The Impact of Sketch-guided vs. Prompt-guided 3D Generative AIs on the Design Exploration Process

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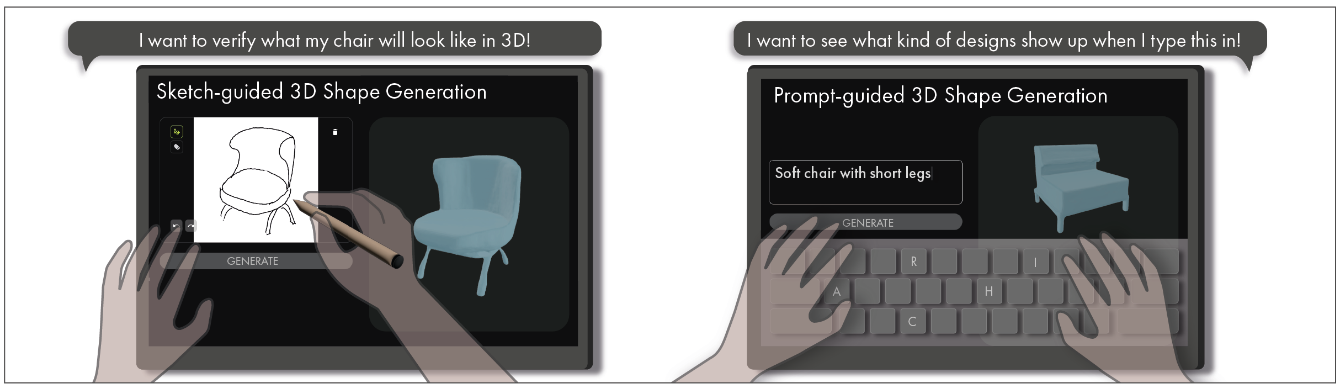

Figure 1: Sketch and prompt-guided system.

ABSTRACT

Various modalities have emerged in the field of 3D generative AI (GenAI) to enhance design outcomes. While some designers find inspiration in prompts to guide their design options, others prefer sketching to embody creative visions. Nonetheless, the impact of the different modalities of 3D GenAI on the design process remains largely unexplored. This study examines the utilization of prompt- and sketch-guided modalities within the design process by conducting linkography and workflow analyses with 12 designers. The results revealed that prompts played a pivotal role in stimulating initial ideation, whereas sketches played a crucial role in embodying design ideas. This investigation highlights the distinct contributions of these modalities at different phases of the design process, suggesting the potential for a more refined and synergistic collaboration between humans and AI. By elucidating the diverse functions of sketches and prompts, we propose prospective directions for the UX framework of the 3D GenAI.

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CCS CONCEPTS

• **Human-centered computing → Interactive systems and tools**; **Empirical studies in HCI**.

KEYWORDS

Generative AI, 3D Reconstruction, AI in Design, Design Process

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1 INTRODUCTION

Designers define design objectives and repeatedly generate solutions for evolving design problems during the design process [2]. They also engage in design thinking by iteratively generating potential solutions from various perspectives for problem-solving [33], and the design process develops through this series of design thinking and decisions [10]. Designers in various domains such as architecture, interior, and product design often express and refine their creative ideas using sketches [1, 3, 26]. Considering these factors, recent advancements in generative AI (GenAI) have inspired designers to explore design options by prompting or sketching [4, 22, 23]. This advancement allows them to obtain high-quality information through prompts or sketches.

Consequently, research in the human-computer interaction (HCI) community and design industry has proposed directions for how GenAI impacts the design process and how it should be used [20, 28]. Tholander and Jonsson [28] found that GenAI can help designers quickly explore a wide range of designs, supporting broad exploration, but has limitations in creating complementary designs. These studies also investigated the impact of using modalities such as prompts or sketches to support designers' ideation with 2D images. In addition, with the advent of 3D GenAIs grounded in a variety of modalities [12, 16, 32], various AI-based tools have been integrated into design workflows. Diffusion-based 3D generative models have shown outstanding performance and quality [12, 16, 32]. For instance, Koo et al. [16] introduced a system that supports text-guided 3D generation, whereas Zheng et al. [32] proposed a system that generates 3D objects guided by sketches. While some designers find inspiration in prompts to guide their design options, others prefer sketching to embody creative visions. Both can be used to discover design stimuli or gain inspiration by creating 3D objects using 3D GenAI. However, most of these studies primarily aimed at enhancing the quality of the generated outputs.

Moreover, according to Kwon et al. [18], during the design process, the modality used by designers to gain inspiration affects their expectations of the outcomes, influencing their design search behaviors. Understanding designers' thinking during the design process is important because it allows us to determine which ideas are significantly affected and developed through the design process. However, few studies have explored the different roles of sketch- and prompt-guided 3D GenAI, and studies that attempt to comprehensively understand how 3D GenAI influences these ideas in design processes in the HCI community remain limited. This creates a research gap, particularly regarding the impact of different modalities (i.e., prompt versus sketch) of 3D GenAI on design.

Recognizing the importance of analyzing the design process, researchers have proposed methods such as linkography and workflow to analyze and visualize the design process [6, 11, 26]. Linkography has been extensively utilized across various design domains such as interaction, industrial, architectural, and interior design [10, 11, 14, 15, 26]. Linkography can be used to track how a designer's design process has developed and identify significant contributions to design ideas and novelty. Son and Hyun [26] proposed a method that provided evaluative feedback on design ideas based on design novelty. Hatcher et al. [11] employed linkography to analyze and compare the convergent and divergent aspects of group ideation according to different design methods. Chang et al. [6] proposed a workflow graph that analyzes commands from multiple users by utilizing design tools to understand their workflows, determine commonalities, and efficiently use commands in the 3D object modeling process. Workflow graphs are beneficial for analyzing the impact of systems on the design process because they enable the identification of similarities and differences in the design actions of designers. Specifically, when a workflow graph is used to analyze designers performing the same task, it reveals how their design actions vary under the influence of different systems. Analyzing both linkography and workflow enables a more in-depth analysis of the design process, uncovering aspects such as novelty within the design process, patterns of design ideation, and diversity of design actions. These are aspects that in-depth interviews and surveys alone may not fully reveal, thereby providing a more comprehensive understanding of designer approaches.

In summary, this study analyzed the use of sketch- and prompt-guide modalities in the design process (Figure 1). It employs linkography and workflow analysis to examine individual designer processes and introduces a method for identifying commonalities across diverse design processes. Specifically, we segmented the design procedure, which employs sketch- and prompt-guided 3D GenAI, into the initial, middle, and final stages of the design conceptualization phase and analyzed the influence and merits/demerits of the system at each stage. In addition, we discuss the prospective implications of 3D GenAI. To achieve this, we conducted the following four major tasks: 1) implementing and training sketch- and prompt-guided systems, 2) developing interfaces for both systems, 3) conducting qualitative experiments with 12 designers using think-aloud protocols, and 4) analyzing the linkography and workflow of the experimental results. Through this approach, we conduct a qualitative assessment of the pros and cons associated with sketch- and prompt-guided 3D GenAI from the user's perspective in the context of designing creative outcomes. Based on these findings, we discuss the implications of integrating these two modalities.

2 RELATED WORKS

2.1 Generative AI Models for 3D modeling

Approaches to 3D modeling through HCI and computer-aided design (CAD) were explored using traditional methods, such as algorithms, optimization, and machine learning, before shifting to the use of neural networks. Ban and Hyun [1] introduced a new approach that combines computational sketch synthesis with interactive 3D reconstruction, making it easier for designers to visualize and explore various design options in the early stages. These earlier attempts were based on the intuitive idea that using inputs such as sketches or text in the design process would be useful. However, there are methodological limitations to this early exploration, particularly when dealing with nonlinear human design processes.

Traditional optimization and machine learning approaches tend to be deterministic, limiting their ability to adapt to these complex design representations.

Recently, active research has been conducted to extend the achiev ements of language-based 2D generative models to 3D generation tasks. In this study, we particularly considered SALAD [16]. SALAD represents a given shape, including its 3D position and orientation, as a collection of abstract chunks. Subsequently, it decodes the given latent chunks, resulting in the generation of specific concrete shapes. We take note of this model because of its ability to achieve language-based latent vector control during the generation process and its capability to handle shapes as sets of subabstract volumes. This model not only provides top-level results at the time of this study, but also offers advantages in interpreting user-intended design attempts through language in the design process compared to other model structures because of its cascaded composition for shapes.

Sketch-guided shape generation has traditionally garnered significant interest in the CAD and HCI domains. Among these, we have highlighted LAS Diffusion [32], which addresses sketch-conditioned 3D generation tasks. Laser Diffusion transforms a task into an image-conditioned diffusion process between the image grids and a voxel set. To enhance the quality of the results obtained from the image grid for the voxel set generation in the previous step, LAS diffusion added another diffusion process from the voxel to the signed distance field. As a result, LAS Diffusion not only achieved top-level 3D shape generation based on sketches through a step-by-step generation process based on segment-wise correlation analysis in images but also demonstrated that the step-wise logical structure can be performed in a manner similar to language models.

Ideally, it is desirable to conduct user tests based on generative models that consider multimodality for both sketches and text. For 2D generative models, models such as ControlNet [31] exist that are conditionally generated based on both sketch and text prompt modalities. However, to date, no generative models that support such multimodality for 3D shape generation have been proposed. Consequently, we opted to use models optimized for the specific purpose of this study. In this direction, SALAD and LAS Diffusion not only achieve close-to-state-of-the-art generation performances, but also have similarities in terms of two-stage generation, diffusion processes applied for each two-stage generation, and language model-inspired model architecture. We focused on demonstrating the experiential differences that generative models bring to the design process by selecting models that have comparable generation speeds, are based on the same dataset, and whose quality of generated output is either state-of-the-art or closely approximates it.

2.2 Generative AI in Design within the HCI Community

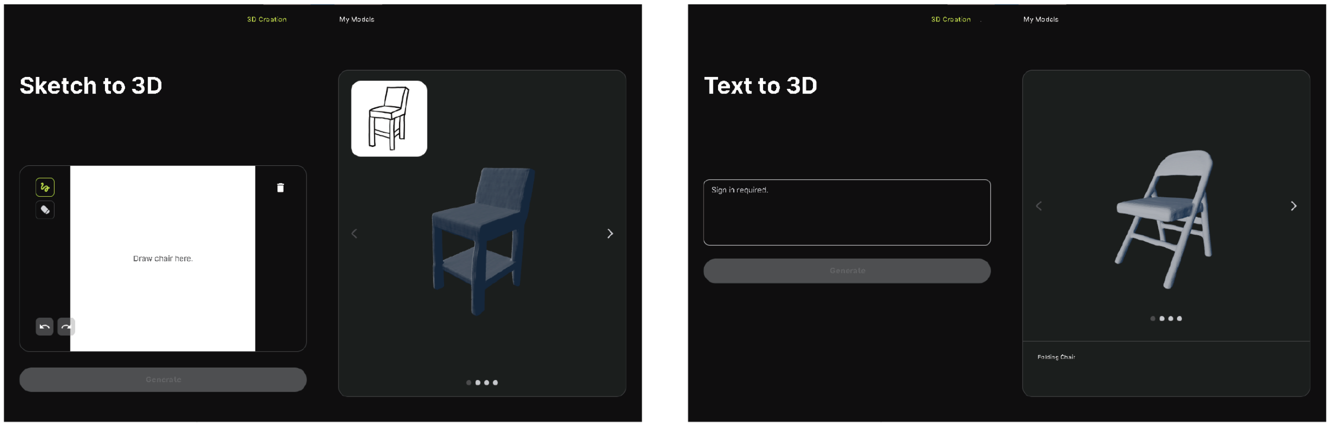
GenAI has shown remarkable capabilities in generating diverse and realistic content across different formats such as images, videos, and text [25]. Because human involvement is essential in GenAI [25], extensive research in the field of HCI, especially in the design industry, has explored the influence of GenAI on the design process, interaction, and effective collaboration between designers and GenAI. Moreover, many studies have been conducted in which designers from various fields collaborate with GenAI on real-world design tasks, analyzing the role and impact of GenAI. Tholander and Jonsson [28] conducted a workshop utilizing GPT-3 to develop design concepts for given design cases, aiming to investigate the role of GenAI in creative design processes, such as ideation, early prototyping, and sketching. During this process, designers found that GenAI helped save time, quickly map out the design space, and identify the most obvious ideas. Studies such as [8] and [21] involving designers in the field of UX design, conducting design tasks, and interviews have shown that GenAI excels in assisting human communication and presentation, and suggests directions for design iterations. Kulkarni et al. [17] investigated the role of prompt-guided text-to-image models (TTIs) in collaborative, goal-oriented design, and discovered that these systems can facilitate the rapid exploration of the design space and enable flexible collaboration. Additionally, Lawton et al. [20] introduced 'Reframer,' a human-AI drawing interface designed for iterative and reflective creativity. This system allows real-time collaborative drawing between users and AI. The abovementioned HCI studies, particularly in the design field, highlight the methods and roles of interaction and collaboration between humans and GenAI. Overall, they emphasized the role of humans in aligning AI and GenAI as design assistants.

While studies in the HCI community have proposed examining the role of GenAI which generates images or texts by elucidating its impact on designers engaged in design tasks through the analysis of their design outcomes and in-depth responses, research on the role of GenAI in generating 3D models remains limited. In particular, 3D design is a highly complex task that requires multiple sketch perspectives and numerous conceptual designs [1, 22]. Thus, the influence of 3D GenAI in the design process is expected to be significant. However, current research on 3D GenAI primarily focuses on quantitative aspects such as the performance and accuracy of the generated 3D outcomes.

Furthermore, as the design process evolves through iterative design ideas and actions, a comprehensive understanding requires analyzing not only the design outcomes and user responses but also the design ideas and actions. Moreover, there is a growing emphasis on a designer-centric role, focusing on supporting the designer's actions rather than just aiding in creating design outcomes [2, 26, 27]. Therefore, understanding the role of 3D GenAI in the design process requires identifying the strengths and limitations of the designer's perspective in terms of specific design ideas and actions. Despite this, a research gap still exists in the HCI community regarding how and where the influence of 3D GenAI is affected by design ideas and actions in the design process. Therefore, our research aims to fill this gap by analyzing how designers think and how design actions develop at each stage of the design process using designer action-based analysis methods such as linkography and workflow graphs.

2.3 Analyzing Design Process and Actions

A workflow is a structured and systematic sequence of tasks and processes that designers adhere to complete a project efficiently and effectively. The aim of a workflow is to streamline the creative process while ensuring that the final design aligns with the intended



(a) Sketch-Guided 3D Generative AI System Interface

(b) Prompt-Guided 3D Generative AI System Interface

Figure 2: Sketch and prompt-guided 3D GenAI system interfaces: (a) User draws a digital sketch on the canvas (left) and then clicks the 'Generate' button below to view a rotatable 3D model output of their sketch (right); and (b) User inputs prompt commands into the text field (left) and then clicks the 'Generate' button below to view rotatable 3D model output of their prompt (right).

objectives. Research in HCI has examined ways to better assist designers using CAD software in their design tasks by comparing various workflow demonstrations to identify commonalities and recommend more efficient workflows [6, 30]. Chang introduced workflow graphs referred to as W-graphs. These graphs encode multiple demonstrations of 3D modeling workflows and are utilized to suggest alternative methods for performing parts of a complex scan, or to identify the most efficient way to complete it. By examining these graphs, users can understand the various paths to achieve 3D models and highlight the commonalities in multiple workflow approaches to achieve the same goal. This methodology is particularly effective for analyzing the design processes of multiple designers. Encoding multiple demonstrations of both fixed and free design tasks enables a comprehensive analysis of designers' ideation processes, further helping in understanding varied approaches, identifying the most efficient or intermediate steps to complete the task, and revealing meaningful insights into designers' creative thinking processes.

Alternatively, Linkography [10] serves as an analytical approach employed for the construction of a linkography, a visual schematic illustrating the interlinked associations and interdependencies between diverse informational elements. This methodology is effective in enhancing the comprehension of intricate information architectures within the context of a designer's design process. Establishing links between convergent and divergent thinking, referred to as design moves, can be utilized to identify patterns occurring within the framework of a design ideation process. Linkography has been used extensively in the literature to analyze the design ideation process of designers [9, 11, 13, 14]. The linkograph's intuitive representation of interconnected relationships throughout the design process enables the identification of how each move impacts the others. This comprehension is further enriched by recognizing patterns that contribute to decision making, an aspect evaluated by examining existing links. These links provide insights into the associations between each move and its antecedent moves, referred to as backlinks, and their subsequent moves, referred to as forelinks [10]. Goldschmidt's framework categorizes backlinks as indicators of convergent thinking and forelinks as manifestations of divergent thinking. Building on this understanding, Kan and Gero [15] introduced the concept of horizonlinks, which represent the distance between design moves to assess the cohesiveness of ideas. The integration of Linkography and Workflow analytical methods leveraged their respective strengths to facilitate a comprehensive exploration of the characteristics of both sketch- and prompt-guided 3D GenAI systems and their impact throughout the design process. From the initial concept to the mid-and late refinement design stages. This synthesis provides a refined evaluation of the efficacy and effectiveness of each input modality across different design phases, pinpointing the specific advantages and limitations of each system and thereby addressing their respective contributions to the overall design process.

Consequently, integrating these two methodologies offers an optimal approach for analyzing the divergence and convergence of ideas employed by designers utilizing GenAI; comparing the representations of the design process facilitates a comprehensive understanding in the exploration and evaluation of how GenAI aids the interplay between designers' ideation process.

3 METHODS

3.1 Sketch and Prompt-guided 3D generative AI systems

3.1.1 Infrastructure and Interfaces. We implemented a simple web-based user interface and cloud-based inference system for each shape-generation modality (Figure 2). For the sketch modality, users were provided with a blank canvas with a pencil, eraser, and undo/redo tools. Upon completion of a sketch, the user clicks a button, and the system generates the corresponding 3d model. A text box was provided for text modality. The cloud-based infrastructure was designed to allow users to make multiple simultaneous requests.

3.1.2 Sketch-guided 3D Shape Generation. Our sketch-to-3d system is based on [32] (called LAS-D), a two-step diffusion algorithm trained on the ShapeNet dataset [5]. Using a sketch as the input, the algorithm creates a coarse voxelized shape, which is later refined into a detailed model. LAS-D uses Canny-edge sketches that are paired with their corresponding 3D shapes using a cross-attention mechanism [29]. Please refer to the original publication for a comprehensive explanation of this algorithm.

Since Canny-edge sketches do not always resemble human-made sketches (specially when there are self-occlusions), we train our own variant of LAS-D with sketches made in Blender [7] using its "Freestyle" sketching shader (Figure 3). Without a loss of generality, we limited our system to ShapeNet's chair category, which consists of 6778 chairs of different styles. Each sketch has a resolution of 224 × 224 pixels.

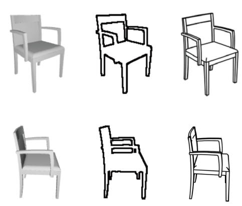


Figure 3: Sketch types for training: left: 3D model; middle: Canny-edge sketches; and right: Blender Freestyle sketches.

3.1.3 Prompt-guided 3D Shape Generation. In this study, we followed a previous study to shape the generation configuration proposed in SALAD [16], which is a two-phase diffusion model for 3D shape diffusion. The first phase of SALAD is Transformer-based noise prediction of extrinsic parameters $\mathbf{e}_i = \{\mathbf{c}_i, \Sigma_i, \pi_i\}$, which represents the target 3D shape in the form of a Gaussian mixture's mean, covariance, and its relative importance. The second stage is followed by another Transformer-based network to predict the conditional distribution of intrinsic latent $\mathbf{s}_i$ conditioned on $\mathbf{e}_i$, or $p(\{\mathbf{s}_i\}_{i=1}^N | \{\mathbf{e}_i\}_{i=1}^N)$, which represents the latent information of local shape conditioned on mixtures of Gaussians. The actual shape, represented as occupancy values in a space, will finally be decoded conditioned on both shape extrinsic and intrinsics, $(\mathbf{e}_i, \mathbf{s}_i)$.

3.2 Linkography

Linkography encompasses links formed based on similarities between design ideas, and is termed design moves (DMs). Links between DMs were established based on two criteria: (1) if two DMs pertained to the same design idea, or (2) if a DM contributed to developing a preceding move's design concept (Figure 4). We employ two key metrics in linkography: (1) the link index, denoting the interconnectedness of design ideas, and (2) entropy, which signifies novelty in the design process [15]. First, the link index was derived by dividing the number of links by the number of DMs. A

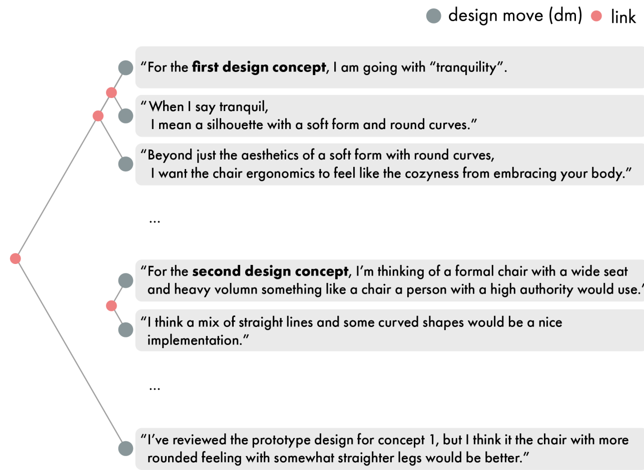


Figure 4: Forming links between DM in transcribed sentence: Two sets of links are formed between transcribed sentences (DM) which associate with preceding DMs.

high link index value implies that there are many ideations similar to preceding ideas, whereas a low value suggests that ideation is more independent of antecedent ideas. Secondly, the entropy value is computed using Shannon's entropy function [24] for the creation status of forelinks, backlinks, and horizonlinks in each row of linkography (Eq.1, 2).

$$H = -\sum_{i=1}^{n} p_i \log_2 p_i \quad with \sum_{i=1}^{n} p_i = 1. \tag{1}$$

$$H_{total} = H_{forelinks} + H_{backlinks} + H_{horizonlinks} \tag{2}$$

Kan and Gero [15] define each row of forelinks, backlinks, and horizonlinks as a state and describe the probability of a link occurring in each state as $p(\text{ON})$, which is the ratio of the actual number of links formed to the possible number of links. The probability of not forming a link, $p(\text{OFF})$, is defined as $1 - p(\text{ON})$. Entropy (H) for each state was calculated using Eq. 1, $-p(\text{ON})\log_2(p(\text{ON})) - p(\text{OFF})\log_2(p(\text{OFF}))$. For example, in Figure 5's forelink illustration, the 1st DM's state has three possible links, and one link is formed. Thus, $p(\text{ON})$ is $\frac{1}{3}$, $p(\text{OFF})$ is $\frac{2}{3}$, and H for the 1st DM's state is 0.918. In addition, the 2nd DM's state has two possible links and two links are formed. Hence, $p(\text{ON}) = 1$ and $p(\text{OFF}) = 0$. Consequently, the H value of the 2nd DM's state is 0. Forelinks tend to exhibit relatively divergent characteristics, backlinks show relatively convergent tendencies, and horizonlinks possess the trait of idea's cohesiveness. DMs with a significant number of forelinks or backlinks are referred to as critical moves (CMs) [10]. Backlink CMs represent essential moves that consolidate or integrate antecedent ideas, whereas forelink CMs denote moves that inspire subsequent DMs, playing a crucial role in design progression. The entropy calculated using these three link types reflects diverse ideas and novelty in terms of cohesiveness. A high total entropy signifies that the DMs acquired a higher amount of information, indicating that the design process involved acquiring new information and was therefore more novel. Conversely, a low total entropy implies a less novel design process characterized by acquiring relatively less new

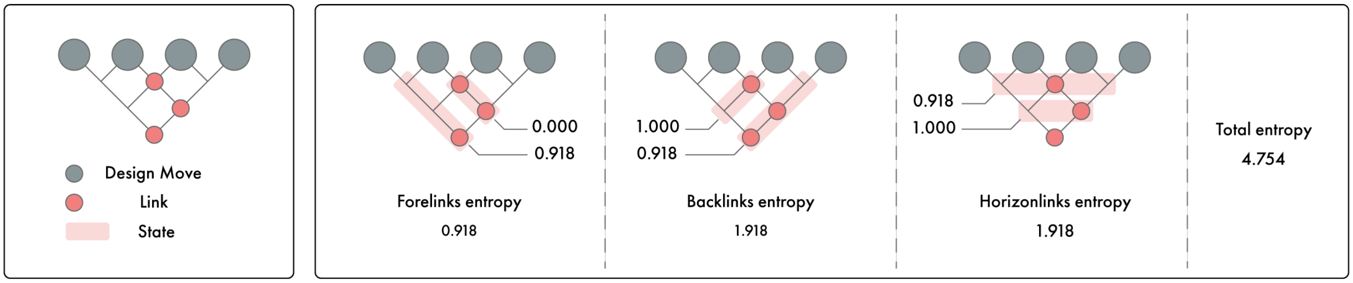


Figure 5: Performing linkography entropy calculation: The entropy of forelinks, backlinks and horizonlinks within a linkography is calculated and summed to determine the linkograpy's total entropy.

information. It is worth noting that even when acquiring the same information, individuals with lower information quantity (i.e., low total entropy) are more likely to perceive the information as novel, whereas those with higher information quantity (i.e., high total entropy) may not perceive the information as novel. Thus, entropy is not solely determined by the density of linkography but rather by how links between DMs are established, influencing the novelty of the design process. In summary, the higher the entropy value, the greater the likelihood of increased novelty in the information during the design process.

3.3 Workflow

Workflow is a structured series of design tasks from the beginning of the design process to the final design. We assessed the similarity of user design processes using a workflow graph. The queries (inputs) that users provide for design generation in the system are defined as design tasks, that is, nodes in the graph. The nodes of the workflow were based on the system input and explicitly expressed intentions derived from the think-aloud protocols.

Three principal criteria guide the categorization of the workflow nodes. The first criterion involves differentiating between create (*C*) and modify (*M*) nodes corresponding to the query inputs in the system. In the case of modification, it was further specified which design elements the user modified: the back (*B*), seat (*S*), arm (*A*), or leg (*L*) of the chair, which can be denoted as *M-B* (modified back), *M-S* (modified seat), or *M-B-S* (modified back and seat) in the case of modifying two elements in one query. The criteria for determining the graph nodes are as follows: 'Create' indicates that designers are generating a design with a new intention, signifying a design with a different purpose or concept from existing designs. 'Modify' is applied when designers alter or refine parts of an existing design. While the overall direction or concept remains unchanged, specific elements can be adjusted, modified, or made detailed.

Additionally, if the user input was for evaluating their design idea, we added '*E-*' to the nodes like *E-C* or *E-M*. This addition reflects the designer's intent regarding the design nodes. The criterion for 'evaluate' involves a designer utilizing the system to check or confirm their design idea. This process involves reviewing design alternatives using the system, particularly when a specific design idea is preestablished.

Finally, the color of the nodes serves as an indicator of whether they contribute to the final design outcome. If a node contributes

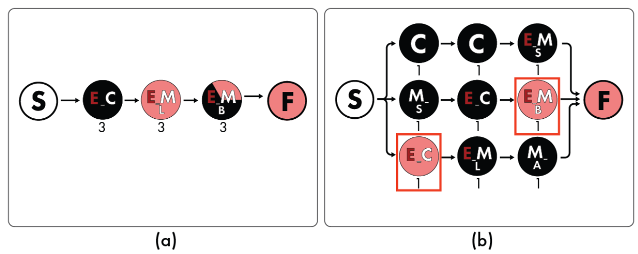


Figure 6: Example workflow graphs of two scenarios: (a) 'Scenario A' depicts a linear sequence where all designers followed an identical approach in their design ideation process; and (b) 'Scenario B' depicts all designers using unique approaches.

to the development of the final design (in the same direction), it is depicted in pink; otherwise, it is shown in black. The pink nodes denote their impact and relevance to the final design. Conversely, black nodes did not affect the final design and were phased out during the process. Therefore, the nodes in the workflow contain rich information about the design process, including the system input, designer intent related to the evaluation, and contribution to the final design. Although these three aspects are related to the design direction, they do not align consistently for every node. For example, even if an input query is related to a previous idea, it does not necessarily contribute to the final design.

The hypothetical scenario, as shown in Figure 6, scenario provides two contrasting examples based on the design processes of three separate designers to illustrate how the individual design processes of distinct designers are integrated into a workflow graph. It was assumed that all designers utilized the system thrice, thereby forming three nodes to complete their final designs, as depicted in Figure 6. In scenario A (Figure 6-a), all three designers completed the final design using an identical workflow. Notably, two designers progressed to the final design from the 3rd node while one did not, resulting in the workflow graph predominantly characterized by nodes in a pink scheme. By contrast, for Scenario B (Figure 6-b), the three designers completed the final design by employing different workflows. Only the 3rd node from the 2nd designer and the 1st node from the 3rd designer ultimately contributed to the final design. Scenario B exhibited pronounced vertical expansion and a prevalent black depiction. In summary, as the design process became more diverse, the workflow graph expanded vertically. Furthermore, the prominence of pink within this visual representation is directly proportional to the extent to which the designers' nodes develop into the final design.

4 IMPLEMENTATION AND RESULTS

4.1 Experimental Design

(a) Hotel Lobby Interior (b) Office Interior

Figure 7: Two spatial contexts used in the study's design brief. Participants are to design a suitable chair to fit the white boxes for the provided interior space.

For this study, the design brief proposed a chair design suitable for specific spatial contexts, such as hotels and offices (Figure 7). The design brief was divided into three sequential tasks: (1) Design conceptualization, in which participants were instructed to propose three or more design concepts; (2) Design selection, in which participants were guided to choose a concept and develop three or more alternatives; and (3) Design finalization, in which one selected alternative was refined into the final chair design. At each stage of the design process, the participants were instructed to produce a paper sketch accompanied by a brief explanation of each design idea. This procedure was applied uniformly across all design stages for all ideated designs, cumulatively resulting in seven design sketches.

Throughout the design process, participants were instructed to utilize a GenAI system tailored to their specific design brief as a tool to aid design ideation. For example, in the conceptualization phase, the system is utilized to generate initial design concepts, whereas in the selection phase, the system serves to refine and/or evaluate these concepts. In the finalization stage, the systems were utilized to assist in the refinement and evaluation of the final design.

To evaluate the effectiveness of sketch-guided and prompt-guided systems as ideation tools for designers, 12 participants, designers with experience in GenAI modeling were recruited. The participants consisted of ten females and two males (age: mean =24.5; max =26; min =23). The experimental procedure encompassed four phases: an introductory session, Experiment Conditions 1 and 2, and a concluding in-depth interview. This study employed a within-subject design in which participants were exposed to both experimental conditions, each involving a specific brief and 3D GenAI system. We randomized the sequence order for the participants to control for ordering effects, thereby ensuring an unbiased distribution of briefs and 3D GenAI system usage among all participants.

In the introductory session, participants were briefed on the functionality and structure of both 3D GenAI systems. While using each system, the participants had access to four windows: three windows were designated as model generation inputs, and one window served as an archive for previously generated models. For both experimental conditions, all the participants' activities were recorded, including sketches on paper and 3D GenAI system usage. The duration of each task was approximately 60 min, with surveys conducted upon completion of each task. Following the completion of all tasks, 20-minute in-depth interviews were conducted.

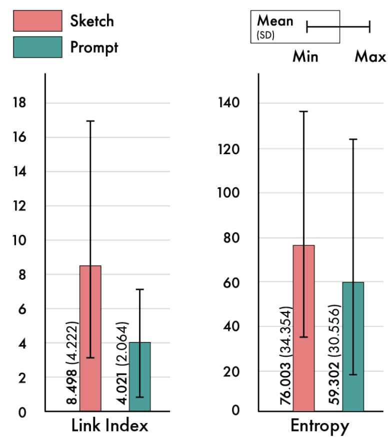


Figure 8: Results of average link index and total entropy of sketch- and prompt-guided systems.

A Microsoft Surface Pro X and its stylus pen were used as digital sketch inputs in digital format. For prompt input, both the Surface Pro X onscreen keyboard and signature keyboard were used. In addition, to facilitate linkography analysis, this study employed a think-aloud protocol that requires several recording devices to capture and document participant activities and verbalizations.

4.2 Results and Discussions

4.2.1 Sketch and Prompt: Tools for Converging (or embodying) and Diverging (or Generating) Design Ideas. Accordingly, throughout the design process, the participants were instructed to verbalize all their cognitive activities to process the think-aloud protocol for our linkography and workflow graph. Real-time transcription of these verbalizations was conducted by two moderators, with video and audio recordings serving as supplementary resources. After the experiments were completed, the moderators identified the DMs and established links between them. In the analysis stage of the study, transcripts were segmented into individual sentences, each sentence representing a distinct DM. The workflow graph represents all the designers' design actions, whereas the linkographies are per-designer.

Based on the results of the linkography, workflow, surveys, and in-depth interviews of the sketch and prompt-guided 3D GenAI systems, we confirmed that each system supported convergent and

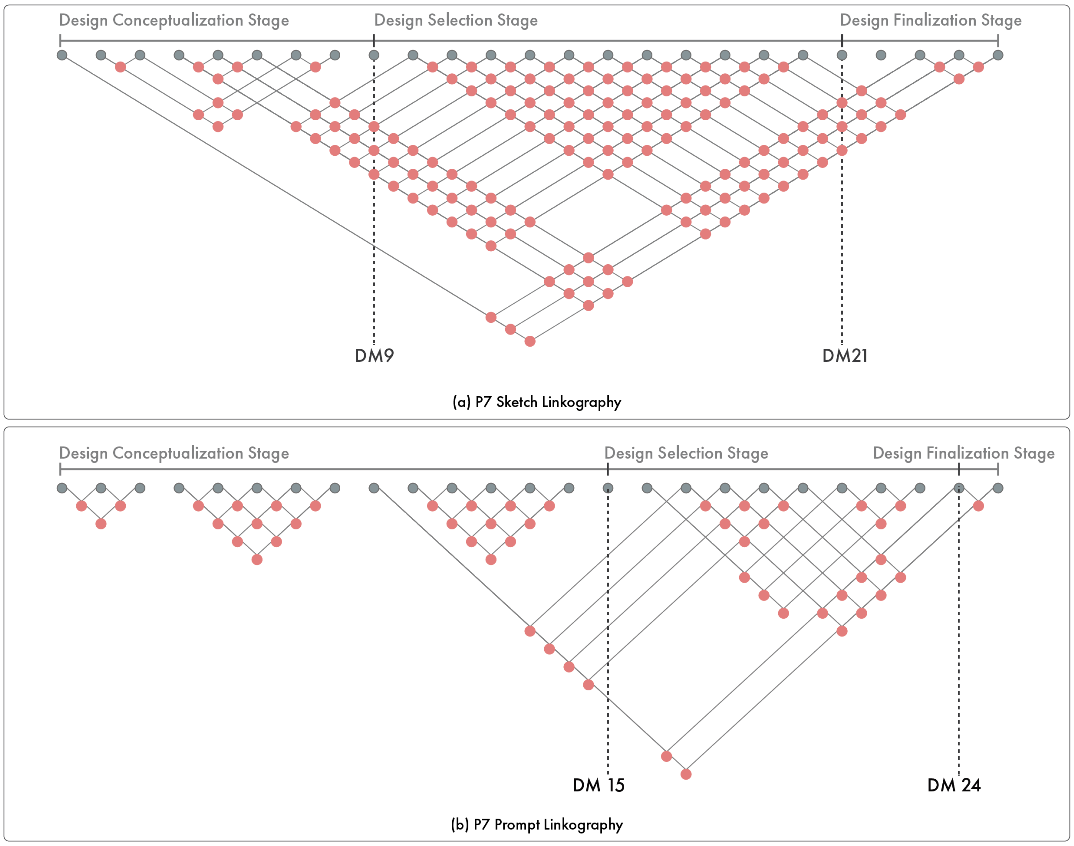
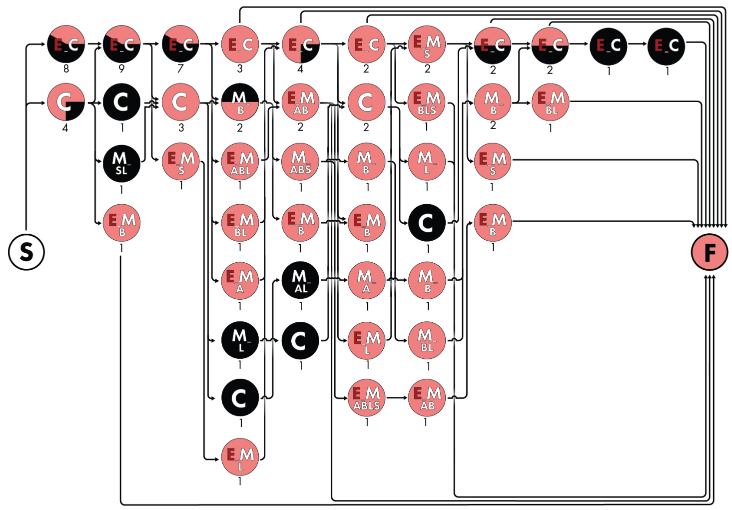


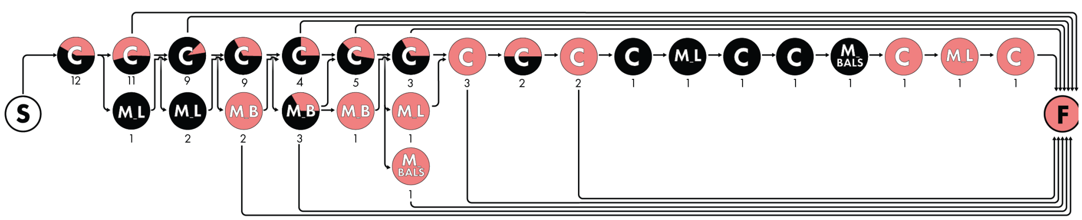
Figure 9: P7's design process linkography: (a) The sketch linkography presents a dense interconnected web of links formed throughout the design process, indicative of convergent thinking patterns; and (b) The prompt linkography comparatively illustrates a more sparse sets of linked-webs across the design process, suggestive of divergent thinking patterns.

divergent design thinking. First, we analyzed the metrics from the linkography of each system to assess the density of ideas during the design process, as measured by the link index, and novelty in the design process, as indicated by entropy. For this purpose, we calculated the average link index and entropy values from the linkography of 12 experimental participants for both sketch-guided and prompt-guided systems (Figure 8). The sketch-guided system had an average link index of 8.497, whereas the prompt-guided system had a link index of 4.021. This suggests that the sketch-guided system engaged in more convergent design processes, with ideations similar to the antecedent ones, whereas the prompt-guided system explored a wider range of ideations, indicating a more divergent design process. Second, when evaluating the novelty in linkography using entropy, the sketch-guided system scored 76.002, whereas the prompt-guided system scored 59.301. This implies that a sketch-guided system is more likely than a prompt-guided system to acquire new information during the design process. In other words, the design process of a sketch-guided system is novel and dense. This is likely because designers can evaluate their design directions using the system and make better decisions. For example, P7 in the sketch-guided system (Figure 9-a) engaged in intensive ideation and decision-making by comparing their ideas with the 3D generated chairs in nodes DM5-7 after ideating about a 'chair with pattern,' and in nodes DM10-20. In contrast, in the prompt-guided system, web-related ideas were prominent in the early stages, with ideation about an office chair in nodes DM1-3 and a shift to ideating about a completely different type of chair, a living room chair, in nodes DM4-8.

These results were also reflected in workflow analysis. As shown in Figure 10, we can observe that there are many nodes in the sketch workflow with a direction similar to that of the final design, whereas in the prompt workflow, there are many nodes with a direction different from that of the final design. This indicates that in sketch-guided systems, many designs generated in the early to mid-stages were similar to the final design direction, whereas in the prompt-guided system, many designs were distinctly designed from the final design direction. For example, when examining P6's sketch workflow (Figure 11-a), five of the nine nodes developed into the final design, and of these five nodes, the last four were for the self-evaluation and design idea evaluation of their design ideas. By contrast, in the prompt workflow, five nodes were created as a reference to understand what form their design might take, but these nodes did not develop into the final design.



(a) Sketch workflow



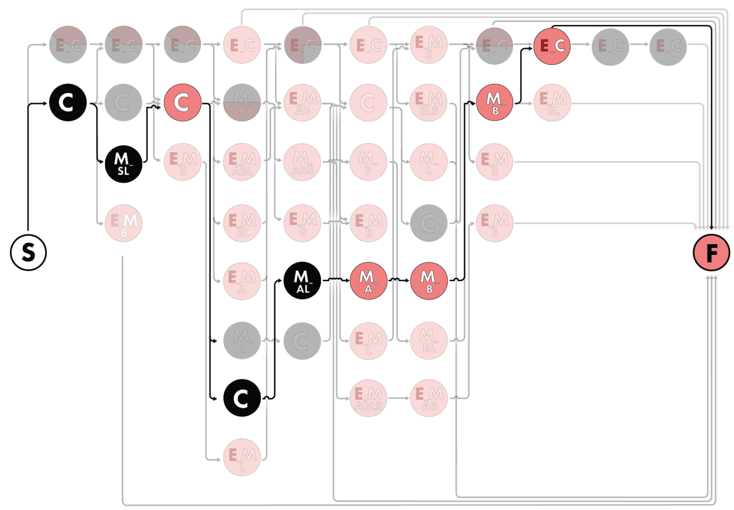
(b) Prompt workflow

Figure 10: Workflow of sketch and prompt-guided systems of all participants: (a) The sketch workflow illustrates the varied approaches taken; and (b) The prompt workflow demonstrates a more uniform approach.

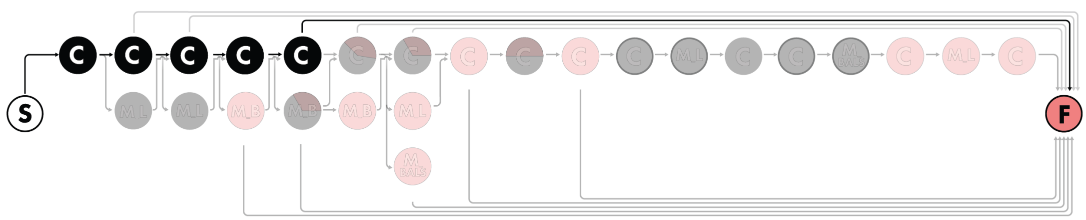
Furthermore, when examining the results of survey questionnaires #2, #3, and #4 (Figure 12), participants reported that the sketch-guided system was more challenging to use in the early stages than in the mid-to-late stages (median of sketch: question #2 = 4, #3 = 3, and #4 = 2), whereas for the prompt-guided system, participants found it more challenging to use in the later stages (median of prompt: question #2 = 4; #3 = 4.5; #4 = 5.5). This suggests that prompt-guided system users face more challenges in the selection and finalization stages than in the conceptualization stage, whereas sketch system users initially find it challenging in the conceptualization stage but adapt more easily in the selection and finalization stages. However, in the user satisfaction survey of the final design results for the sketch-guided and prompt-guided systems (question #1), the values of 1^{st} quartile were 5 and 4.25, respectively, while the median values were 5 and 5.5, and the 3^{rd} quartile values were 6.75 and 6. These results indicated no substantial difference in user satisfaction between the two systems. These survey results align with the findings of the in-depth interviews.

- P2: *"The sketch-guided system was not very helpful for generating new design concepts in the early stages, but it became valuable for evaluating my ideas after designing the overall forms. By contrast, the prompt-guided system was easy to use in the early design stages by simply entering keywords to generate complete chair shapes. However, in the later stages, it was challenging to obtain the desired results, and I had to manually synthesize the design elements among the generated outputs, making it less helpful."*
- P5: *"I used the sketch system in the mid-stage of design because it required sketch input, primarily for the purpose of refining my designs once I had a basic input. The objectives of the sketch and text systems seemed different. The text was useful in the initial stages, but the sketch system worked well when I already had some design ideas in mind."*
- P8: *"The sketch-guided system became helpful for me from the mid-stage onward as my sketches were refined into 3D forms. The prompt system was beneficial in the early stages of exploring various shapes, but in the later stages, it was challenging to obtain the desired forms, making it less usable."*

In summary, our analysis of sketch- and prompt-guided systems revealed their distinct roles in fostering convergent and divergent design ideation. The sketch-guided system is more effective in the later design stages, aiding convergent design ideation by focusing on specific design aspects. By contrast, the prompt-guided system excels in the early stages, encouraging divergent design ideation by offering a range of design possibilities. While the sketch-guided



(a) P6 Sketch workflow



(b) P6 Prompt workflow

Figure 11: P6's workflows: (a) The sketch workflow illustrates the system's utilization for design evaluation during mid-to-late stages of the design process; and (b) Conversely, the prompt workflow indicates its utilization for reference checks.

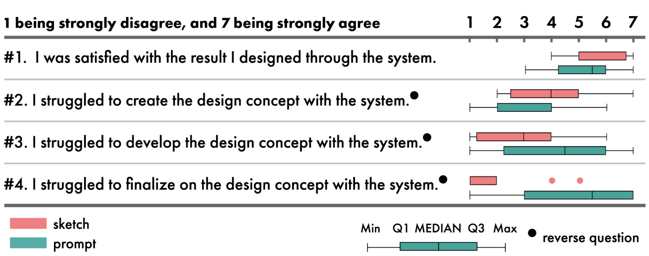


Figure 12: Results of 7-point Likert scale survey showing the 4-quartile ranges for satisfaction and usability experienced using 3D GenAI systems during the design process.

approach narrows down the design choices for refinement, the prompt-guided approach broadens the ideation spectrum, catering to different stages of the design process.

4.2.2 The Role of Sketch and Prompt in 3D Generative AI: Generating Design Ideas easily or Encouraging Self-Evaluating. Analyses of the workflow and linkography for both input modalities show how the exploration of both input modalities in the design process illuminates their distinct yet critical roles. This differentiation provides a comprehensive understanding of the framework for leveraging these systems effectively. Based on the findings of this study, the **prompt-guided system** was shown to function as a catalyst for divergent thinking in the initial stage of the design process. It supports designers in expanding their creative horizon, offering a broad spectrum of ideas and inspiration —a wide range of design possibilities. It is strong in its ability to introduce designers to a diverse array of concepts that stimulate innovative thinking and widen the scope of design ideas. This expansive approach is particularly beneficial because the exploration of various designs early in the design process is crucial. In contrast, the **sketch-guided system** was shown to be the most effective in the convergent phase of the design process, particularly during the mid-to-late stages. This supports designers in refining their ideas by allowing them to delve deeper into specific design aspects. Through sketch input, designers were able to explore the intricacies of their ideation, focusing on the refinement and feasibility of their chair designs. This system serves as a critical tool for self-evaluation/self-checking, enabling designers to visualize in 3D form and iterate on their sketches, further transforming their ideas into concrete design elements. The capacity of a sketch-guided system to provide detailed feedback on specific design components makes it an invaluable support tool for finalizing designs with precision and clarity. Accordingly, in the remainder of this section, we explore the observations and

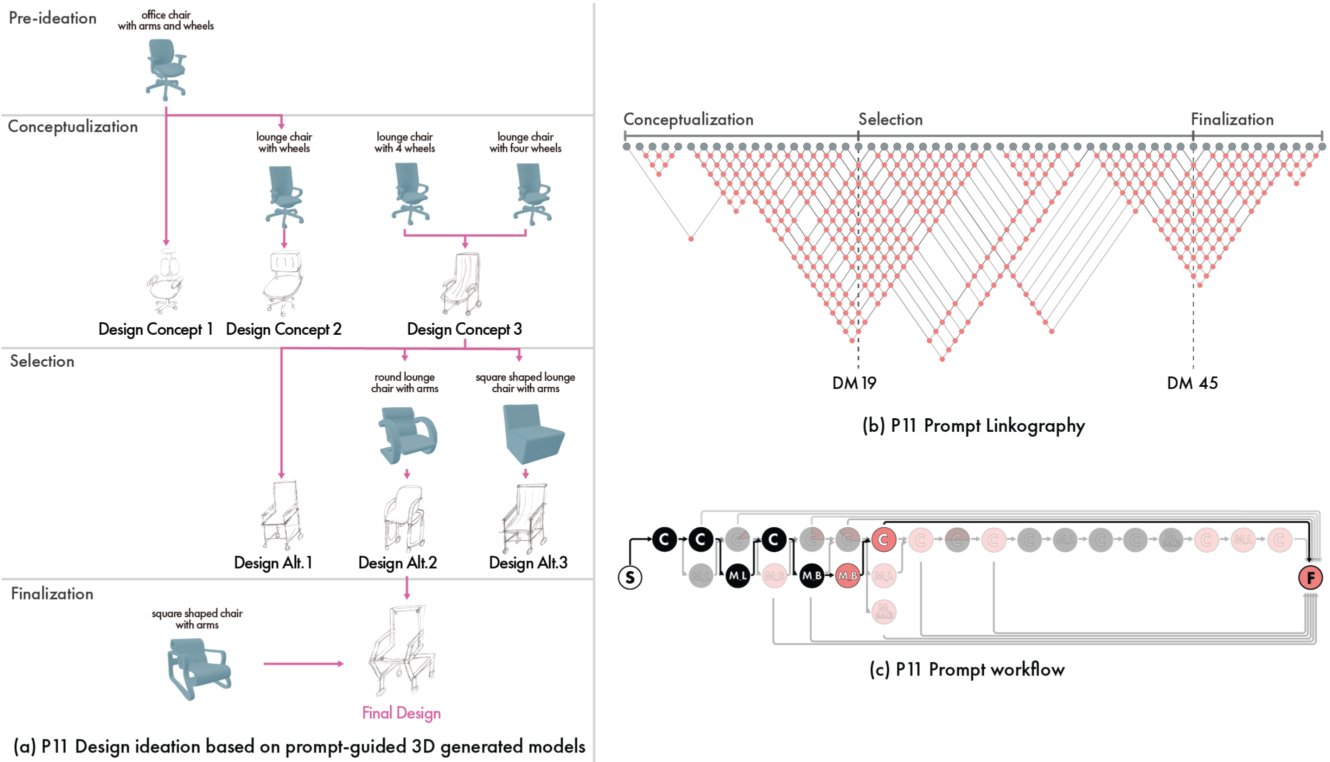


Figure 13: Analysis of P11’s prompt-guided design process: (a) Design ideation process; (b) Linkography reveals a pattern of divergent thinking; and (c) Workflow depicts the system’s primary utilization for reference checking.

interpretations based on the findings of the study for each input modality.

Prompt-Guided 3D Generative AI System. Our observations revealed that the prompt-guided system plays a key role in exploring design references to formulate innovative design concepts by easily generating design ideas. A prime example of this usage is evident in P11’s Linkography (Figure 13-b), which demonstrates that links are consistently established between moves across the design conceptualization, selection, and finalization stages. This denotes a continuous search for chair design references, which culminates in the synthesis of design elements from the generated 3D models to either innovate entirely new chair designs or redesign existing ones (Figure 13). This observation aligns with the workflow (Figure 13-c), which illustrates the system’s recurrent use for obtaining design references and shaping design ideation.

P11 described its effectiveness in the initial exploratory phase, focusing on generating design ideas. P11 explained, *“There weren’t many difficulties as it was a phase of examining various options before actually designing my own design in a concrete way... I mainly used the prompt-input to gather ideas, and this system was most significant in generating ideas.”* Delving deeper, P11 added, *“During the initial and mid-stage of the design process, I explored references through the system... Utilizing such ideas to narrow down the decision-making process, I obtained inspiration for the shape the chair could have, and although I may have used it to self-check designs in the middle stage, it was the generation of ideas that played a pivotal role, rather than the self-checking for the prompt-guided system.”* A comparison of the workflow graphs of both systems highlights this distinction, indicating that the majority of participants predominantly used the prompt-guided system for idea generation and reference identification, rather than for self-checking to compare their envisioned chair designs with keywords and the resulting outputs generated by GenAI. However, the prompt-guided system showed lower average total entropy and link index values than the sketch-guided system. This suggests that the information and ideas generated through the prompt-guided system during the design process were relatively irrelevant to each other or difficult to consistently use throughout the design process. This pattern is evident in P11’s linkography, which predominantly features a web structure consisting of links. This indicates that a prompt-guided system is less novel for designers. Thus, the prompt-guide system has proven limitations in its capability as a design support tool to focus deeply on specific design aspects, such as the detailed refinement of chair components.

Leveraging Unexpected Discoveries with Prompt-Guided System. In design, unexpected outcomes that defy initial predictions or anticipation often lead to innovative opportunities [19]. This study emphasizes the effectiveness of the prompt-guided system in the initial stages of design. However, it is noteworthy to point out another discovery of its utilization. While many users expressed dissatisfaction with system outcomes that did not align with their expectations, primarily owing to challenges in selecting the correct keywords, P3 perceived this differently. P3 found the

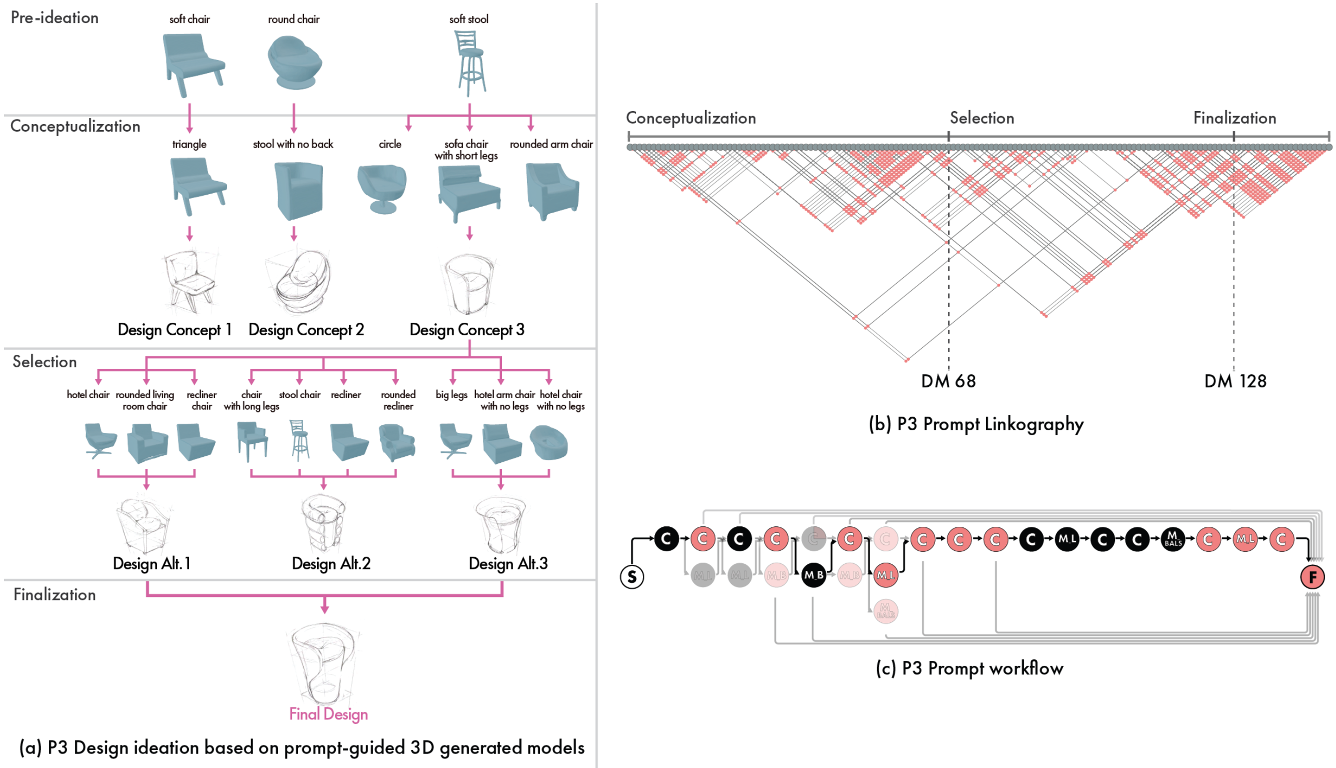
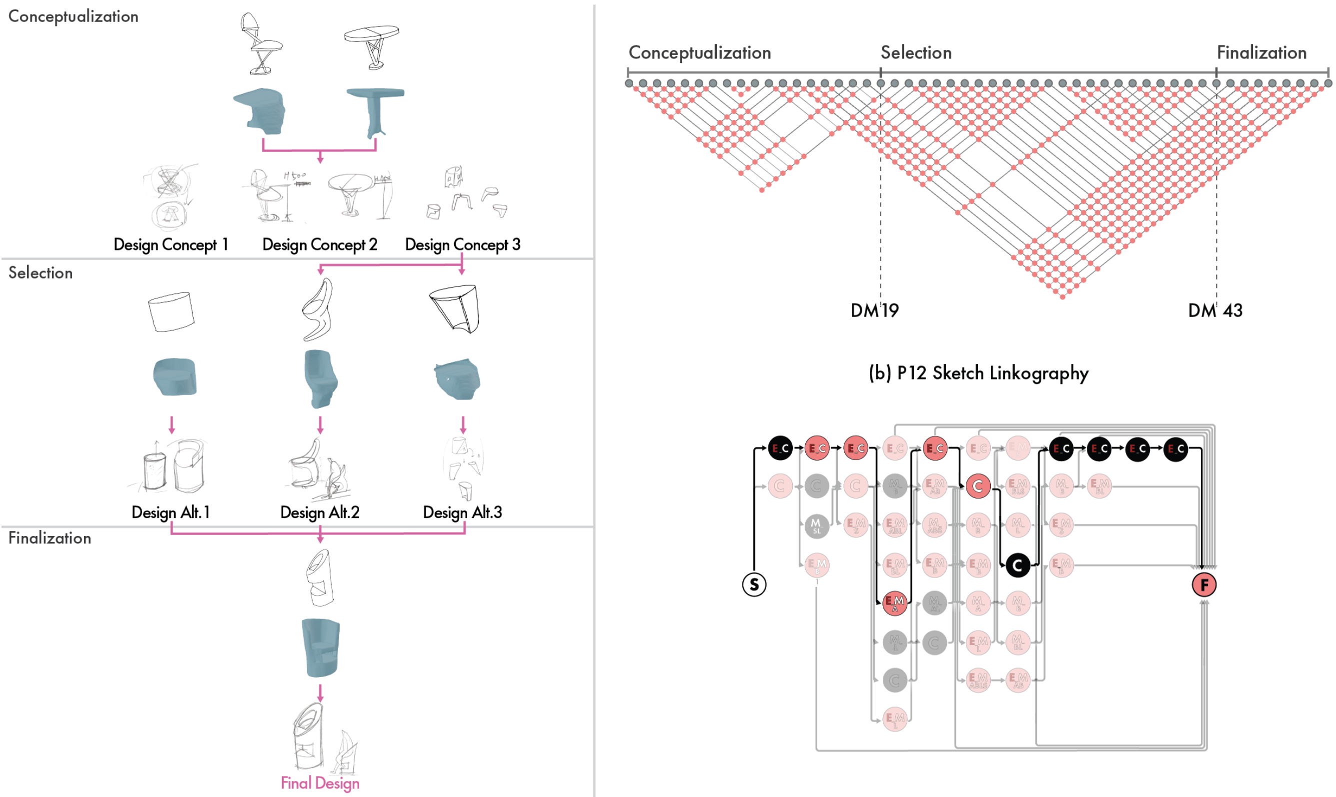


Figure 14: Analysis of P3's prompt-guided design process: (a) Design ideation process; (b) Linkography reveals a pattern of divergent thinking; and (c) Workflow depicts the extensive utilization of the system for reference checking.

misinterpreted results produced by the prompt-guided 3D GenAI intriguing and further utilized the system for more innovative design ideation, stating, *"I like it when the AI shows something nonsensical and reflects unfamiliar features, . . . I looked for features I haven't seen before and incorporated those."* Figure 14 illustrates P3's extensive use of prompt-guided systems throughout the design process. Using varied keywords, P3's distinctive approach, seeking unconventional outcomes to inform and enrich design development, suggests a minor yet another viable and interesting approach that designers can utilize throughout the latter stages of design.

Sketch-Guided 3D Generative AI System. Conversely, the sketch-guided system primarily serves as a tool for designing self-evaluation and checking ideas, which often informs participants of pivotal design decisions, as evidenced by the prime example of P12's iterative process and subsequent decisions (Figure 15). This finding indicates that the sketch-guided system provides designers with a different form of effective design assistance than prompt-guided systems. For instance, P12 highlighted its role in evaluating design feasibility—either completely overhauling its initial designs or refining and developing its current ones— emphasizing its benefits in refining intricate details and inspiring unexpected creative bursts. Specifically, P12 noted, *"I was able to use it for self-checking ideas because the design I vaguely thought of in my mind could actually change or become an impossible design. Therefore, I could use the system to check the volume or the form..."*, and further characterized the system as, *"It's advantageous in situations where you're designing directly, as it helps to refine intricate details and can inspire creativity in unexpected areas."* An analysis of the sketch-guided workflow (Figure 15-c) further reiterates its predominant use for self-checking design ideas throughout the design process. Expanding the findings in the literature [17, 28], which address the utilization of GenAI systems to support designers by facilitating the rapid exploration of design alternatives with significant ease, the findings of this study address a distinct purpose of exploration in design. The utilization of the sketch-guided system is found to be more oriented towards promoting designers to self-check their design ideations because of its ability to effectively provide interpretations of intricate design details more so than its use as a GenAI system for exploring a wider array of alternate design ideas.

Promoting Self-Evaluation with Sketch-Guided System. Our findings regarding the sketch-guided system demonstrate the efficacy of human-computer collaboration in the design process. In particular, the sketch-guided system had higher average total entropy and link index values than the prompt-guided system. We believe that this is closely related to the system's promotion of self-evaluation among designers, which in turn led to the creation of numerous informative DMs and diversified the designer's actions. Consequently, the information obtained through this process was novel. We found this trend in P1 and P2, who actively engaged with the sketch-guided system during the design-selection and finalization stages (Figure 16,17). Their interactions were marked through self-evaluations using sketch inputs. This collaboration highlighted



(a) P12 Design ideation based on sketch-guided 3D generated models

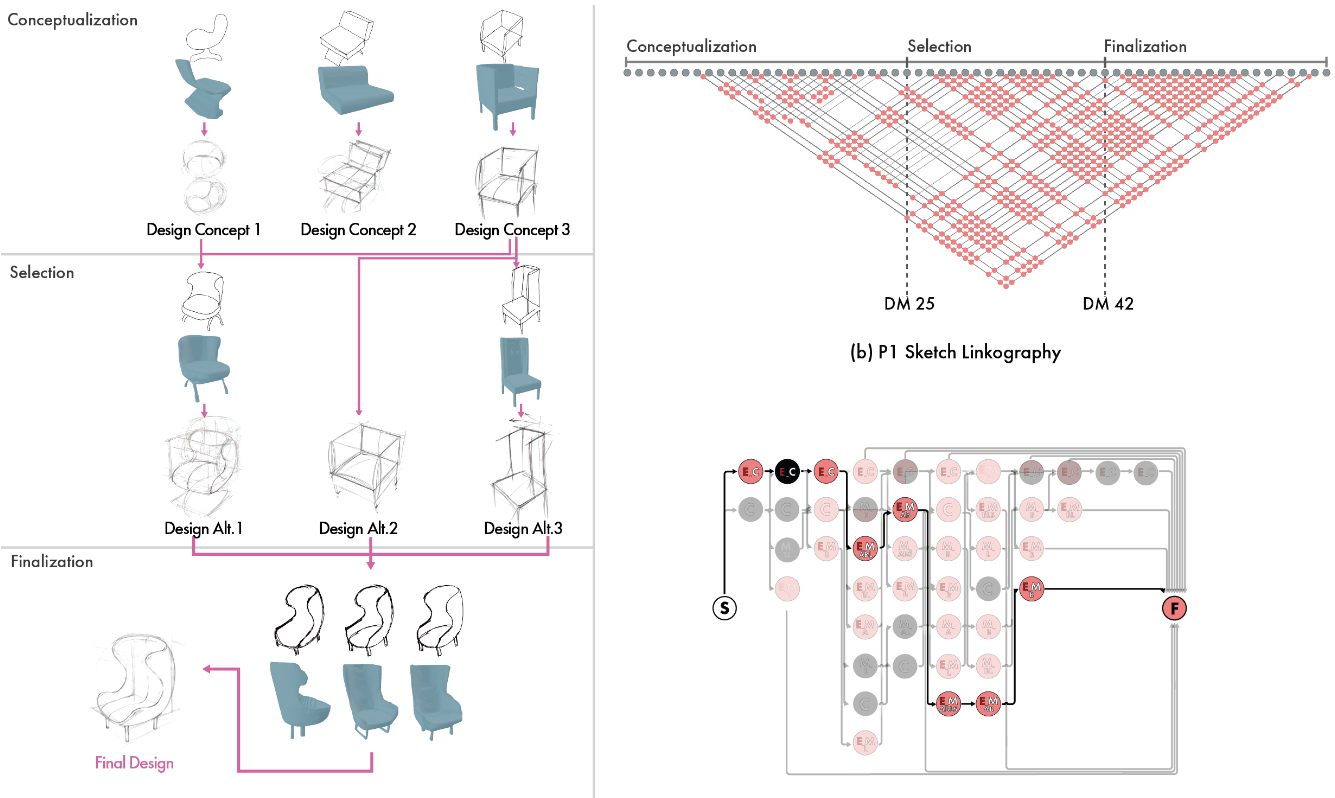
(b) P12 Sketch Linkography

(c) P12 Sketch workflow

Figure 15: Analysis of P12's sketch-guided design process: (a) Design ideation process; (b) Linkography illustrating a dense interconnected web of links reveals a pattern of convergent thinking; and (c) Sketch workflow reveals a similar iterative utilization of the system to refine design ideas.

the role of 3D GenAI in assisting designers. The system aided in the intricate refinement and development of designs, bringing to light overlooked design elements. Both participants recognized the iterative feedback loop established using the GenAI system. For instance, P1 remarked, *"Through the system, when I detailed my sketches, their 3D transformation provided insights on possible enhancements... I was able to communicate with the system."* This interaction is further illustrated when P1 observed, *"While I sketched without detailing the chair legs, the 3D renderings depicted them intricately, suggesting diverse leg connection possibilities."* In addition, P7 likened its use to ChatGPT's role in information evaluation, specifically in self-evaluation, and in facilitating iterative design adjustments. One participant, P7, drew a metaphorical comparison to ChatGPT illustrating the effectiveness of the sketch-guided system in communicating and refining design ideas, *"Similar to how GPT is widely used for evaluating whether the information I know is correct or understandable; I used this system similarly to check and see whether others will understand the design as I have envisioned... as a means of evaluating chair expressions."* The system allowed designers to explore various chair components in depth by examining AI-generated interpretations of their sketches. A key advantage of the evaluation phase is the ability to transform 2D sketches into 3D sketches, allowing for precise alterations and multi-angle reviews. P9's design ideation process is a prime example, illustrated in Figure 18, showing cases consistent with a consistent cycle of self-evaluation and iterative adjustments, culminating in a final design that met their satisfaction leading to a final satisfactory design. This pattern of iterative refinement was also evident in the workflows of other participants. This collaboration between the designer and system was invaluable. It not only directed them during the mid-to-late design stages by pinpointing areas for meticulous adjustments but also led them to their final design iterations.

Accordingly, this study accentuates the importance of understanding and leveraging the unique strengths of each 3D GenAI system within the design ideation process; understanding the distinct roles and strengths of each system is crucial in maximizing their potential. By strategically employing these systems at different stages of design ideation—prompt-guided systems for initial, wide explorations and sketch-guided systems for detailed refinement and finalization—designers can harness the full potential of the creative possibilities offered by these tools. Understanding the findings not only enhances the design process, but also provides a more efficient and effective realization of design ideas.



(a) P1 Design ideation based on sketch-guided 3D generated models

(b) P1 Sketch Linkography

(c) P1 Sketch workflow

Figure 16: Analysis of P1's sketch-guided design process: (a) Design ideation process; (b) The linkography reveals a pattern of convergent thinking in the mid-to-late stages of the design process; and (c) The sketch workflow illustrates the utilization of the system to refine design ideas.

4.2.3 Implications of Integrating Prompt- and Sketch-Guided Input Modalities. By analyzing the DMs and actions at each phase of the designer's process using linkography and workflow, we were able to make the following discoveries: users engaged in divergent thinking through the prompt system at the beginning of the design process (i.e., conceptualization stage) and convergent thinking through the sketch system during the middle and later stages (i.e., design selection and finalization stage), suggest that GenAI should provide adaptive modalities for each phase of design. Because the design process often involves iterative rather than linear progression, offering adaptive input modalities that support both divergent and convergent thinking throughout the early, middle, and late stages may lead to a more novel design process. This concept is in line with the suggestion of Zhang et al. [31] in the GenAI domain, where they proposed the simultaneous use of images and prompts as conditions. We believe that this approach is equally crucial in the 3D GenAI domain and discuss in detail how these insights can be adapted and implemented for each modality.

Prompt-Guided + Sketch Supported. As discussed in Section 4.2.1, the prompt-guided system was effective in promoting divergent thinking, particularly during the early design stages. However, their effectiveness is limited when designers want to converge the directions. We suggest that integrating a sketch modality as a support to a prompt-guided system can be beneficial particularly in the initial design stages. To illustrate this, we refer to P2's case to demonstrate how sketch modality can be used alongside prompt modality during the early stages of design. P2 extensively utilized a prompt-guided system during the conceptualization stage to extract diverse references for chair-design ideas. P2 highlighted its benefits, stating: *"It's easy to use because relevant designs appear when I enter keywords, . . . , It's convenient as I can see the results just by adding words."* P2 also added, *"However, there are difficulties because the results don't always come out as I expected."*

P2's linkography, as shown in Figure 19-b, further illustrates this pattern of usage, showcasing a divergent, idea-generating approach; it also highlights the difficulties in narrowing down the design direction. If GenAI could integrate simple sketches with prompts, it would maximize the advantages of the prompt-guided system, overcoming the difficulty of generating the desired designs. For instance, imagine a system flow as shown in Figure 20-a, where 'lounge chair' is searched first to create various design alternatives, followed by searching 'round arm' as a sketch condition. In such a scenario, designers can explore a broad design space for lounge chairs, supporting divergent thinking, and then generate variations of 'curved shape' chair designs, further advancing the design

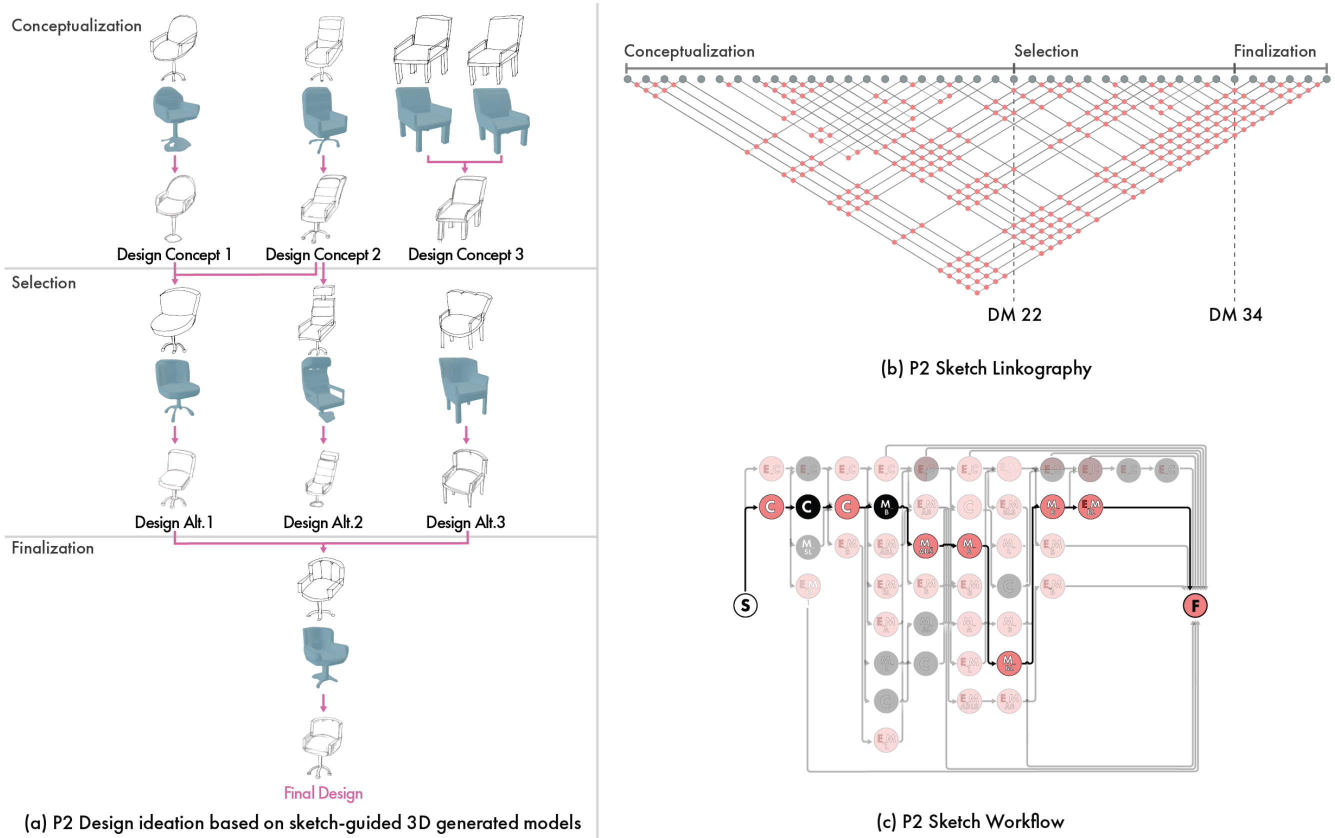
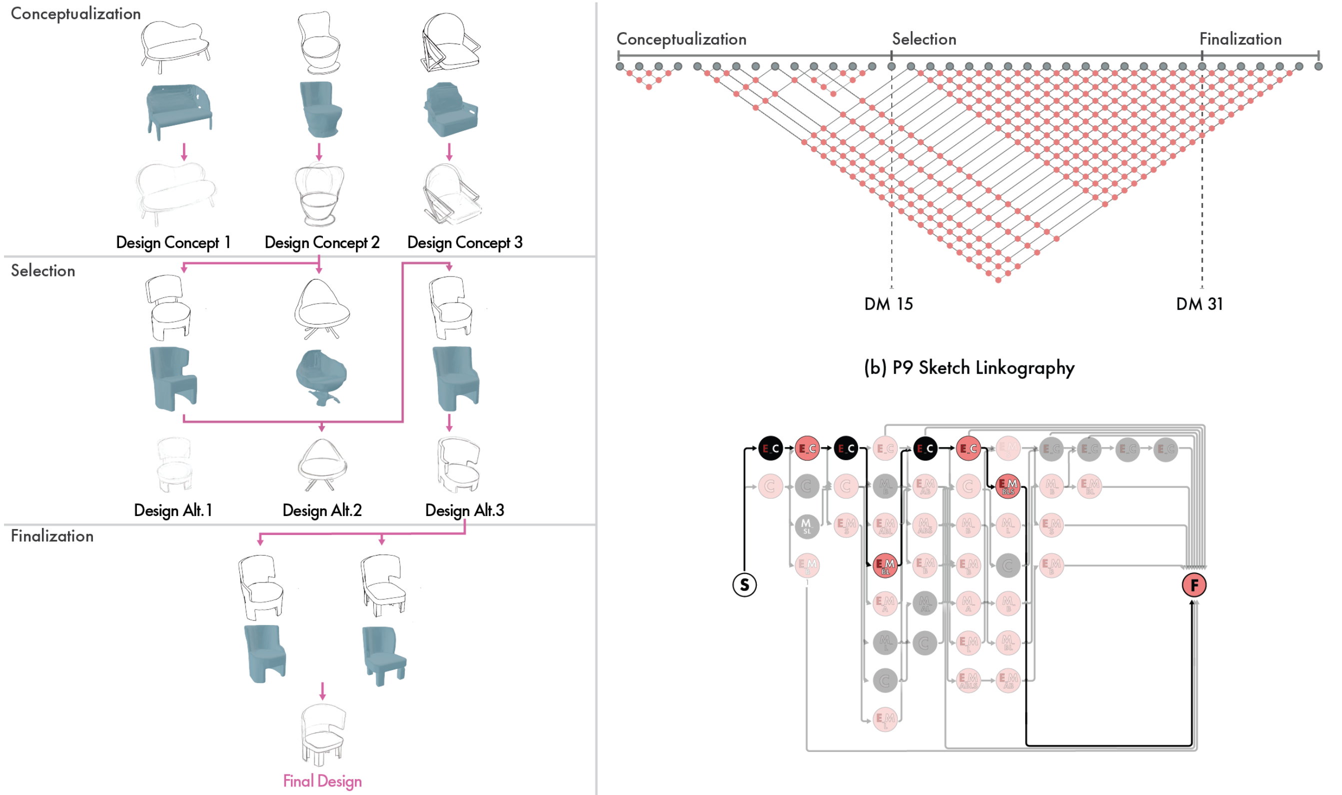


Figure 17: Analysis of P2's sketch-guided design process: (a) Design ideation process; (b) Linkography reveals a pattern of convergent thinking; and (c) Sketch workflow demonstrates the utilization of the system to refine design ideas.

process. Thus, a prompt-guided sketch-supported approach could support a cycle of divergent and convergent ideation, collecting and focusing on various design ideas, and enhancing the creative design process.

Sketch-Guided + Prompt Supported. Although the sketch-guided system supported convergent thinking during the middle and later design stages, the prompt-guided system had limitations in detailing designs at these stages. However, we observed through P9's case how the sketch modality, alongside the prompt modality, could be effectively applied even in these stages. P9 stated, *"The sketch system was great for modifying parts of the chair design and seeing the results, but it required checking all directions. ... The prompt system was useful when I needed information about parts I was unaware of."* Additionally, P9's linkography in the middle and later stages showed links formed between almost all the DMs, indicating a highly convergent design process. If the AI could understand both the sketch and text inputs simultaneously, P9 could easily explore various design alternatives within a refined design direction. For example, as in the system flow shown in Figure 20-b, if a designer's detailed sketch and a prompt like 'more curved back' are understood by the system, the designer could review multiple 3D design outputs from a single sketch. This would not only bring out the 'unexpected idea discovery' advantage of the prompt system in the middle and later stages, but also significantly mitigate the labor-intensive nature of the sketch-guided system. Thus, a sketch-guided prompt-supported 3D GenAI could encourage self-checking to support convergent ideation, while also creating microvariations within a design direction to support divergent ideation.

In conclusion, our research accentuates the profound synergy between designers and 3D GenAI systems, highlighting the necessity for adaptive integration of sketches and prompt modalities in each design process by analyzing linkography and workflow graphs. This relationship exemplifies the possibility of strong human-computer collaboration throughout the ideation, development, refinement, and finalization stages of the design process. Our experimental findings revealed that each modality has unique advantages and limitations at different stages of the design process, suggesting that their combined use can facilitate both convergent and divergent design ideation, thus supporting a more creative design process. Using this combined approach, designers can leverage the strengths of both modalities to enhance their creative design processes. Thus, it is vital to acknowledge that both 3D GenAI systems are invaluable design tools, with each playing a distinct and crucial role in the design process.



(a) P9 Design ideation based on sketch-guided 3D generated models

(b) P9 Sketch Linkography

(c) P9 Sketch Workflow

Figure 18: Analysis of P9's sketch-guided design process: (a) Design ideation process; (b) Linkography reveals a pattern of convergent thinking; and (c) Sketch workflow illustrates the system's utilization to refine design ideas.

5 CONCLUSIONS

We investigated the utilization of both sketch- and prompt-guided systems as design tools in the design process with linkography and workflow graphs, and analyzed their distinct contributions to the design process. The results highlighted that the sketch-guided system primarily facilitated a convergent design process, particularly during the mid-to-late stages of the design process, emphasizing a denser design ideation process. Its primary use has emerged as a tool for self-evaluation. Conversely, a prompt-guided system encourages a divergent design process in the initial stage of the design process, promoting a wide spectrum of design ideations and serving primarily as support in design exploration and idea referencing. This emphasizes the need for 3D GenAI systems that can simultaneously condition sketches and prompt modalities. Specifically, a system that bases prompts on simple sketch conditions could help narrow the design space in the initial and divergent stages of design, whereas conditioning prompts on specific sketches could easily create various variations within a concrete design direction during the convergent middle and later stages. Based on these findings, future research into integrating both GenAI modalities across design stages can enhance the design process and facilitate collaboration between humans and AI.

Although our experiment was conducted in a laboratory setting to simulate an environment as close as possible to the actual design practice, it is important to note that a real-world professional setting may yield different detailed results for the link index, entropy, and workflow graphs. Also, during our experiments we observed that some users found it challenging to use the system when the 3D GenAI outputs did not align with their intentions. This suggests the necessity for further research on the impact of 3D GenAI adjusted with user feedback using reinforcement learning from human feedback (RLHF) or integrated with user intent inference models, such as the Bayesian information gain framework and preferential Bayesian optimization, on the design process. In conclusion, we hope this study lays the foundation for a 3D GenAI framework by highlighting the unique contributions of input modality throughout the design process, encouraging further research in this domain.

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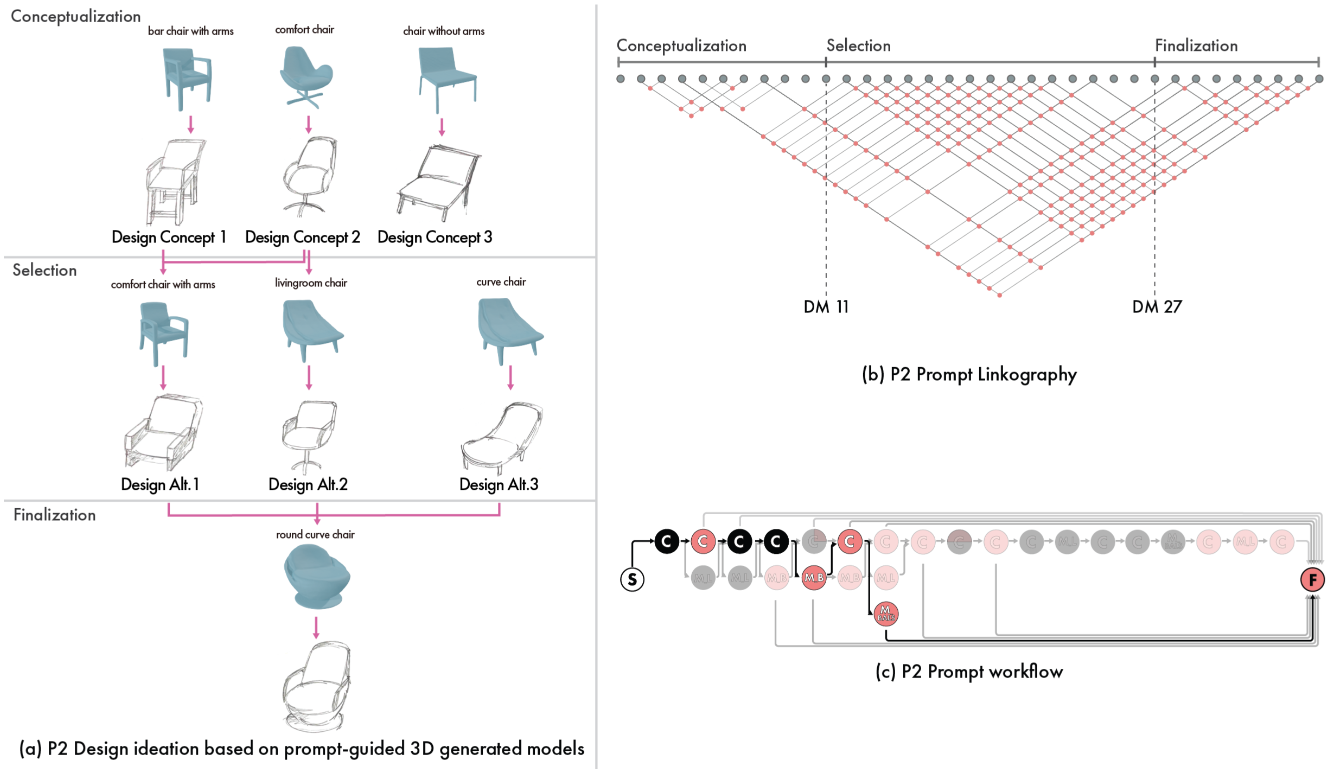

(a) P2 Design ideation based on prompt-guided 3D generated models

(b) P2 Prompt Linkography

(c) P2 Prompt workflow

Figure 19: Analysis of P2's prompt-guided design process: (a) Design ideation process; (b) Linkography reveals a pattern of divergent thinking; and (c) Workflow depicts the system's primary utilization for reference checking.

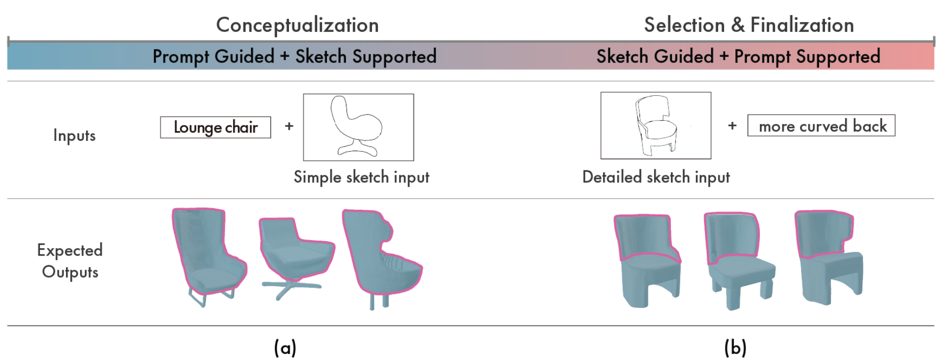

Figure 20: System flow model of Sketch and Prompt modality integrated system: (a) prompt-guided and sketch supported; and (b) sketch-guided and prompt supported.

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