, image-to-3D	Create an initial digital asset	Clean geometry, scale, and retexture
D-Exploratory use only	Plans, RCP, sections, details	Create a draft or explanatory representation	Rebuild and verify in CAD/BIM and provide professional approval

The classification shows that reliance on generative AI varies by task. Its role is stronger in analytical, exploratory, and visual operations, whereas human intervention becomes increasingly important as geometric and construction accuracy requirements rise. Generative AI should therefore be employed as a supporting system within a human-validated workflow rather than as an independent replacement for the designer or for specialized technical documentation tools.

Research findings

- Generative AI tool efficiency varies according to the design task; no single tool achieved the best performance across all interior design processes.
- Best-fit tools differed by task: ChatGPT performed best in planning and programming, sketch-to-render, multi-view generation, and overall furniture asset extraction; DALL·E ranked highest in ideation; Gemini ranked highest in visual development and 3D-model-to-photorealistic rendering; and Hi3D.ai ranked highest in image-to-3D generation. In technical documentation, no tool reached a level suitable for direct construction reliance, although Gemini performed relatively best in furniture layout and ChatGPT in construction details.
- Generative AI achieved stronger performance in ideation, visualization, and visual development than in technical documentation; output reliability decreased as dimensional, symbolic, and construction accuracy requirements increased.
- The most effective use of generative AI was achieved through a multi-tool workflow in which the tool is selected according to the task rather than the platform alone.
- Selective integration of outputs from different tools was more effective than relying exclusively on a single platform, particularly when one output was transferred into another representation or development task.
- Combining the architectural plan, visual references, and explicit textual constraints improved preservation of design identity, composition, and spatial relationships, but did not guarantee complete geometric accuracy.
- Generative AI can support preliminary technical-documentation ideas and drafts, but the tested outputs should not be used directly as final construction documents and require review or reconstruction in CAD/BIM environments.
- Human intervention remains necessary throughout the workflow and becomes more critical in engineering and construction-oriented tasks; outputs should be validated against references and constraints before they become inputs to subsequent operations.
- The study resulted in the proposed AI-IDWF, which connects planning, ideation, visualization/visual development, digital asset generation, and technical documentation with best-fit tools and human validation gates.
- Professional use can be classified into direct support, conditional development, preliminary digital-asset generation, and exploratory use, depending on the level of reliability required by the task.

Research recommendations

- Adopt a multi-tool workflow in which tools are selected according to the requirements of each design task rather than relying on a single platform.
- Insert human validation between workflow operations to verify accuracy and consistency before outputs are reused in subsequent tasks.
- Develop generative methods that better

understand and preserve relationships between two-dimensional plans and three-dimensional spaces.

- Do not rely directly on AI-generated construction drawings; investigate deeper integration between generative tools and CAD/BIM environments to improve technical accuracy and documentation.
- Develop designer and student skills in prompt formulation, reference and constraint management, output evaluation, and detection of generative errors.
- Apply the proposed AI-IDWF to other interior typologies and more complex projects to test its adaptability and broader applicability.
- Continue evaluating future tools and versions and refine task-specific evaluation criteria as generative AI capabilities evolve.

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