Catalyst for Creativity or a Hollow Trend?: A Cross-Level Perspective on The Role of Generative AI in Design

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Abstract

Generative AI image creation tools have the potential to transform design education and practice, but raise critical concerns for creativity and ownership. We leverage the 2022 launch of tools like Midjourney and DALL.E as a point dividing design enthusiasts into pre- and post-tool learners. In this paper, we conduct 28 artifact-based interviews with designers at varying levels of tool introduction, to understand how they perceive and use generative AI in their design roles. Our results indicate a rift in the value system of designers, with experienced designers being more circumspect about the loss of traditional creativity and foundational design skills. On the practical side, there exists a tension between the growing marketability of AI-related skills for design vs. the limited affordances of these tools for achieving meaningful designs. We discuss implications for the shifting definitions of design as a field, creativity and ownership, and AI in the design curriculum.

CCS Concepts

• **Human-centered computing → Empirical studies in HCI**; • **Applied computing →** *Arts and humanities.*

Keywords

Generative AI, Design, Creativity

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1 Introduction

Recent advances in text-to-image models have propelled generative AI into mainstream use for graphic design for all skill levels. Generative AI for image generation traces its roots back to 2014 with the introduction of Generative Adversarial Networks (GANs) [39]. This breakthrough with GANs laid the foundation for further advancements, including architectures like variational autoencoders (VAEs) [56], diffusion models [45, 93], etc., which significantly enhanced the image creation capabilities of generative AI. Building on these foundational models, text-to-image tools like Midjourney [48], Stable Diffusion [4], and DALL.E [7, 80] allow users to create high-quality images from textual descriptions or early-stage visual inputs and editing instructions. Easy access to generative AI has effectively democratized visual expression by reducing the reliance on traditional artistic skills and knowledge [19, 88].

In making design accessible to more users from diverse backgrounds and skillsets, generative AI has the potential to reshape design learning and practice. Novices and enthusiasts, who may lack advanced design skills or artistic knowledge, can now produce high-quality images, easing their visual creativity and expression [9, 19, 88]. However, the tool can be a crutch and impact their learning of foundational design skills [31, 69]. For professional designers, the feeling may be that their roles and opportunities in the industry are being threatened by the accessibility of these powerful tools [49, 61, 101]. After all, these tools lower the barriers to creating high-quality visuals, simplifying certain aspects of design work. This democratization might lead to concerns among professionals about the potential devaluation of their expertise, as individuals with less design skill could encroach on their professional territory [82]. On the other hand, generative AI holds the promise of enhancing efficiency in current workflows, particularly by supporting ideation processes and the rapid creation of prototypes. Several studies have focused on developing AI-based systems for image generation to streamline specific workflow phases, highlighting both the opportunities and uncertainties brought about by this technological shift [14, 18, 65, 94].

However, salient aspects of the design process—such as creativity and ownership—once purely human-centered, now become distorted with generative AI in the loop. Creativity has always been a fundamentally human concept [35, 84], with technical approaches performing a support role (e.g., fixing lines and angles, color correction, post-hoc image editing, etc.). Even when technical approaches transformed into creativity support tools, they were included in specific processes within the design task (e.g., brainstorming different ways to sketch a known object [52], visualizing 2D drawings in 3D [67]). The core ideation and creation processes, stylistic identity, and ownership aspects of design were not challenged when AI performed these support roles. With generative capabilities, the new AI models and tools can influence more critical aspects of the creative process and product, raising questions like: what are the fundamental skills and processes we expect from trained designers,

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and who has ownership over the final design artifact? As we try to answer these questions, the AI technology continues to get more advanced, making it hard to capture its longitudinal impact.

In this work, we take a cross-level comparative approach to understanding the impact of generative AI on stakeholders with varying levels of expertise, focusing on both the learning and practice of design. We leverage the mainstream introduction of these tools (e.g., Midjourney, DALL.E, Stable Diffusion) in 2022 as a longitudinal point that stratified designers into groups that learned design skills pre- or post-tool availability. This split design stakeholders evenly at three levels of experience: (1) first- and second-year undergraduates in design (junior students), i.e., new students who began their design education *after* generative AI became commonplace in design; (2) third- and fourth-year undergraduates and and graduate students in design programs (senior students), i.e., experienced students for whom generative AI was introduced *midway through* their design education; and (3) design professionals, who were graphic designers in practice *before* the latest developments in generative AI. We conducted artifact-based interviews with these design stakeholders (N = 28), focused on answering the following research questions:

RQ1. How has the integration of generative AI changed the design practice?

RQ2. How do people navigate ownership of design artifacts when using generative AI tools?

RQ3. What, if any, changes are needed in design education to account for these new technologies?

Our findings reveal a growing rift in the value system of designers at different levels of expertise and generative AI introduction timeline. Experienced professionals express concern over the erosion of traditional creativity and foundational design skills, while junior designers are more enthusiastic about embracing the potential of AI. Extending this divide to design learning and curriculum, junior students advocate for early AI integration, while senior students and professionals stress the importance of foundational skills before adopting these tools, to the extent of suggesting restricted access to them earlier in the program. A debate on ownership emerges about the design artifacts produced, with junior students viewing AI as a collaborative tool and others worrying about the blurred lines between originality and plagiarism. Finally, despite the growing marketability of AI-related skills, the limited affordances of AI-generated outputs reveal a tension between the increasing demand for these tools and their practical limitations in achieving meaningful designs. On this last aspect, experiences of all levels of designers are aligned, begging the question: is current generative AI useful in design or a hollow trend? We discuss the implications of these results, including what computationally-mediated creativity looks like compared to known models of creativity (e.g., Sawyer's eight characteristics [89]), how we might regulate generative AI based on known frameworks for dual-use technology, the essential features of a generative AI tool for design practice, and opportunities for positive support from generative AI in design learning.

2 Related Work

2.1 Models of Creativity

Creativity is central to the social and intellectual evolution of people—people often use it as a mechanism for articulating and critiquing their relationship with themselves, others, and society [35, 84]. To concretize this in practice, creative artifacts are evaluated based on three criteria: (1) novelty, i.e., how innovative the idea is; (2) quality, i.e., how appealing or feasible the idea is for the task it was proposed for; and (3) contextual relevance, i.e., the social and emotional connection it evokes pertaining to a specific task or period of time [53, 68].

Many scholars have sought to articulate the stages of the creative process. From Graham Wallas' four-stage model published in 1926 [102] to Mumford et al's eight-stage one published in 2012 [72], most models describe creativity using stages related to finding the problem; acquiring the knowledge; gathering related information; incubation of ideas; idea generation, combination, and selection; and externalizing the idea [8, 10, 85, 89, 95]. While Wallas' model—being the first—described these stages as linear, others extended his work and showed that people go through these stages in a more dynamic and cyclical fashion [8, 85].

More recently, Keith Sawyer proposed a model that moves away from discrete stages altogether, instead framing creativity as an nonlinear, iterative, and improvisational process [89]. Rather than processes or stages, Sawyer's model identifies eight essential characteristics of creativity. First, *iteration*, a characteristic that represents the unpredictable, non-linear shifts in the directions that ideas take. This applies to all elements of creativity, from brainstorming to externalization. Second, creativity thrives in *ambiguity*, when people have to engage in finding and defining problems as much as solutions. Third, *exploration*, i.e., the experimentation and trial and error that people go through to discover the right problem definitions and solutions. Fourth, *emergence*, which describes the procedural nature of creativity, in that ideas emerge from making and doing rather than the latter processes happening after an idea has been established. Fifth, *failure*, which is a critical learning step in problem definition and idea evolution, and speaks to the improvisation necessary in achieving good quality creative outcomes. Sixth, *deliberate intentionality*, a characteristic Sawyer uses to fundamentally reject the idea that creativity is a mysterious process that results from "unconscious incubation" of ideas or a "self expression of an inner voice" [89]. Instead, creativity is deliberate and intentional. Seventh, *conscious reflection*, which is the procedural equivalent of deliberate intentionality. It helps people evaluate and refine whatever processes they have for engaging in creative endeavors. Eighth, *constraints*, which notes that creativity cannot be completely open-ended and unstructured, as this can lead to decision paralysis on how to proceed. This characteristic rings true particularly for people new to creative endeavors (novices, students, etc.). In this paper, we consider the influence of generative AI tools on people's creative processes and outcomes, and how these tools shape the characteristics of creativity defined above. With prior knowledge of these different models of creativity, our work offers an opportunity to explore whether generative AI alters or reinforces traditional creativity stages in design workflows.

2.2 Creativity Support Tools

Creativity support tools (CSTs) have been an area of innovation since before AI and intelligent systems were used for design. Broadly defined as digital-interactive tools for the enhancement of creativity [90], for design, these have taken the form of sketching and editing support, and brainstorming ideas [20, 33, 62, 76]. For instance, Karimi et al. introduced a creative sketching partner aimed at helping designers avoid stylistic fixation in a design task [52]. They categorized participants' behaviors into three creativity types: combinatorial, exploratory, and transformational. Their system effectively facilitated ideation and helped designers overcome fixation. Similarly, Davis et al. presented the Drawing Apprentice, a co-creative drawing application that collaborates with users in real-time to create abstract drawings [24]. CSTs are particularly popular in game design: they lend themselves to automated elements of game level design [67] and customizing visuals [63].

2.2.1 Generative AI for Creativity Support. Traditional CSTs support various stages of creativity in generating and refining ideas, keeping people in control of the creative process. In contrast, generative AI has the potential to shift this dynamic, with AI autonomously producing outputs. The landscape of generative AI image creation has undergone significant transformations: starting with Generative Adversarial Networks [39, 71, 109] and Variational Autoencoders [56], to transformer-based models (e.g., ImageGPT [16]) and diffusion models (e.g., DALL.E [7, 73, 80], Imagen [86]).

With generative AI models and architectures being easily accessible, research has capitalized on these technologies to propose innovative CST formats. One common class of CSTs offers a natural language component along with image generation, so that end-users can easily communicate their desired outputs via prompts. Example systems that rely on this combined approach include Opal for creating news illustrations [65]; PromptCharm [104] and Promptify [9] for prompt exploration and refinement; and DesignAID for a two-step idea generation and visualization approach to avoid fixation [14]. Instead of purely text-based generation, Paint-By-Example allows users to share example images as seeds for image generation [108]. Combining text- and example-based approaches, Son et al.'s system finds suitable text for initiating searches or discovering images for similarity-based searches [94]; and Creative-Connect does the same with keywords and images [18]. CICADA, a vector-based generative AI approach [46], and Reframer, a drawing interface built on CICADA [59], allow users to interact with generative AI through shared drawing. PromptPaint follows a similar drawing approach, but with a shared canvas that allows area-specific prompting [19]. For long-form design, Antony et al. combine Chat-GPT and Stable Diffusion to generate and synchronize story elements in their multi-stage visual story authoring workflow, ID.8 [6]. Clearly, generative AI-based CSTs are a popular research avenue.

Beyond academic research, a wide array of generative AI image creation tools are available in industry and widely adopted by stakeholders. Notable examples include Stable Diffusion [4], Midjourney [48], DALL.E series [73–75], Craiyon [30], and Leonardo.Ai [1]. These systems boast user-friendly interfaces, and with their natural language interaction component, they are used by individuals with varying expertise. As the accessibility and adoption of generative AI-based CSTs rises, we seek to understand the impact of these tools on people's design workflows and outputs. To that end, we consider questions such as: does AI remain an assistive tool, or does it change how people generate and develop ideas? Our study also explores how different user groups adapt to this shift in creative control. To scope this work, we focus specifically on generative AI CSTs that facilitate visual design tasks (e.g., DALL.E, MidJourney).

2.3 User Perceptions on Generative AI for Creativity

Although human-centered research cannot always keep up with the pace of technical advancement in generative AI, there is important work that studies and theorizes about relevant factors. Thibault et al. [97] provide a framework for studying the impact of generative AI on a creative ecosystem, grounded in Actor Network theory. They propose a cross-sectoral approach to navigate AI's effects on labor, professionalization, and management across various industries; at each level, theorizing about AI's role as expanding, cloning, replacing, or surpassing human agency. Weisz et al. [105] propose six principles for designing generative AI applications, addressing challenges such as variability, co-creation, and user trust. Rezwana and Maher [82] explored ethical dilemmas and challenges in human-AI co-creation, using a design fiction methodology. They collate key themes of ethical challenges, such as ownership, collaboration vs. leadership roles, accountability, data concerns, and personification of co-creative AI. Van Der Maden et al. [98] also raised questions about authorship and ethical considerations in a workshop setting.

Similar to our goals, several studies have surveyed people's use of generative AI in design settings with mixed findings. Li et al. [61] interviewed 20 UI/UX designers across various organizations and found that while they acknowledge the role of generative AI as an assistive, experienced designers remain confident in their originality, creativity, and empathy. Vimpari et al. [101] investigated the perspectives of game industry professionals on generative AI image creation, with some expressing concern that its potential impact could devalue creative work and discourage the learning and application of traditional artistic skills. Inie et al. [49] qualitatively surveyed 23 creative professionals on their perceptions of generative AI, bringing up concerns such as diminished output quality, a weakened creative process, and copyright issues. However, participants also highlighted reasons for optimism, including the belief that AI cannot produce outputs without human input, resulting in a proposed participatory AI framework for creative AI. Chiou et al. [17] conducted empirical research-through-design activities to understand how designers ideate with AI, uncovering similar opportunities and challenges in AI-assisted collaboration. Focusing more on novice use-cases, Sanchez [88] explored the social aspects, motivations, and practices of AI art hobbyists. For this population, they identified five main motivations for using text-to-image generators: leisure, curiosity, self-expression, work-related reasons, and the creation of design artifacts. Overall, for novices generative AI image generation is often seen as a recreational activity.

We build on this work by taking a cross-level comparative approach on similar questions about the use of generative AI in design workflows. By comparing the experiences of people at different career stages when generative AI was introduced for public use—junior students, senior students, and design professionals—we seek to add clarity on how, why, and where these perspectives differ. Moreover, our cross-level approach describes perspectives on not only the practice of design, but also on learning and education.

Type	ID	Major Field of Study	Level of Experience	Primary Tools
Junior Design Student	P1	UI/UX	5	Canva, DALL.E, Meta AI
	P6	UI/UX	6	Meta AI
	P15	UI/UX	6	Meta AI, MidJourney, Craiyon, DALL.E
	P17	Typography Design	7	DALL.E, GANBreeder
	P18	Game Art and Design	6	MidJourney, Leonardo AI
	P19	Creative Technology and Design	7	MidJourney, Meta AI
	P20	Graphic Design	7	Meta AI, Craiyon, MidJourney, Adobe Firefly
	P22	Design	7	MidJourney, DeepArt, Craiyon, Art Breeder, Stable Diffusion
	P23	Animation	6	MidJourney, Meta AI
	P25	Web Design	5	Canva, DALL.E
Senior Design Student	P4	Computer Science	5	MidJourney, Starland AI
	P5	Graphic Design	5	MidJourney, Stable Diffusion, Adobe Firefly
	P7	UI/UX	7	Craiyon, Photoshop
	P8	Arts	6	Leonardo AI
	P9	Computer Science	6	Canva
	P10	Graphic Design	6	Adobe Firefly, MidJourney, Stable Diffusion
	P13	Graphic Design	7	Microsoft Designer, Photoshop
	P16	Graphic Design	7	Adobe Photoshop, Art Breeder, Deep Dream Generator
	P24	Animation	7	MidJourney, Stable Diffusion
	P26	Industrial Design	7	MidJourney, Stable Diffusion
Design Professional	P2	Architecture	7	DALL.E, MidJourney
	P3	Data Analysis	6	Canva, Gemini, DALL.E
	P11	Graphic Design	7	Stable Diffusion, Adobe Firefly, NightCafe
	P12	Graphic Design	7	Adobe, MidJourney
	P14	Graphic Design	6	Stable Diffusion, Adobe Firefly, NightCafe
	P21	Photo Design	6	MidJourney
	P27	Web and Graphic Design	7	DALL.E
	P28	Industrial Design	7	MidJourney, DALL.E, Adobe

Table 1: Participant categories, their fields of study, level of experience with generative AI (scale of 1–7), and primary tools used.

3 Methods

Our goal was to understand perspectives of designers at different levels of expertise on the integration of generative AI in design education and practice. To that end, we conducted 28 semi-structured interviews with an artifact-based component. Our participants were categorized at three levels of experience with generative AI: (1) junior design students (first- and second-year undergraduates), i.e., new students who began their design education *after* generative AI became commonplace in design; (2) senior design students (third- and fourth-year undergraduates, as well as graduate students), i.e., experienced students for whom generative AI was introduced *mid-way through* their design education; and (3) design professionals, who were graphic designers in practice *before* the latest developments in generative AI. Our study protocol and methods were approved by the University of Minnesota Institutional Review Board.

3.1 Participants

We recruited participants via university student groups, mailing lists for design departments, social media (Reddit, Instagram), and snowball sampling. We shared our recruitment flyer in our posts, with a link to an intake survey on Qualtrics. The survey collected demographic details, verified eligibility, and assessed participants' prior experience with generative AI image generation tools.

From the pool of survey respondents, we selected people who fulfilled our inclusion criteria: (1) age (>18 years), (2) residents of the United States, (3) some level of prior experience with generative AI image generation tools (>2 on a scale of 1–7), and (4) willingness to share an image artifact they had previously created using these tools. Our consent form was also shared via this Qualtrics survey. A total of 397 individuals consented to the study, and 46 were selected based on the eligibility criteria, with 18 participants subsequently withdrawing due to unanticipated time conflicts.

Our participants ($N = 28$) comprised 10 junior students, 10 senior students and 8 design professionals. Table 1 lists each participants' category, field of study, and level of prior experience with generative AI tools. Participants ranged in age from 20 to 52 years (M = 25.9, SD = 5.14). Our sample included 20 males (1 identified as cisgender male), 7 females, and 1 queer participant. In terms of proficiency with generative AI tools, 10 participants identified as advanced users, 16 as intermediate, and 1 as a beginner. For their prior experience with generative AI tools, 12 participants reported 1-2 years of experience, 8 had more than 2 years of experience, 7 had 6-12 months, and 1 participant had less than 6 months of experience.

Participants were interviewed via Zoom between June and August 2024. Upon completion of the interviews, they were compensated with a $25 gift card to either Target or Amazon, whichever they preferred. The interviews typically lasted between 30 and 45 minutes, 33 minutes on average.

3.2 Interview Procedures

We conducted artifact-based, semi-structured interviews with 28 participants.[1] Each interview began by re-affirming participants' eligibility and consent. Despite having multiple response and fraud

[1]Our semi-structured interview protocol is included as Appendix A.

detection activated in our Qualtrics intake form,[2] we noticed almost identical responses from a few of our initial participants who joined the interview in an audio-only capacity on Zoom. We excluded this data and updated our protocol to include a video requirement for the consent procedure and initial background questions, to ensure legitimate participation. Strategies for fraud detection, identity verification, and experience matching have become increasingly critical in qualitative research conducted via online platforms; we followed the suggested guidelines from prior work for handling this [77].

3.2.1 Background and Context-Building. Post-consent, our interview began with background questions about prior experience with design and any generative AI tools used in participants' current design workflow. We asked context-building questions about the types of tasks these tools were used for, their familiarity and engagement with the past and current features of these tools, and, at a high-level, what was (not) useful about them. This part of the interview was intended to establish people's current understanding of these tools and their capabilities, and their feelings about usage.

3.2.2 Artifact Discussion. The second segment of the interviews centered around an artifact (i.e., an image) that each participant had previously created using a generative AI tool. Participants were asked to share this artifact in advance, with consent obtained during the intake process. Participants did not create artifacts for our study; we simply asked them to share something they had already created in any capacity such as for personal use, a class project or for work. This artifact-based component asked similar questions about tool familiarity and use, engagement, and feelings, but now with a clear artifact in mind during the conversation. Artifact-based interviews are known to be an effective recall strategy that helps people ground their experiences with a technology [22, 27, 43, 54, 70, 103]. Questions in this segment explored various dimensions of people's interactions with generative AI tools in designing the artifact, including: (1) motivation behind the design idea; (2) why they relied on generative AI for this design task; (3) details of generative AI workflow (e.g., the level of prompting needed, their own edits if any); (4) challenges and opportunities specific to the use of generative AI for their design task; (5) their notion of ownership of the final design; and (6) general satisfaction with the final product as well as the AI-supported design process.

3.2.3 Semi-Structured Follow-up. The third part of the interview was designed to elicit perspectives on the impact of generative AI on design education and practice. The language of the questions here varied depending on the stakeholders' experience levels. For example, for a junior student, the classroom is the current context and design jobs are future context; these contexts differed for a design professional. Participants were asked to discuss their experiences using these tools for learning and skill development, as well as the potential impact of AI on traditional design education. Similarly, the interview questioned the implications of generative AI image creation tools in the professional design industry. This section aimed to capture participants' perspectives on the current and long-term impact of AI on design education and profession.

[2]https://www.qualtrics.com/support/survey-platform/survey-module/survey-checker/fraud-detection/

3.3 Analysis

We used auto-generated transcripts of interviews from Zoom recordings as our raw data, and edited these transcripts (as needed) by reviewing the original recordings. We assigned participants anonymous identifiers and did not record any identifying information about them or their design experience in the transcripts.

The interview data was analyzed using Braun and Clarke's approach for inductive thematic analysis [11, 13]. Two researchers conducted open coding on the data using Dedoose, a qualitative research tool. Open coding was applied across all three categories of participant design experience consistently. The initial set of codes was then reviewed collectively by all three researchers, leading to some re-coding. Subsequently, all three researchers participated in axial coding, wherein they organized the open codes into themes using affinity diagramming. At this axial coding stage, participant experience categories (junior students, senior students, and design professionals) were re-introduced to understand if any differences existed in their responses. This comparison of codes amongst the three participant categories was done iteratively until we found thematic clusters that contextualized our research questions.

4 Results

We discuss themes from our participant interviews at two levels: high-level descriptions of their perspective on the opportunities, challenges, and use-cases of generative AI in design learning and practice; and low-level grounded experiences in generating a design artifact. Table 2 presents a summary of our results and Figure 1 showcases a subset of design artifacts shared by our participants, added here with their consent. For brevity, we use the term "AI" to represent "Generative AI" in this section.

4.1 The Impact of AI on the Design Workflow

4.1.1 Junior Students: Embracing AI for Efficiency and Creativity. Junior design students (i.e., first- and second-year undergraduates) perceive AI as a transformative force in the design process, one that offers a practical means to streamline and enhance their work. They appreciate how AI can act as a "shortcut" (P15), making the design process "faster, more efficient, and cost-effective"(P19). These outputs are produced by AI with "relative ease" and are "high-quality" (P22). AI assists designers in being creative with their initial ideas, and in refining and completing final products. Speaking about the efficiency of this new AI-supported creative design process, P18 notes:

> "Before, when you wanted to design something and did not know exactly what... you draw, you brainstorm, you go through a lot of drawings like this which could take a lot of time... But now, if you're trying to brainstorm, it doesn't even take you 3 hours to generate more than 50 pictures you could actually have different ideas from... It's like collaborating with your own private designer."

However, this positive sentiment is not unanimous—a small minority of junior students express concerns about traditional design practices becoming obsolete. These individuals acknowledge the ongoing shift towards AI-driven design but argue that the foundational principles of traditional design should still hold value.

Theme	Junior Students	Senior Students	Design Professionals
Impact of AI on the Design Workflow	Use AI for efficiency and creativity; view AI as a collaborative tool that accelerates idea generation.	Integrate AI strategically to enhance creativity and problem-solving; balance technical skills with creative vision.	Cautiously use AI as an assistant; worry about over-reliance diminishing creative skills and traditional expertise.
Designers' View of Client Perceptions of AI Skills and Use	AI proficiency boosts marketability and signals competence; expect AI to be integral in client projects.	AI skills seen as essential for meeting client demands of efficiency; emphasize strategic use of AI.	AI lowers skill barriers, leads to higher client expectations, and potential devaluation of design skills.
Defining Design Skills in an AI-Assisted Future	Believe AI will redefine design skills; prioritize proficiency with AI tools over traditional methods.	Maintain that creativity remains core; advocate for a hybrid skill set combining AI proficiency with foundational design knowledge.	Stress the necessity of traditional skills; view AI as supplementary tool and caution against it replacing fundamental design competencies.
AI in the Design Curriculum	Advocate for integrating AI into the curriculum as essential for modern design education.	Recommend introducing AI after foundational skills are established; caution against early reliance on AI.	Support a balanced curriculum with both skills; recognize some benefits afforded by AI; question design as a standalone curriculum.
Ownership and Intellectual Property	View AI as a co-author, sharing ownership of designs; acknowledge collaborative creation with AI.	Link ownership to the extent of their input and editing; see AI as a tool rather than a co-creator.	Assert that ownership lies with designers or AI developers based on tool usage; emphasize accountability and intellectual property rights.
Practical Challenges with AI in Design	Struggle with prompt engineering and achieving desired specificity; experience frustration with inconsistent outputs.	Face issues with prompt precision and tool reliability; manage technical constraints and cultural biases in AI outputs.	Deal with reliability and consistency across AI tools; navigate technical/resource limitations and biases in AI-generated designs.

Table 2: Summary of Results: Perspectives on AI in Design Across Stakeholders

Designs created through personal effort and craftsmanship should be highly regarded, as P17 explained:

> "Something you made with your sweat and something you made [yourself] physically is always going to be more expensive than something you did with a machine, because there is sentiment."

Despite their concerns, they recognize that the industry's trajectory seems to be moving towards greater reliance on AI, suggesting that its centrality in the field is becoming inevitable. All junior design students feel this way, whether they are coming from a positive, enthusiastic place (majority) or resigned to this outcome (small minority).

4.1.2 Senior Students: Strategic Integration of the Technical (AI) into the Creative. Senior design students (third- and fourth-year undergraduates, as well as graduate students), like their junior peers, agree that AI makes the design process much more efficient, saving time and cutting down on costs by reducing the need for "manual labor" (P16). However, they also note that AI shifts the focus of design from pure creativity to "strategy and problem-solving" (P13). In this AI-driven environment, creativity is no longer solely about ideation but about how effectively designers can combine their technical skills—or technical understanding of AI—with their creative vision. P13 hints at this strategic use of AI tools to "provide fresh ideas and creative directions that designers might not have considered."

Participants brought up several interesting variations of relevant technical aspects, such as: (1) a data-driven component to creativity, where designers have to try different approaches (e.g., prompts) and test which results in the best design outcome (P4,P24); (2) abstract conceptualizations, because AI can generate unexpected outputs about known things, different from what a human mind would conceive (P5,P8,P10); and (3) knowledge of computational resource allocation, because paywalls and differences in model capabilities lead to wildly different outputs (P9,P26).

While AI offers powerful tools to streamline the design process, senior students believe that successful results still depend on a solid foundation in traditional design skills. They emphasize that AI can enhance these skills but cannot replace them. Of course, understanding how to effectively communicate with AI (e.g., through the right prompts) is essential to achieving the desired results. However, what is critical is having the foundational design knowledge because you need the "right design language to get what you want from the design process, with or without AI" (P10).

4.1.3 Design Professionals: Cautiously Balancing the Benefits and Risks of AI in Design. Design professionals recognize the efficiency and time-saving benefits that AI has brought to the design process, yet they express reservations about over-fitting on these advantages. Their perspective diverges from students in that they see AI as altering the skill requirements for design, but not necessarily in a beneficial way. There is a concern that AI has enabled individuals to claim proficiency in design through a process of "trial and error" (P14) with AI prompts, rather than through actual skill development.

Moreover, design professionals like P11 worry that relying too heavily on AI can lead to a decline in designers' creative abilities:

> "AI can sometimes diminish your creative skills...like if you are dependent on AI to make most of your creation, your own creative skills begin to die off because you're [only] looking at outputs from tools...and then

> you're off, you've created an image...Designers are going to be very lazy."

Design professionals believe that AI cannot serve as a standalone design tool; it cannot even be an equal partner in a collaboration. At best, it can be viewed as an assistant in the design process, one that you rely on to get to the final product more quickly. It cannot, and should not, replace the creativity and expertise of a human designer. All design professionals are in agreement that frequent use of AI distracts from the design process.

4.2 Design Stakeholders' Perspective on Client Perceptions of AI Skills and Usage

4.2.1 Perceived Competence and Marketability with AI Skills. Participants across all categories note that designers with AI skills are perceived as more competent and sophisticated, which can lead to "higher pay" (P3) and "increased demand" for their services (P1). Junior students, in particular, recognize that proficiency with AI tools enhances their marketability, as it signals to clients that they can deliver results more efficiently. Senior students further note that using AI conveys an ability to "streamline project logistics... reduce labor cost and time" (P13), and ultimately provide higher quality results.

4.2.2 Heightened Client Expectations. According to senior students and professionals, the widespread availability and publicity of AI tools have raised client expectations considerably. Clients now often anticipate higher quality outputs in shorter timeframes. Moreover, with the ease-of-use and "democratization of AI technology for design" (P13), clients are harder to satisfy, as they question the value of paying for services they believe they could accomplish on their own with the help of AI. As P14 notes:

> "People can use AI in their own time... You might have something that you want to do and can prompt AI to do with a couple of trials. I [as a designer] cannot give you exactly what you want that quickly."

4.2.3 The Lasting Appeal of Traditional Craftsmanship. On the other hand, the use of AI in design can send a negative signal, depending on the client's perception of AI's role in the design process. Some clients still place great value on traditional craftsmanship, where the "designer's personal touch" (P17) and manual effort are evident. Participants in the study noted that positioning oneself as a "pen and paper" (P16) designer, who relies on traditional methods, can resonate with these clients by emphasizing the sentimental value and authenticity of the work. This approach not only distinguishes such designers from those using AI but also allows them to "justify higher prices" (P13). Clients who prioritize originality and the human element in design are often willing to pay more for a product that reflects these qualities. Thus, while AI skills can be an asset, there remains a viable market for traditional design methods in the industry.

4.3 Defining Design Skills in an AI-Assisted Design Future

What does it mean to be a designer? Which skills are fundamental to design? The answers to these questions are changing due to the rapid proliferation of AI in design. Our participants are all existing or soon-to-be designers, but their value system for the job differs significantly. As such, defining design skills for the future will be a complex and contested issue. We synthesize here the key differences in how our three populations define design skills.

4.3.1 Junior Students: AI Is the Future of Design. Among junior students, there is a strong belief that design skill requirements will inevitably evolve, with AI becoming an integral component. Many anticipate that some traditional design skills will be replaced by AI, and a designer's competence will be measured by their proficiency with AI tools. P18 mentions:

> "I think rather that design is going to be more based on how good you are with prompts and how good you are in exploring these tools. I think the whole traditional design is going to go into extinction, and graphic design itself is not going to be as complex as it is."

4.3.2 Senior Students: Design Is About Creativity, With or Without AI. Senior students express more caution. They acknowledge that the design landscape has changed, leading to greater competition, but they insist that creativity remains the core competency for designers. Whether or not AI is used in design, design skills should still be evaluated based on the creativity of designer and their final product. From P9:

> "AI will influence people's creativity. But their competency will be based on either: how creative you are [on your own], or how a designer puts their creativity into action using AI."

Senior students argue that while AI might assist in the design process, it is not a standalone professional skill; traditional skills will continue to be essential for anyone aspiring to be a professional designer. The future of design skills involves an inclusion of AI, but not an exclusion of traditional design.

4.3.3 Design Professionals: Design Can Be Supported by AI, but Should Not Need It. Design professionals stress the importance of preserving traditional skills and caution against "over-reliance on AI" (P21). They acknowledge that those who effectively integrate AI into their established design practices—using it as a supplementary rather than a primary skill—will prosper as designers. But AI cannot be a designers' primary skill, nor should it be taught as a shortcut to these traditional design skills. Professional designers express concern that AI is lowering the overall skill requirements to be considered a design professional. Anyone with some experience with AI tools can now claim to design and become a part of the field. They disagree with this level of democratization when it comes to defining a designer, their job, and their expected skill-set, as seen in this quote from P2:

> "Designers are people who can't be too dependent on AI. You should know how to use your design skills perfectly: in case, if you are in the position that AI is not available and you had to do a job, you should still be able to do that job. If you cannot [do your job without AI], you are not a designer."

4.4 AI in the Design Curriculum

While there is disagreement on what constitutes the fundamentals of design, our three populations agree that AI skills are necessary for effectively handling the current job expectations and market. However, there is still the question of when and how it should be integrated into curriculum. Participant perspectives differ on this.

4.4.1 Junior Students: Advocating for AI in the Classroom. Junior students argue that AI should be an expected component of "modern design education" (P15), noting that many students already incorporate AI tools into their classroom assignments. They view AI as an integral part of the future of design, suggesting that it should be taught in educational settings.

4.4.2 Senior Students: Cautioning Against Premature AI Exposure. Seniors, while recognizing the necessity of AI skills, express concerns about introducing these tools too early in the educational journey. They emphasize that traditional design skills form the foundations of design thinking and practice, and this foundational knowledge is critical. As P16 remarked:

> "I think that it's also important for a person to learn how to create images, or to create art with their hands, and traditionally, before learning how to use AI."

P7 agreed, stating:

> "The existence of AI doesn't mean that everyone can design. You still need to learn the basic knowledge."

In most cases, we find senior students to be a bridge between the perspectives of the junior students and design professionals. However, on this topic, senior students have the most negative reaction to "premature AI exposure" (P16) in the classroom. They are perhaps the most well-suited stakeholder for careful consideration of this question given their own early education—which did not include AI skills—and their rapidly changing educational context, with AI being introduced midway through it.

4.4.3 Design Professionals: Calling for a Balance Between AI and Traditional Design. Design professionals share the concerns of senior students about introducing AI into the curriculum during the early stages of design education. They argue that premature exposure to AI could lead to an over-reliance on these tools before students have developed the necessary foundational skills, potentially resulting in a generation of "lazy designers" (P11).

One interesting suggestion was that "maybe students in the first 1 or 2 years shouldn't get access to AI" (P2). However, design professionals also acknowledged that AI can serve as a valuable tool for bridging gaps in traditional education: it can offer a visual, "example-based approach...easily accessible" (P12) via text-to-image models, which can enhance comprehension of abstract design concepts.

On a more philosophical level, design professionals like P27 question the longevity of design as its own curriculum:

> "I believe there will be a shift. Not many people will go to school to study design [alone] because AI support and a few YouTube tutorials will get you to the basic level. Is the tuition chargeability worth it?"

4.5 Ownership and Intellectual Property

It is hard to navigate ownership with AI in the picture, given that AI's role in the creative process itself is ill-defined at the moment. As such, the fracture in values among cross-level stakeholders continues on the notion of ownership as well, with junior students enmeshing AI more significantly in their designs and, subsequently, in the ownership of their outputs.

4.5.1 Junior Students: Shared Ownership with AI. There is clear consensus amongst junior students that, while they put significant effort in creating the work, they cannot claim that it was their original work "subject to copyright" (P25). This group views the output as a collaborative effort, and this distinction of "shared authorship" (P19) is important. They recognize that although they initiated the creative process and made several adjustments to the AI-generated work, the involvement of AI takes away the claim to full ownership. As P22 explained:

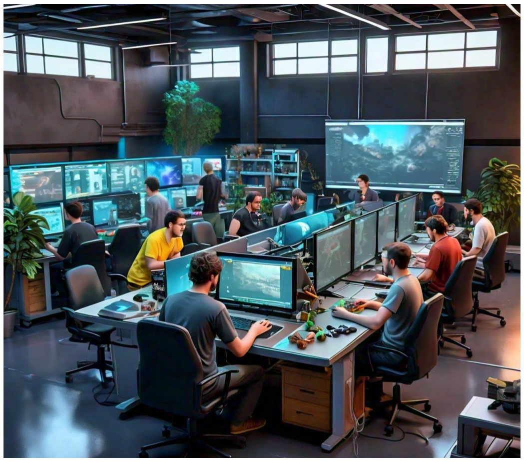
> "Mine and not mine at the same time. The idea of the picture of the image right now was mine because I was the one who imputed the prompt to the AI. But the rest was collaborative."

4.5.2 Senior Students: Ownership Depends on Input. Senior students take a more nuanced approach to the idea of ownership, often linking it to how (much) they contributed to the design process. Ownership depended on how much prompting they provided and whether they had to directly "edit the AI generated image in Canva" (P8). When they did considerable prompting and editing, they wanted full ownership because they designed the artifact using AI as a tool (e.g., similar to using "a color corrector or line straightener tool" (P13)). When they did not do considerable prompting or editing, they leaned towards giving AI ownership instead of taking a collaborative partnership position. Senior students view AI as a tool that helps with their creative work, similar to other design software, rather than as a co-creator.

4.5.3 Design Professionals: Ownership and Accountability Shift to AI Developers. Design professionals align closely with senior students but add another layer of consideration on ownership: when AI tools are heavily involved in the design process, ownership should be with the developers who created the AI. This perspective acknowledges the implicit role that AI developers play in the creative process when their tools are used. P21 explained:

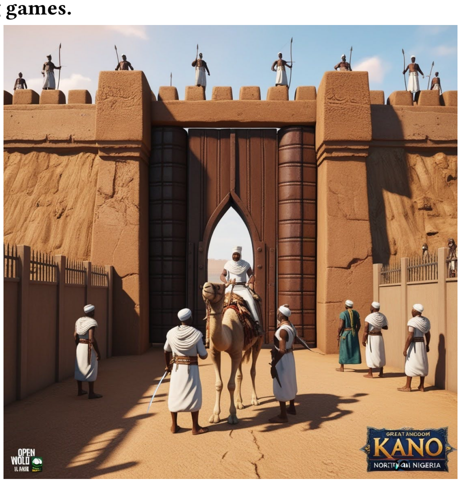
> "It does not belong to me. It belongs to the programmer, like the person who actually created the app."

This idea extends beyond ownership, suggesting that accountability for the final result should also rest with the AI developers, especially in instances of policy violations like plagiarism. Designers asserted that policy and regulation around ownership should consider the role of "people developing these tools as sharing responsibility for the images generated and how they are used" (P28), similar to how designers' take responsibility for their creations.

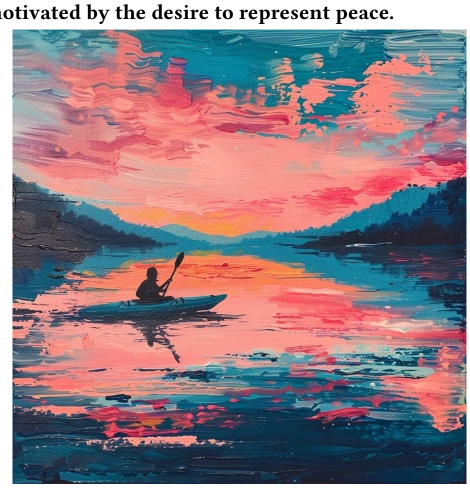


(a) Artifact created by P15, a junior design student, for a class project using Meta AI. The aim was to depict a collaborative gaming space, with people gathered at computer stations, playing games.

(b) Artifact created by P21, a design professional, as part of a professional project. The image, generated using Midjourney AI, was motivated by the desire to represent peace.



(c) Artifact created by P18, a junior design student, using Leonardo AI for a video game design project representing an African tribal scene. The image shows the grand gates of the ancient Kano Kingdom in Northern Nigeria, with guards in traditional attire and a mounted figure on a camel. However, AI made an error in the costume design, leading to a cultural misrepresentation in the traditional attire of the guards.



(d) Artifact created for a class project by P13, a senior design student. Generated using DeepArt.io, the piece is based on a photograph of a kayaker on a peaceful lake at sunset. Manual modifications were applied to adjust the colors, enhancing the pinks, blues, and oranges reflected on the water. The changes were made to emphasize the peaceful atmosphere and color contrast surrounding the lake.

Figure 1: Some artifacts created by our participants using generative AI tools and manual modifications.

4.6 AI in Design: A Practical Tool or a Hollow Trend? Challenges Identified from Practice

We note a striking difference in how participants described AI when they were asked generally about its use, opportunities, and challenges for education and practice, compared to what they described as their experience during the artifact-grounded questioning (see Figure 1 for example artifacts from participants). When asked generally about challenges with using AI, many participants initially downplayed difficulties. However, when interviews shifted to specific artifacts the participants had created, a more complex picture emerged. In essence, the artifact-based interview method enabled us to uncover these otherwise overlooked challenges and the invisible labor involved in integrating AI into creative workflows.

When examining how people actually use AI, participants conveyed a recurrent pattern of frustration. Despite AI's promise of efficiency, the reality often falls short, with time and effort invested not always yielding the expected results. Participants across the board—whether junior students, senior students, or professional designers—highlight consistent themes of limitations and challenges. We first present some general patterns of perceptions for specific tools, and then collective high-level challenges across all AI tools.

4.6.1 Tool-Specific Perceptions. Looking at subgroups of participants experienced with the same tools, users of MidJourney praised its high-quality and diverse outputs, and the prompting and editing capabilities. DALL.E outputs were similarly high in quality, but users struggled with control over outputs and the need for prompt refinement. Professionals, in particular, wanted manual adjustments, but realized that DALL.E ignored parts of their prompt that were highly specific unless their prompts explicitly instructed that this specificity was desired. Stable Diffusion users valued its customization capabilities but noted that style consistency was unpredictable and prompting was time-intensive. Junior students found it too complex, while senior students and professionals saw its flexibility. Adobe Firefly users, mostly professionals and senior students, used it for refining AI-generated work. Canva and Meta AI users, mainly junior students, preferred these for their ease of use and, ironically, lack of control, compared to more complex tools. These tools offered outputs that were "take it or leave it" (P6) which made the workflow simpler.

4.6.2 Challenge: Prompt Engineering. Crafting and fine-tuning prompts is a frequent challenge. People find it hard to communicate via basic text prompts and image editing capabilities, with results often straying far from the intended design output. AI tends to "over-edit" (P17), often producing completely different outputs based on minor adjustments to prompts. Small changes, such as differences in punctuation or grammar, can lead to wildly different and sometimes unrelated results, as shared by P18:

> "Most times when trying to modify the original picture [output by AI], you get an entirely different image from what you first got. It keeps redoing it with exponential changes."

It is very rare to achieve a final product that does not require some level of adjustment even after careful prompt engineering. This leaves designers with a dilemma: whether to spend time manually refining the results or to keep adjusting prompts in pursuit of a better outcome.

4.6.3 Challenge: Level of Specificity Required. The level of specificity needed when working with AI can be frustrating. On one hand, getting a reasonable output often requires an overwhelming amount of detail, making the process cumbersome. Yet, even when you provide a carefully detailed prompt, AI does not always interpret it correctly. It can overemphasize certain aspects of the prompt while completely overlooking others, resulting in outputs that are skewed or incomplete, and ultimately not what was intended. For example, as shared by P23:

> "Not all words are accepted or understood by AI, even when you use long sentences to depict what you want. Maybe you're trying to say the Roman soldier is running down the steps. There's a blade in his hand. Blood smeared on his face. His ammo is on the left side. And all that bunch of information sometimes cracks AI out, and most of the times it doesn't give you what you want. It'll give you like half of the image. And it's not actually what you want and much harder to edit."

4.6.4 Challenge: Editing Frustrations Due to Lack of Explainability. When AI generates an image or makes an update, it does not explain why it produced a certain result, turning the editing process into a guessing game. Without any clear guidance, users often find themselves trying to figure out how to steer the AI towards the desired outcome. P26 commented on this limited control and "the random images I keep getting" being a time sink. It can seem as though random patterns are being inserted or the same errors are being repeated across different prompts, with no clear way to correct or learn from these issues. As P6 noted:

> "You are thinking about what the AI is thinking, and you have to try and make it think like what is in your mind. When it doesn't [work], it [the reason why] doesn't seem to be in language that the AI is giving you. How would you know what to do?"

4.6.5 Challenge: Cultural and Linguistic Bias in AI-Generated Outputs. As with other applications of AI, these tools also have issues of bias. Most of them rely heavily on English language inputs, with limited capabilities for other languages, which can leave non-English, or multi-lingual speakers wanting to design in a non-English language, feel excluded or lead to inaccuracies in translation. Additionally, the outputs are often rooted in Western cultural norms and perspectives, resulting in misrepresentation and stereotyping. For instance, P14 noted an issue with skin color representation:

> "The main challenge I had was skin color. My client didn't want a white person; they wanted to show people from Asia and other parts of the world."

These bias insights confirm, yet again, the arguments in prior work on misrepresentations in training datasets and problematic outputs from AI [37, 50, 100]. AI does not reflect diverse cultural and ethnic backgrounds, leading to outputs that can be both culturally insensitive and technically flawed.

4.6.6 Challenge: Lack of Consistency and Reliability Across Tools. Participants note that they have to experiment with multiple tools to find the one that best responds to a given prompt. However, even when using the same prompt, the outputs can vary considerably from tool to tool, making it difficult to achieve consistent results. Reproducibility is a major issue, as the same input might produce different outcomes on different occasions. P13 discussed this, saying:

> "Reproducing the same or similar output with an AI tool can be unpredictable. I can use the same input [photo], but the outcome might be different if I use it twice or more."

Another substantial issue is the lack of stylistic consistency across multiple images. Most AI tools do not have the capability to save a specific style and apply it uniformly across different images, which is a critical drawback when approaching design from a cohesive, stylistic perspective. It can be "hard to maintain a similar style, or maintain details you want to for more than one thing" (P19).

4.6.7 Challenge: Technical and Resource Constraints. Senior students and design professionals, being more embedded in practice, encounter technical issues when integrating AI into their design workflow. Without some technical expertise and know-how, the design outputs tend to be basic and lack the sophistication needed for professional work. Hardware and resource limitations add to this difficulty. Participants note that tools like Stable Diffusion can

Figure 2: Sawyer's characteristics of creativity [89] re-imagined with generative AI in the loop. Characteristics with a shared color are impacted similarly by generative AI use.

be frustratingly slow when customizations are applied, and they often need to invest in better resources to maintain efficiency in their projects. "You have to keep paying or buying some things" to get "real advantage" from these tools (P12), and those skills are an entirely different category of learning for many designers.

4.7 Principal Results

We discover a growing rift in the value system of designers: junior students embrace AI in design, while senior students are cautiously optimistic, and design professionals fear the loss of traditional creativity and core skills. At the same time, all design stakeholders recognize that AI in design is here to stay, driven in part by the rising marketability of technical know-how and client expectations for AI use. This shift is reshaping the profession, emphasizing a hybrid skill-set that combines both traditional design expertise and proficiency with AI. Compounding these rifts are issues of ownership and accountability, where students consider it co-authorship, while professionals worry about plagiarism and intellectual property. On the other hand, practical use of AI is riddled with frustrations given the limited affordances of these tools for achieving meaningful designs (e.g., black-box prompt engineering; lack of specificity, consistency, and reliability; representational bias; and resource constraints). This begs the question: will AI actually be used in practice long-term? Ultimately, our findings highlight the need for a nuanced approach to both using and understanding AI in design, one that navigates the complexities of technological change while addressing the shifting demands of design education and practice.

5 Discussion

5.1 Computational Reification of Creativity

With generative AI in the mix, the processes and characteristics of creativity in design are also evolving. The dynamic and non-linear model of creativity may be becoming linearized as people follow AI outputs. Across all levels of experience, our participants noted how generative AI adds a data-driven layer to the design process: helping with brainstorming a large number of ideas before committing to a design direction, prompt engineering for idea filtering, and edits for achieving the desired final output.

Although models of creativity might still use the same processes to reach creative outcomes, their characteristics are being altered to be characteristics of generative AI. Comparing directly to Sawyer's eight characteristics of creativity, Figure 2 presents an overview of the influence of AI (Section 2.1 covered Sawyer's original definitions). For *iteration*, *deliberate intentionality*, and *conscious reflection*: people iterate on prompts and tool outputs instead, and reflect on AI outputs rather than their own ideas. Instead of creativity being influenced by the *constraints* and *ambiguity* of a problem/task and people learning from their *failures* in achieving the necessary outcomes, creativity is primarily influenced by the failures of AI tools and the lack of explainability in exposing these. Idea *exploration* and *emergence* from failures and trial and error is rather attributed to the pros and cons of using AI: on one hand, AI tools can quickly pigeonhole people in certain ideas; on the other hand, they also offer a quick way to explore different design concepts, add concreteness to abstract ideas, and quickly customize aspects of design (e.g., changing color palettes, costume styles, calligraphy in logos, etc.).

These shifts in creativity point to a trend with human-AI collaboration for design: fundamental characteristics of creativity being offloaded to AI, with people playing a support role. Designers are no longer the primary creators; rather, they are becoming curators who fine-tune AI outputs. Moreover, there is a growing population that prefers this curation role because it saves them time and effort, and requires minimal design expertise. We call this a "**computational reification of creativity**," i.e., a fundamental re-shaping of creative processes wherein AI is at the creative helm with people as the supporting cast [29]. This shift in creativity is not consistent across all designers—professionals have similar experiences using generative AI tools and they, instead, often choose their traditional approaches. However, the challenge becomes maintaining this traditional state when expectations of process and output change in the industry.

To counter this, our work strongly argues for maintaining the support role of AI, so that creativity remains primarily a human endeavor. Generative AI can still be revolutionary in this support role by, for example, affording quick illumination on different styles/representations of an idea that a designer has outlined, or helping with high-definition polishing and editing of a designer's early-stage artifact. Seminal scholars in HCI have consistently argued in favor of this amplifying role for AI and cautioned against aiming for AI to imitate or displace human capabilities [12, 38, 42, 91]. We hope future work will design for these kinds of amplification use-cases and evaluate them against current dominant paradigms of generative AI use.

5.2 Towards a Framework of Expertise-Grounded Generative AI Use

We observed contrasting perspectives on generative AI across junior design students, senior design students and design professionals. While we cannot speak to a generalized framework based on these differences, we identify important facets of expertise that impact people's perspectives, and hope that future work can further evaluate and explore these. These facets belong to three high-level dimensions along which expertise is often described [21, 36]: the *content* of knowledge required for a task (e.g., traditional design skills, AI skills), the *context* of this knowledge and its application (e.g., AI exposure, task familiarity), and the *process* by which it is acquired and applied (e.g., practical experience, client expectations).

Content: Experience with Traditional Design Skills. Junior students are just beginning to learn traditional design skills, senior students are refining advanced design skills, and professionals possess extensive experience and mastery over these skills. Consequently, those with more expertise in traditional design are more resistant to the idea of AI replacing these skills, as they are more comfortable and can fall back on these skills to work through challenges and frustrations posed by AI.

Context: Timing of AI Exposure. Junior designers with AI exposure earlier in their career view it as a natural part of their skillset. In contrast, design professionals are introduced to AI during their careers, requiring them to integrate AI into their existing workflows. As a result, junior designers feel less threatened by AI potentially replacing their jobs, whereas established professionals are more concerned about its implications for job security and skill obsolescence.

Context: Task Profile. Junior designers primarily design for low-stakes projects, using AI to expand their skills and experiment. Professionals design for higher-stake client tasks which makes them approach AI cautiously, citing concerns about explainability, ownership, and accountability. Professionals, therefore, emphasize the use of AI as a supplemental tool rather than a standalone tool.

Context: Age and Generational Influences. Younger individuals (e.g., students) are more adaptable to emerging technologies, therefore they find it easier to incorporate AI into their workflows. Older individuals are more hesitant due to the learning curve and a shift in their workflows and practice. This aligns with established models of technology adoption (e.g., Rogers' Diffusion of Innovations Theory, which identifies younger individuals as early adopters [83, 87]; and Kotter's Change Management Model, which highlights resistance to change without clear benefits or support [58].

Process: Practical Experience. Professional designers evaluate AI with a more practical lens, considering factors like client expectations, marketability, and project timelines. Traditional skills, they believe, are more valuable, enabling them to meet professional goals efficiently without getting stuck in the feedback loops caused by the limitations and lack of explainability of AI.

5.3 Generative AI in Design as a Dual-Use Technology

Given our mix of positive and negative results, we consider generative AI a dual-use technology, i.e., a technology that can significantly benefit society but also has the potential for misuse and causing harm at a large scale [41, 57, 107]. Our participants acknowledged both AI's ability to enhance creativity and democratize design, but also its potential risks, such as over-reliance and skill degradation. At a societal level, issues of content homogeneity, copyright infringement, disinformation spread (e.g., using deepfakes), ownership and accountability, and job security, have been exacerbated since these tools entered mainstream use [3, 25, 40, 64]. Similar to other dual-use technologies (e.g., GPS, nuclear technology, biotechnology), the potential harms and risks of generative AI warrant some form of regulation.

With a dual-use classification, we seek inspiration from historical regulatory frameworks to contemplate policy structures for generative AI in creative settings. Prior legal work on dual-use technology presents two common perspectives on policy: (1) personality theory, which prioritizes individual rights (e.g., freedom of expression); and (2) welfare theory, which prioritizes societal benefits and welfare, sometimes at the cost of individual rights [32]. However, these approaches present a dichotomy: focusing too much on personality theory might limit technological innovation and pursuit of open science, while prioritizing welfare theory could worsen ethical issues around human creativity and authorship. This tension is evident in our findings, where junior designers for whom using AI is commonplace emphasize its benefits in democratizing design, citing an improved freedom of expression (i.e., personality theory). Meanwhile professionals advocate for stronger safeguards to protect traditional skills, maintain design integrity, and avoid the harms of generative AI use (i.e., welfare theory).

The governance of previous dual-use technologies balanced insights from personality and welfare theory. One concrete example is in the application of the Precautionary Principle, which prioritizes caution even when there is scientific uncertainty on causes and effects [28]. When applied to synthetic biology research (e.g., recombinant DNA), the precautionary principle skewed towards welfare theory at first: safety measures like licensing and restricted publication prevented potential misuse, but research was not prohibited [96]. However, when some risky laboratory situations surfaced, regulatory bodies imposed a moratorium on this research, skewing it towards personality theory (i.e., protecting individuals over the potential for societal benefits) [51]. Over time, governance models emerged via multi-stakeholder collaborative efforts, which encouraged self-compliance with ethical standards while preserving academic freedom [44].

Generative AI has followed similar trends already, most recently with the letter to pause giant AI experiments with foundational models and the resulting debates [2, 47]. How do we move forward with generative AI regulation? Seeking inspiration from dual-use technology of the past, Williams-Jones et al. [107] propose starting with assessing risk thresholds. In the past, low-risk research has been governed by open science principles, medium-risk research by institutional review boards, and high-risk research by government regulation and international conventions [107]. Reviews of low, medium, and high risk governance mechanisms in prior work (e.g., [81, 107]) offer examples to adopt for generative AI. For instance, mandatory education on dual-use implications for design students, and voluntary AI skill training courses for professionals could help bridge the gap on responsible AI use. This would also appropriately differentiate generative AI use by our participants for, say, class assignments vs. setting industry standards. Similarly, codes of conduct and coordinated review mechanisms (e.g., watermarks) could define ethical standards of ownership while ensuring accountability. Importantly, designers want this—more experienced designers in our study wanted to hold themselves and AI developers accountable for potential harms. By learning from these past dual-use frameworks, generative AI governance can incorporate educational programs and oversight mechanisms to mitigate its risks while promoting societal benefits [34].

5.4 Generative AI: A Perfect Genie or an Explainable Support Tool, Nothing In-Between

With AI-based tools being deployed at large scales by well-known technical organizations, people's expectations of these technologies resemble notions of seamless mind-readers, i.e., a perfect genie. Our participants' standards for generative AI in design mirrored this. Their description of intended usage often included phrases like "read my mind" (P22) or "reflecting what is in my mind" (P8), assuming that AI could immediately understand their intent and ideas. This is in line with prior work on automation bias with AI- and ML-based tools [23, 55, 78]—people often expect publicly-deployed tools to be frictionless.

In practice, these technologies are far from that capability. Unless participants were seeking design outputs for fairly simple tasks, they ended up having to work significantly to get to their desired output. This included handling challenges around prompt engineering and specificity, the need for considerable investment of time in post-production refinement, lack of cross-application consistency in outputs, and no long-term design context (e.g., no saved design styles and configurations). This hidden labor challenged people's perception that AI universally accelerates design workflows.

What made people's frustration worse was a lack of explainability or transparency in what was causing issues, i.e., no information on why a tool was not returning the desired output given a prompt. In some cases, participants noted that minor changes in prompts would lead to wildly different outputs; other times, parts of a detailed prompt were ignored entirely. There was no way for people to course-correct other than blind trial and error.

We observed a desire for either a perfect genie-type system that could read people's minds, or, if that was not possible, then having appropriate mechanisms for understanding how the system worked and levers for controlling it. The challenge was that people got neither, and this in-between was a critical point of discontent regarding generative AI in practice. While the desire and need for explainability and control has been discussed extensively in the application of AI for decision-support [26, 99, 106], our results show that it is a vital direction of future work in creative settings as well.

5.5 Opportunities for Positive AI Support in Design Learning

Generative AI for design has had a one-dimensional role: as a co-creative tool helping people realize design goals easily and effectively (though results in Section 4.6 describe challenges in practice). We offer insights into other forms of support possible with generative AI—in design learning—which do not have the same concerns or challenges as co-creativity. We hope these will inspire more positive future work designs for generative AI applications.

5.5.1 Interactive and Example-Based Conceptual Learning. The use of generative AI as an education-support tool can take the form of helping design students and enthusiasts visualize abstract or complex concepts that might be difficult to understand through traditional methods. Complementary to theoretical knowledge of a concept, generative AI can provide examples of prior designs where these concepts have been applied, or generate images that play on different concepts. Professors in these classrooms can use these tools to quickly create visual representations of their lecture ideas, aiding student understanding and retention. Additionally, generative AI can complement traditional design education by offering a more visual, interactive, and example-based learning experience. Indeed, some design students in our study already use generative AI for this type of learning, and recent work has shown initial success of this use-case [60, 66].

5.5.2 Exploration and Discovery of Creative Styles. Generative AI can provide students with a broad range of styles and perspectives on the same design task, which can encourage creative exploration. By generating multiple design examples or suggestions, these tools can help students experiment with different styles and approaches, pushing the boundaries of their creative horizons as shown by recent literature [5, 79, 92]. This can also make learning more engaging and enjoyable. The ability to quickly see the results of their work and experiment with different ideas can motivate students to explore and learn more. This was another use case that came up frequently in our future-facing discussions with our participants.

5.5.3 Accessibility and Inclusivity in Learning. There is no doubt that generative AI tools have democratized access to design by making it easier for people with varying backgrounds to create design artifacts [15, 98]. This can now happen both within a traditional classroom setting and outside of it. In the traditional classroom, generative AI can level the playing field, allowing all students to participate more fully in design projects regardless of their design or artistic backgrounds. Outside of the classroom, novices and enthusiasts now have the opportunity to learn concrete skills in design and transform what might have been a hobby into employment opportunities. However, as noted by our more experienced design participants, the value of foundational design skills should not be lost in this process. The challenge will be in utilizing this inclusivity in positive ways by creating appropriate job opportunities and regulatory frameworks to support designers.

6 Limitations

This study has some limitations that may affect the broader applicability of our findings. First, there is a potential for self-selection bias due to our recruitment process, which relied on targeted outreach through mailing lists, social media posts, and snowball sampling. This may limit the external validity of our findings, as participants might not represent the broader population of design students and professionals. Second, the artifact-based component of the study could have skewed the conversation depending on which artifact was shared during the study. We cannot say to what extent this one artifact represents participants' general use of generative AI tools for design. Additionally, the rapid evolution of generative AI tools presents a temporal limitation, as the insights drawn from this study could become outdated quickly with the introduction of new tools or significant updates to existing ones. Relatedly, we did not include any non-prompt based tools like sketch-to-image in our study which might limit the applicability of results to only prompt-based tools. Finally, our sample was exclusively U.S.-based, which restricts the generalizability of the findings to other cultural contexts, as design practices and educational experiences may vary significantly across different regions. More work with a similar cross-level perspective as ours is critically needed to form a predictive understanding of generative AI use—this will require systematically setting up methodologies that address the limitations identified above using design, grounded theory, quantitative, and theory-building methods.

7 Conclusion

We present results from an artifact-based interview study with 28 designers at three levels of generative AI perspectives: junior design students (introduced to generative AI from the very beginning of their education), senior students (for whom generative AI became mainstream midway through their education), and professional designers (who had no generative AI considerations during their foundational design training). While junior design students embrace AI and integrate it in their design learning, senior students and professionals worry about skill degradation and loss of creativity and ownership. This divergence highlights a broader tension between the rapid technological progress in AI and the preservation of design as a skill rooted in human creativity. Moreover, the shifting value systems among designers necessitate a larger conversation about the future of creativity, ownership, regulation, and the role of technology in shaping design education and practice. We discuss implications for these human facets of design, and offer opportunities for using generative AI in design in ways that do not target the creative aspects of the design practice.

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A Interview Protocol

Background Questions.

(1) What is your background in design?
(2) How long have you been working in graphic design?
(3) What is your academic background? [*If they are a student:*] how many years have you been in your current program?
(4) What do you normally design for? (Professional, personal, or other activities?)

Context-Building Questions.

(1) What are some generative AI image creation tools that you have used? Is there one you use more than the others?
(2) How do you use these image creation tools? What types of tasks have you used them for?
(3) What do you like about having access to these tools?
(4) Are there things you don't like about these tools? How would you want them to be different?

Artifact-Based Questions.

Note: open the image artifact created by the participant on a shared screen before asking the following artifact-based questions. These artifacts are shared with us beforehand with participant consent.

(1) What was your motivation behind generating this image?
(2) What was the topic you were designing for?
(3) Was this for a class or professional project?
(4) Was this image an outcome based on a single prompt to the generative AI tool, or did you make edits? How long did it take to get to the final image here?
(5) What challenges did you encounter when you generated this image using the tool? How did you address these challenges?
(6) Are you satisfied with the generated image? Did the quality of the image match your expectations?
(7) Do you think this is your own work, or does it not belong to you? What are your thoughts on the authorship and ownership of this image?
(8) What do you think are the strengths and weaknesses of the tool that you used to create the image?

Perceptions on Education.

Note: follow-up questions for design students.

(1) Have you used generative AI image creation tools for learning or skill development during your design education?
(2) If so, could you describe a specific situation where this was particularly beneficial?
(3) If not, are there specific concerns or limitations that have deterred you?
(4) In what learning contexts do you think they might be useful?
(5) Do you think these tools will benefit traditional design learning experiences or not?

Perceptions on Professional Design Jobs.

Note: follow-up questions for design professionals.

(1) How do you perceive the impact of generative AI image generation on traditional design processes?
(2) In what ways do you think generative AI image generation tools might influence the future skills and competencies required for designers?