“We Are Visual Thinkers, Not Verbal Thinkers!”: A Thematic Analysis of How Professional Designers Use Generative AI Image Generation Tools

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ABSTRACT

Generative artificial intelligence (GenAI) has become increasingly popular, influencing various creative domains. However, while broader societal perspectives have been analyzed, specific examinations of how practitioners utilize GenAI tools to enhance their current workflows remain limited. To address this gap, we conducted a qualitative study involving 16 professional designers from the automotive industry. We aimed to identify their challenges with existing GenAI image generation tools in daily design practices. Thematic analysis revealed four key themes: (1) the need for visual input-centric multi-modal interfaces that extend beyond textual prompts, (2) the lack of support for the iterative nature of design processes in GenAI tools, (3) difficulties in controlling prompts to achieve desired outputs, and (4) the significance of incorporating human experiences and emotions into design. Based on our findings, we propose and discuss potential design considerations for enhancing future GenAI image generation tool interfaces.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**.

KEYWORDS

generative AI, creativity support tools, human-AI interaction, qualitative research

ACM Reference Format:
Hyerim Park, Joscha Eirich, Andre Luckow, and Michael Sedlmair. 2024. “We Are Visual Thinkers, Not Verbal Thinkers!”: A Thematic Analysis of How Professional Designers Use Generative AI Image Generation Tools. In *Nordic Conference on Human-Computer Interaction (NordiCHI 2024), October 13–16, 2024, Uppsala, Sweden.* ACM, New York, NY, USA, 14 pages. https://doi.org/10.1145/3679318.3685370

NordiCHI ’24, October 13–16, 2024, Uppsala, Sweden

ACM ISBN 979-8-4007-0330-0/24/10
https://doi.org/10.1145/3679318.3685370

1 INTRODUCTION

The increasing popularity and advancement of generative AI (GenAI) technologies have significantly impacted various domains, including design. GenAI refers to AI systems capable of generating different types of content, such as images, sounds, and videos, using inputs like text, images, and voice. Most image generators driven by GenAI technologies can create high-quality images from simple prompts, even if users lack advanced skills in visual design or detailed artistic expertise. This capability can be particularly beneficial in creative fields, providing inspiration, speeding up manual processes, and assisting in developing new concepts. Among the leading GenAI tools are Midjourney [35], Stable Diffusion [18], and DALL-E [11], which generate images based on text prompts, either alone or combined with user-defined images or sketches. However, their interfaces remain predominantly text input-centric.

While research on GenAI image generation tools in design fields has been conducted, much of it has centered on broader implications for design practitioners, including their expectations and both positive and negative perspectives on GenAI [21, 31, 52]. For example, Ko et al. [28] interviewed 28 visual artists from diverse art domains to explore the adoption of large-scale text-to-image generation models in their creative processes, focusing on participants without prior experience with these models. Additionally, Tholander et al. [47] organized a workshop with five designers and three design researchers to examine how GenAI tools, such as the large language model (LLM) ChatGPT [6] and DALL-E, assist in ideation and early prototyping.

However, there has been limited research into how practitioners actually use GenAI tools in their *daily* workflows. We extended the existing line of work by conducting a qualitative study through interviews with 16 professional designers from a large multinational automotive company. Our participants included interior, UX/UI, concept, early phase, and 2D/3D designers working on projects beyond automotive design. While focusing on a single company may limit generalizability, the diverse roles of participants help mitigate this issue by providing a wide range of perspectives. In contrast to previous studies, which often focus on a specific phase of the creative process, our study aimed to understand the challenges designers face throughout various stages of their daily creative work. We recruited designers with varying levels of experience with GenAI image generation tools. Our main goal was to gain practical insights into how these tools are used, identify challenges, and explore perspectives on appropriate interfaces for effective interaction with GenAI. For data analysis, we employed thematic analysis [4], allowing for an iterative examination and interpretation of the collected data. Our analysis identified four central themes describing the challenges of using GenAI tools in professional design practices. Throughout this study, 'GenAI tools' refers explicitly to GenAI image generation tools.

The findings of the study highlighted the following issues:

(1) Current GenAI tool interfaces are not well-suited for visual thinkers.
(2) These interfaces do not align well with the iterative and non-linear nature of the creative process.
(3) Designers encounter challenges in controlling GenAI prompts.
(4) There is a need for GenAI tools to support the integration of tangible, physical experiences, which are crucial for creativity and uniqueness in design.

Based on our findings, we explored design implications for GenAI tools in design practices. We recommend that GenAI interfaces support diverse input methods, including visual material-centric options, to better meet the needs of visual thinkers. These interfaces should also accommodate the non-linear, iterative nature of the design process, enabling seamless navigation of creative workflows. Addressing the challenges of controlling and sharing GenAI outputs and prompts through intuitive and collaborative interfaces is crucial. Additionally, integrating real-world experiences into digital workflows is key to enhancing creativity and fostering uniqueness in designs. Finally, investigating GenAI from a social interaction perspective could further improve collaboration and its impact on the design process.

This paper makes the following contributions: We conducted a qualitative study to identify the challenges designers face when integrating GenAI image generation tools into their daily practices. By interviewing 16 professionals with varying experience levels and conducting thematic analysis, we gained practical insights into these challenges. From our findings, we proposed design implications to enhance interfaces for better integration of GenAI into design workflows.

2 RELATED WORK

In this section, we first review existing research on GenAI within HCI and related fields. Then, we explore related work on GenAI-driven creative support tools and delve into research on the applications of GenAI across diverse industries.

2.1 GenAI Research in HCI

GenAI is a subset of AI technologies that specialize in generating new content, such as text, images, music, and videos. Well-known GenAI models include Generative Adversarial Networks (GANs) [14], Variational Autoencoders (VAEs) [27], Generative Pretrained Transformers (GPTs) [42], and Denoising Diffusion Probabilistic Models (DDPMs) [16]. Unlike traditional AI or machine learning (ML) models, which have been widely used for tasks such as predictive analytics, classification, natural language processing (e.g., machine translation), and speech synthesis, GenAI models have the unique capability to *generate* new content that is comparable to human-created outputs. This generative capability shows considerable potential across various creative domains, including design, where it can provide inspiration, accelerate workflows, and aid in developing new concepts.

In recent years, qualitative research has increasingly focused on the impact of GenAI on creative professions, with particular attention to image generation models. Inie et al. [21] conducted an online survey with 23 designers and design students from various fields, including UX/UI design, 3D art, and game design, to explore their views on GenAI. Although the study did not specify the types of GenAI discussed, responses primarily focused on image generation models. The findings revealed mixed opinions, with some participants expressing concerns that GenAI might increase output quantity at the expense of quality, potentially weakening creative capabilities, while others were more optimistic about the potential for collaboration, noting that GenAI still requires human input to produce meaningful outcomes. Research by Li et al. [31], focusing on the perspectives of 20 UX designers on GenAI, found that while designers possess confidence in their creativity, originality, and empathic skills, they are also concerned about skill degradation, job displacement, and creativity exhaustion. These concerns were highlighted as having a more pronounced negative impact on junior designers. Additionally, Takaffoli et al. [46] interviewed 24 UX practitioners to investigate how GenAI is integrated into UX workflows. Their findings revealed a lack of formal GenAI policies and consistent team practices, as well as the challenges in using GenAI for design tasks such as wireframing and prototyping. These challenges include the need for outcome validation, concerns about overreliance on GenAI, and the necessity for GenAI training. Yoon et al. [52] addressed key ethical concerns in using GenAI tools like ChatGPT and Midjourney in creative processes. Through observation and interviews with ten UX designers, they identified issues such as reliability, bias, and the risk of unemployment, underscoring the need for fact-checking, empathy-based decision-making, and effective communication when integrating GenAI into the workplace.

Prior research has primarily focused on the impact of GenAI tools on creative professionals or non-professionals, highlighting their perspectives, expectations, and concerns. However, there has been relatively limited exploration of the practical challenges professional designers encounter in their actual workflows when using GenAI tools. For instance, Gmeiner et al. [13] engaged 14 industrial designers in the manufacturing sector in think-aloud studies and follow-up interviews to investigate the challenges they face while learning to use GenAI and ML-supported tools like Fusion360 and SimuLearn. One key finding was that designers have difficulty interpreting GenAI-generated outputs and making necessary adjustments or corrections. Tholander et al. [47] conducted a workshop with five design practitioners and three researchers to evaluate the utility of GenAI tools, such as ChatGPT and DALL-E, for ideation and prototyping in the early creative phase. Participants appreciated the time savings and the generation of complementary materials by GenAI, such as scenarios and personas, but they doubted its ability to produce high-quality, innovative solutions due to its lack of contextual understanding of specific tasks. Additionally, Ko et al. [28] interviewed 28 visual artists across various art domains to explore the potential adoption of large-scale text-to-image generation models in the creative processes. The study uniquely focused on participants without prior experience using these models, aiming to understand their perceptions and prevent preconceptions.

These studies provide valuable insights into the use of GenAI by design practitioners. However, they primarily focus on challenges during the learning phase or early creative stages or involve participants with no prior experience with GenAI. In contrast, our research included interviews with designers who use GenAI tools to varying extents in their daily professional work. While our results also indicated that GenAI tools are predominantly used in the early creative phase at present, our study did not limit its inquiry to any specific creative stage. This approach allowed us to highlight the daily drawbacks and perceptions associated with GenAI image generation tools, offering a more nuanced understanding of how these tools are integrated into ongoing professional practices.

2.2 GenAI-Driven Creativity Support Tools

In the HCI community, the analysis and development of Creativity Support Tools (CSTs) are central to understanding and enhancing creativity [12]. A CST is defined as a tool that *"runs on one or more digital systems, encompasses one or more creativity-focused features, and is employed to positively influence users of varying expertise in one or more distinct phases of the creative process"* [12]. The growing integration of AI technologies into consumer-level digital creative tools has expanded the research scope for AI-driven Creativity Support Tools (AI-CSTs) [8]. The distinct capability of GenAI to produce new, high-quality outcomes enhances its utility as a CST in creative fields. Hwang et al. [20] suggested that GenAI-driven Creativity Support Tools (GenAI-CSTs) could replace users in completing parts or even the entire creative process, making them more accessible to novices compared to traditional CSTs. Verheijden et al. [48] analyzed leading GenAI image generation tools and noted that they are typically single-user and result-oriented, focused on fine-tuning desired image output. Additionally, Hwang et al. [20] analyzed GenAI tools based on their utility across different stages of the creative process and found that most existing tools are designed to aid idea generation and execution, aligning with the 'hands-on' stage in their study.

In line with this trend, recent research on GenAI-CSTs has primarily focused on enhancing the ideation phase within creative processes. For example, Wan et al. [49] introduced a StyleGAN-based digital mood board that supports creativity during ideation by allowing users to generate new images, blend two images, and visualize outcomes directly on the mood board. This tool significantly supported creativity, enabling enjoyable and effective exploration of visual ideas. Expanding on collaborative ideation tools, Koch et al. [29] developed a digital mood board featuring curated image discovery, a search function combining text and image inputs, and GenAI-generated suggestions for discovering new images. Feedback from participants showed that this tool largely facilitated the exploration of design alternatives and the collection of valuable images, improving the ideation process. The exploration of similar inspirations can lead to design fixation, limiting the novelty of design work [23]. Mozaffari et al. [36] addressed this issue with a GenAI-supported tool generating diverse inspirations, ensuring both variety and relevance to the input design. Participants found the suggested examples to serve as viable sources of inspiration.

Recognizing that the design process is inherently iterative and involves multiple tasks and cognitive activities [10, 24], some research has focused on enhancing this aspect of design work. Zhang et al. [54] introduced a GenAI-CST that integrates various GenAI models, including text-to-image, sketch-to-image, and image-to-image, to enhance collaboration between designers and GenAI. This tool, featuring collaborative mind mapping and a creative canvas, reportedly improved performance compared to non-integrated tools. Quanz et al. [41] proposed a co-creative design framework that combines various GenAI and ML models to support the iterative nature of the creative process. This framework consists of three components, each tailored to different design stages: a 'Creator' for generating initial designs and variations for exploration, an 'Evaluator' for assessing designs based on aesthetic criteria such as shape and color, and an 'Iterator' for refining designs through feedback.

Some research has explored the benefits of input beyond text prompts. Sun et al. [44] developed a co-creative drawing system using GANs that generates cartoon paintings from human sketches, simplifying the design process for both novice and professional users. Kazi et al. [25] presented a GenAI-supported sketch-based interface that generates 3D objects from freehand 2D sketches, aiding idea exploration and decision-making in early design stages. Chung et al. [9] created a generative story ideation tool that combines line sketching with GPT-based language models to support intuitive interactions and iterative story generation. Additionally, Verheijden et al. [48] introduced a tool supported by Stable Diffusion that enhances image generation, editing, and sharing by integrating a chatbot and online whiteboard, allowing users to refine images with sketches and text prompts for more interactive visual work.

Previous studies have introduced novel GenAI interfaces to support ideation, iterative design processes, and the integration of inputs beyond text, such as sketches. While these studies show that their systems can enhance user creativity and inspire ideas, they often lack in-depth insights from experienced practitioners who use GenAI image generation tools in daily workflows. This reveals a research gap in understanding how professional designers practically apply these technologies in their everyday work routines.

2.3 Applications of GenAI in Industry

Research has explored GenAI applications across various industries. Bilgram et al. [3] examined how LLMs, such as GPTs, support early innovation stages, including exploration, ideation, and digital prototyping, in corporate projects over six months. They applied GenAI to tasks like automotive market analysis, user journey and persona development, and customer solution creation, highlighting the effectiveness of LLMs in these initial phases. The study also recommended further research on optimizing team interactions with GenAI to better integrate these tools into workflows. Yin et al. [51] surveyed professionals in the creative industry to examine GenAI acceptance, extending the Unified Theory of Acceptance and Use of Technology (UTAUT) to include AI anxiety. They found that factors like performance expectancy, social influence, enjoyment, habit, and AI anxiety significantly predict GenAI acceptance, emphasizing the role of emotional attitudes toward technology. Workers in the creative and cultural sectors showed a higher willingness to adopt GenAI despite AI anxiety. Arenander [1] explored the use of 3D GANs in the defense industry, focusing on automating design processes. Through qualitative interviews and the UTAUT framework, the study identified 21 implementations of the 3D generative models, categorized them into four groups, and highlighted their potential in AI-driven simulation processes. However, challenges such as data collection and security were noted as significant barriers to broader adoption, underlining areas that require attention.

Overall, these studies underscored the potential of GenAI tools in improving the ideation and simulation stages of creative processes within industries. They identified critical drivers of GenAI acceptance and utilization, such as performance expectancy, social influence, enjoyment, and AI anxiety. However, there is still a gap in research on practical approaches to enhance interface design and user interactions to better address these factors.

3 METHODOLOGY

Our qualitative study employed open-ended questions to gather in-depth, unbiased responses about professional designers' use of GenAI tools, especially for image generation. We aimed to understand their challenges and views on integrating these tools into their daily workflows. We defined *designers* as individuals employed in industries where software tools are predominantly utilized. They hold the job title of *designer* within their teams, with creativity and expertise in visual design being crucial aspects of their work.

3.1 Participants

We interviewed 16 professional designers at a single automotive company from October to December 2023. The group included seven females, eight males, and one participant who preferred not to specify their gender. Their design experience ranged from 1 to 26 years and encompassed roles in UX/UI, 2D/3D, interior, early-phase, and concept design. We combined purposive and snowball sampling methods [15] to ensure a diverse and representative sample. Purposive sampling (N = 7) allowed us to select participants based on specific criteria, including job roles, tasks, and willingness to participate. Subsequently, snowball sampling (N = 9) expanded our participant pool as interviewees referred us to their professional networks, enriching our insights into the topic. Detailed profiles of the interviewees, including their roles, years of design experience, primary tasks, conventional tools used, and any GenAI tools they employed or experimented with, are outlined in Table 1.

3.2 Interviews

Our interview questions were open-ended to minimize bias and encourage more in-depth responses, allowing participants to freely express their thoughts, experiences, and insights without being restricted to predefined answers. We categorized our questions into four sections to ensure a structured yet flexible interview process. Initially, we introduced the interview's objective and obtained consent from participants for participation and recording. Following this, we inquired about the participants' roles, primary tasks, workflows, and challenges they face as designers, aiming to gather background information and understand their tasks comprehensively. Next, we explored their use of GenAI tools, particularly image generation models, investigating motivations, challenges, and the impact of these tools on their creative processes. Finally, we discussed their perspectives on the future of GenAI in design, including expectations and suggested improvements, while allowing room for additional comments throughout. Of the 16 interviews, six were in-person, and ten were via video call, ranging from 30 to 90 minutes. All sessions were recorded except for two.

3.3 Thematic Analysis

For our data analysis, we used interview transcripts and notes, applying the thematic analysis approach outlined by Braun et al. [4, 5]. This method involved six phases: *familiarization, coding, searching for themes, reviewing themes, defining and naming themes, and producing the report.* To ensure consistency and depth in the analysis, the analysis was primarily conducted by a single author, with iterative input and feedback from co-authors to incorporate multiple perspectives. We used Notion [1] and Figma [2] to facilitate coding and theming. Notion offered features like data grouping, filtering, and multiple tagging, while Figma provided diagramming and visual aids. Both tools supported real-time collaboration among co-authors. During the coding phase, we used the table function in Notion to systematically organize and code the transcript data. This process included an iterative review of the data and the assignment of tags to create initial codes. These codes identified interesting aspects of the data, representing the most basic segments that could be meaningfully interpreted in relation to the phenomenon [4]. Following Braun et al.'s advice [4], we coded for a broad range of potential themes and ensured comprehensive coding by including surrounding data with each extract to maintain context. In the theming phase, we used Figma to visually organize all 131 codes. Our initial step was identifying potential themes by recognizing patterns or recurring elements related to our research objective and representing meaning within the dataset [4]. This phase included combining, refining, separating, and discarding specific codes to better define our themes within an iterative process. After identifying 23 themes, we thoroughly examined all collated codes for each, considering whether they exhibited a coherent pattern. We then evaluated the themes, merging similar ones. This recursive selection and refinement process allowed for continuous revisiting and adjustment as our study progressed. Following a comprehensive review, we selected four themes that most reflected the key challenges designers face when using GenAI image generation tools.

[1]https://www.notion.so/
[2]https://www.figma.com/

Table 1: Summary of Interviewed Designers: This table provides an overview of the designers interviewed from the automotive industry, detailing their design roles, main tasks, years of experience, and the design and GenAI tools they use.

ID	Exp. (Yrs)	Job Role	Tasks	Design Tools	GenAI Tools
P1	2.5	Interaction Designer	Concept development, visual design	Photoshop, Illustrator, Figma, Microsoft 365	RunwayML, ChatGPT, Midjourney
P2	6	Early Phase Designer	Concept, vision development	Photoshop, Illustrator	Vizcom, ChatGPT, Midjourney
P3	26	Project Lead	Storytelling, presentation, planning, training	Photoshop, Microsoft 365	Adobe FireFly, Midjourney, RunwayML, Vizcom, Pika
P4	13	Concept Designer	Responsible for holistic design experience, visualization	Blender, Figma	Stable Diffusion, Midjourney, ElevenLabs
P5	1	3D Designer	3D Modeling, animation, video editing, 3D printing	Adobe Creative Suite, Microsoft 365, Blender, Figma	Midjourney, ChatGPT, DALL-E
P6	1	3D Designer	Animating 3D video, 3D texturing, modeling	Blender, Substance 3D Painter, After Effects	ChatGPT, DALL-E
P7	3	2D/3D Designer	UX/UI design, 3D modeling	Blender, Unreal Engine, Figma	Stable Diffusion, Midjourney, DALL-E, Vizcom
P8	20	Senior Concept Designer	UX/UI design for concept car	Photoshop, After Effects, Figma	Adobe Built-in AI Tools, Visual Electric, ChatGPT
P9	15	Director Interaction Designer	Face to clients, project management, presentation	Figma, After Effects	Midjourney, ChatGPT
P10	4	Junior Interior Designer	Designing the interior parts of cars	Photoshop, InDesign, Illustrator, Blender, Autodesk Alias	Midjourney
P11	2.5	Junior Interaction Designer	Designing UX/UI	Figma, After Effects, Illustrator, Photoshop	Midjourney, AI Voice, ChatGPT
P12	5	Experience Designer	Designing holistic experiences for visionary concepts, research, prototyping	Adobe Creative Suite, Blender, Unreal Engine	Midjourney, Adobe Firefly, ChatGPT, Upscaler, RunwayML, AI Voice
P13	25	Design Lead	Digital and print design, project and team management, Mixed Reality and 3D spatial computing design and development	Photoshop, Illustrator, Figma, Premiere Pro, Blender, Unreal Engine, Unity	Adobe Built-in AI Tools, ChatGPT
P14	20	Interior Designer	Designing interior	Blender, Photoshop, Illustrator	ChatGPT, Adobe Built-in AI Tools
P15	2.5	Junior Interior Designer	Designing interior surface and seats, sketching	Photoshop, Blender, Autodesk Alias	Midjourney, Vizcom
P16	7	UI Design Lead	Design direction, guidance, feedback on features for mobile application, car themes guidance	Figma, Illustrator, After Effects	Midjourney, ChatGPT, Intern AI tools

To provide a comprehensive view of our findings, we included a list of all themes identified in the early analysis phase, specifically during the 'searching for themes' stage, in Appendix A. While our analysis and discussion focus on the four key themes relevant to our research aim, this complete list offers a broader context for our findings.

4 FINDINGS

Our study identified four key themes that illustrate the challenges designers encounter when using GenAI image generation tools for creative work. The difficulties are as follows: (1) the interfaces are not well-suited for visual thinkers *(Theme 1: Interfaces for Visual Thinkers)*, (2) the interfaces do not align with the non-linear and iterative nature of creative workflows *(Theme 2: Interfaces for Design Workflows)*, (3) there are difficulties in controlling prompts *(Theme 3: Prompt Control)*, and (4) integrating tangible, physical experiences with GenAI in the digital design process is challenging *(Theme 4: Integrating Human Experiences into Design)*.

4.1 Theme 1: Interfaces for Visual Thinkers

Nine designers highlighted their reliance on visual thinking and suggested that GenAI interfaces should incorporate sketch-based input features, including multi-modal input selection and a combination of input methods. Designers use GenAI image generators primarily for two purposes: to source inspiration for their projects and to quickly translate the visions they have in mind into tangible images. This rapid visualization is advantageous for efficiently delivering their ideas to coworkers or, on occasion, stakeholders. The thematic network [2] for this specific theme, along with its sub-themes and associated codes, is depicted in Figure 1. We organized this section into two subsections based on the sub-themes derived from our interviews: (1) *Visual Input-Centric Interfaces* and (2) *Easy Input Support.*

Visual Input-Centric Interfaces. The code ***'Visual Thinking Users'*** in the first sub-theme underlines the designer's preference for GenAI interfaces that support their visual-centric thinking. Many designers experience difficulties since current GenAI image

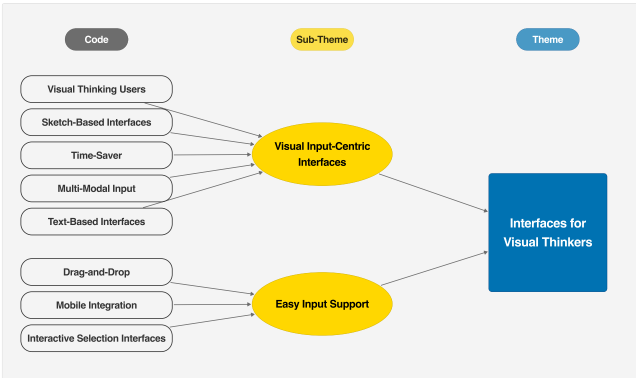

Figure 1: Thematic network diagram for Theme 1: 'Interfaces for Visual Thinkers,' with associated codes (left) and sub-themes (middle)

generation tools, such as Midjourney and DALL-E, rely predominantly on text-based prompts, which often do not sufficiently support visual thinking. Oftentimes, designers have vivid images in their minds that are challenging to articulate just through words alone. P15 mentioned, *"Sometimes you can express things better with a sketch than with words."* Similarly, P10 commented, *"There is a medium of language between me and the AI, so it is not easy to solve everything in language."* While some GenAI tools have image input features, they often require typing text prompts as well, necessitating a verbal transition of visual thinking, which can be demanding, especially for visual thinkers. P9 pointed out that using Midjourney felt *"more like thinking the way a developer does, which isn't easy for those who are used to thinking visually."* As a result, designers often spend considerable time experimenting with various text prompts in order to create the expected image. Notably, 7/16 participants explicitly stated their struggles with formulating effective text prompts.

To solve these problems, six participants suggested implementing hand sketching or drawing as an alternative means of input, which is encapsulated under the ***'Sketch-Based Interfaces'*** code. For instance, P8 described utilizing *"a simple hand-drawn sketch on paper,"* while P12 mentioned using *"a quick doodle, similar to a 'napkin sketch'"* to guide GenAI tools in generating desired outcomes. Furthermore, P10 noted that using sketches as inputs can be more time-efficient compared to using text-based input for expressing visual concepts, as underscored by the ***'Time-Saver'*** code. While tools like Vizcom [3] employ this approach by creating variations from user sketches, participants commented that this use tends to be limited to rapid rendering. P10 and P15 also indicated that while Vizcom delivers *"relatively high-fidelity results,"* it may not be ideal for the initial stages of inspiration, focusing instead on *"more developed design concepts."*

Designers expressed a preference for interfaces that accommodate hand sketches, emphasizing the need for multi-modal input capabilities, identified under the ***'Multi-Modal Input'*** code. This preference is rooted in their practice during the inspiration phase, where mood boards are commonly used, incorporating various source materials such as images, drawings, architectural work, photographs, and video clips. The desire for multi-modal input capabilities reflects this practice, with designers seeking an input system that can handle 2D sketches, images, 3D models, animations, text, and photos (P10 and P15). Such a system is considered essential for fostering the creative process, allowing designers to blend and manipulate various inputs to spark and refine their creativity. P9 proposed a unified tool to meet these diverse needs in a single application, simplifying the process of generating a variety of formats without switching between different tools. P9 stated, *"Having one big thing where you're covering all the needs, you don't have to open every specific AI tool [for different input formats]. That would also be much easier."* This concept of an all-in-one tool underscores designers' desire for platforms that accommodate diverse inputs and deliver versatile outputs. While there is strong interest in visual material-centric inputs, the significance of text-based interactions is also acknowledged, as indicated by the ***'Text-Based Interfaces'*** code. Designers like P13 and P15 expressed comfort with using text prompts to convey ideas. P13 stated, *"But again, I still think text prompting will play a big role. [...] I think I feel like we've all been trained pretty well to use a text box, hit submit and generate."* This perspective underscores the importance of GenAI image generation tools supporting a range of input modalities, ensuring that designers are not limited to solely visual or text inputs but can combine various inputs to enhance their creative work.

Easy Input Support. In discussions about integrating multi-modal input systems, designers stressed the need for intuitive user interfaces. The concept of using drag-and-drop gestures to incorporate sketches or images directly into the design process was particularly stressed by P9 and P10, marked by the ***'Drag-and-Drop'*** code. P9 envisioned a tool that allows for image inputs by *"dragging them across different tools,"* thereby eliminating the hassle of downloading, uploading, or copying and pasting. P13 also emphasized the potential of such input gestures for finding similar images and generating new ones on the working canvas, suggesting, *"You can drag and drop that image in, and then all of a sudden, it generates a bunch of stuff."* The discussion also covered the ease of using various formats as input sources and the ability to directly transfer images from mobile devices such as smartphones and tablets to digital design workspaces, as noted under the ***'Mobile Integration'*** code. P13 described the process, stating, *"You take a picture, and [...] you can drag it as input [to GenAI] [...] without a lot of instruction or a lot of context."* P10 expressed a desire for tools that allow for the straightforward use of *"inspirational photos taken by smartphones during everyday activities,"* such as *"exhibitions or travels,"* emphasizing how these images can serve as a foundation for new designs with GenAI tools. This capability enables designers to integrate daily inspirations into their digital workflows seamlessly.

Additionally, interfaces that offer broader selection beyond traditional text inputs were addressed under the ***'Interactive Selection Interfaces'*** code. P12 pointed out the limitations of text prompts and the learning curve required to use them effectively. Mentioning tools like *"Adobe Firefly"*, designed to enhance user interaction by allowing selections from various predefined options. P12 elaborated, *"You just have some certain points that you can select, and then you say, I want to have this style; I want to make it more realistic; I want*

[3] https://www.vizcom.ai/

to make it more comic." This method aims to *"reduce reliance on text inputs,"* promoting a more intuitive and accessible approach to creative processes.

4.2 Theme 2: Interfaces for Design Workflows

We gathered valuable insights from our interviews about how designers find inspiration, engage in key design activities, and use GenAI tools in their workflows. The insights are categorized into two sub-themes: (1) *Design Process Characteristics* and (2) *GenAI Use in Current Design Workflow*, as shown in Figure 2. These sub-themes describe iterative, reflective design workflows and highlight that the current GenAI interfaces do not fully meet the practical needs of designers.

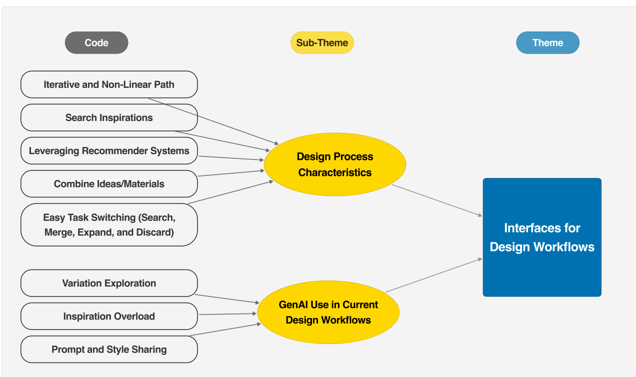

Figure 2: Thematic network diagram for Theme 2: 'Interfaces for Design Workflows,' with associated codes (left) and sub-themes (middle)

Design Process Characteristics. Designers described their work processes as iterative, reflective, and non-linear. However, they observed that existing GenAI image generation tools do not sufficiently support this complexity in the design process, as indicated by the ***'Iterative and Non-Linear Path'*** code. Designers commonly engage in iterative processes involving exploration, reflection, and refinement. In contrast, GenAI tools typically follow a more linear, end-to-end approach. P13 identified a limitation in the current systems, noting that *"[GenAI tools] typically generate a response based on a request, allowing the user to iterate based on that response or start a new request. However, this process remains fundamentally linear."* This discrepancy between the single-response generation approach and the non-linear creative design processes poses a significant challenge for integrating GenAI into design workflows.

The ***'Search Inspirations'*** code highlights the importance of seeking inspiration in the design process. According to P6, P10, and P11, designers commonly start their search with project-based keywords and then supplement them with their unique keywords. Some designers are skeptical of using GenAI for this purpose, with concerns that it might limit creativity and require substantial time and effort to craft appropriate prompts. Instead, as the ***'Leveraging Recommender Systems'*** code indicates, designers often turn to platforms like Pinterest and Instagram, which utilize recommender systems. Recommender systems curate existing content based on user preferences and interactions, whereas GenAI models primarily create new content in response to user prompts. These recommender system platforms allow designers to quickly browse a large number of existing photos, make selections, and receive new suggestions based on those choices. P6 elaborated on the benefits of this approach, stating, *"You want a diverse pool of images to look at, so you're not just focusing on one idea and narrowing down too quickly. [...] The platform will show you different stuff-some of it similar, some different—and you end up a long way from where you started pretty quickly."* P10 also noted the effectiveness of these platforms, commenting, *"[These platforms] have good algorithms with a vast number of images. It's for searching for inspiration or sparks when you need to create something from nothing."*

Besides gathering sources of inspiration, designers often curate these elements on digital platforms like Figma or traditional analog mood boards, a practice categorized under the ***'Combine Ideas/Materials'*** code. They continuously iterate by combining various ideas, expanding or discarding concepts, and often moving back and forth between these activities. P10 explained, *"I try to find my images and combine them with my specific idea as an inspirational mood board. And then you can always connect these two things. You have a sketch, and it's inspired by these kinds of things: products, architecture, whatever."* Similarly, P14 noted, *"We're really playing around with certain ideas and stories, mixing them."* This part of the process is regarded as *"the most challenging"* and *"most enjoyable"* aspect of design, as emphasized by P1, P6, and P16. Some designers stressed that this process requires human thinking and a complex ideation process, making it irreplaceable by GenAI, as noted by P10, P14, and P16. A subgroup of four designers (P6, P10, P11, and P15) expressed the need for interfaces that facilitate easy task switching between activities like searching, merging, expanding, and discarding materials and ideas while working with GenAI tools. This requirement is encapsulated under the ***'Easy Task Switching (Search, Merge, Expand, and Discard)'*** code.

GenAI Use in Current Design Workflows. Our study, which explored the adoption of GenAI image generation tools in design practices, identified a sub-theme *'GenAI Use in Current Design Workflows'* focused on their current use. Designers generally use GenAI to gather inspiration, particularly during the early stages of concept development, such as mood board creation. The creative process often benefits from the element of surprise and the serendipity of unexpected results, which can serve as a stimulus for ideas or inspiration. Designers intend to use GenAI for exploring variants while also controlling its unpredictability to some extent, as captured by the ***'Variation Exploration'*** code. P15 explained, *"Designers use sketch input as both a prompt and inspiration for search images, whether they create slight or big variations from the original sketch."* P8 noted that GenAI could yield diverse outcomes from the same input depending on the task, emphasizing, *"You get some results based on your drawing. [...] This time, the result focuses on the drawing style, not introducing a new idea."* However, as P11 observed, the variations provided by GenAI tools are often perceived as *"either too similar or too different from the initial idea[, which was not expected]."* Designers prefer to determine when they receive surprising outcomes, favoring *"unexpected results with control over the variation"* (P15) to ensure these outcomes are deliberate choices rather than random outputs. P9 pointed out that GenAI tools are beneficial *"when you have a clear vision and need to quickly visualize ideas for sharing with others during the ideation phase."* The concept of ***'Inspiration Overload'*** was discussed, noting that the high volume of results from GenAI during the inspiration phase can be overwhelming, in contrast to the experiences with traditional recommender systems, which are relatively less overwhelming. P15 expressed concerns about the inundation of ideas from GenAI, saying, *"Generative AIs give me a thousand ideas in one day. Does this lead to too much information? In the end, it might not be helpful at all."* He also suggested exploring why the volume of results from GenAI feels more overwhelming than those provided by recommender systems with existing images could be an interesting area of study.

Many designers emphasize that teamwork and feedback from colleagues are critical components of their work. With the increasing integration of GenAI tools into the design process, their use in collaborative settings has also grown. However, due to confidentiality concerns, a few designers (4) have utilized GenAI for team projects but have restricted its use to less critical work to manage risks related to sensitive information. Nevertheless, as GenAI use is expected to grow in collaborative projects, designers emphasized the importance of collectively developing a consistent style and ensuring that both the style and its corresponding prompts are easily shared within their team, as captured by the ***'Prompt and Style Sharing'*** code. P1 shared their experience with GenAI tools, stating, *"We do a lot of testing, adjusting the amount of text input together. [...] We even have channels in Discord for storing and swapping images [and used prompts]."* P11 described their teamwork approach, saying, *"We all try it out, organize it, and share it. [...] Once we have a certain style, we create variations based on that."* To minimize the hassle of sharing images, they use *"a single shared account"* to make it easier to access their work history (P1 and P11). P9 discussed the challenges of teamwork, particularly in sharing and determining the right prompts, mentioning, *"It also depends on how many people work on a project. If more people are working, they might both try to find images and then compare them. [...] Eventually, they align on one image expression. But usually, it takes time to find the right prompts and share them."*

4.3 Theme 3: Prompt Control

Theme 3, referred to as *'Prompt Control'*, explores the challenges designers face in controlling prompts when using GenAI tools. This theme has a sub-theme called ***'Mastering GenAI Tools'***. The visual representation of this thematic network is shown in Figure 3.

Mastering GenAI Tools. Designers faced ***'Outcome Control Challenges'*** when using GenAI image generation tools, despite the tools' capability to facilitate the ideation phase and rapidly visualize the designer's ideas. Achieving satisfactory images from GenAI can often be challenging and frustrating, even with substantial dedication of time and effort in generating text prompts. P1's experience explained this issue, noting, *"We do a lot of testing, adjusting the amount of text input together. However, despite all that, there are times when the generated images turn out differently."* P12 also mentioned the tools' unpredictability, stating, *"One time it's maybe really similar to the image that you put in, and then it does something completely different, and that is this unexpected. And sometimes it's horrible that you say like, Ah, yeah, I don't need it."* Even with these efforts, the resulting images sometimes require additional retouching due to their unexpected artificial appearance. P1 underlined this by noting, *"Relying solely on Midjourney can sometimes make things look too artificial and disappointing."* One common approach to addressing this issue is analyzing prompts that have generated images similar to the target images. For example, designers often search for similar GenAI-generated images in chat features of tools like Midjourney before creating their own. As P15 described, *"[...] you can view the chat history to see what others are doing and what [prompts] they typed in. This transparency is helpful."* By analyzing and experimenting with these prompts, designers can reduce trial-and-error and improve their skills in creating effective prompts (P7, P11, and P15). P7 emphasized this approach, mentioning, *"It is similar to scientific work. You try to reproduce it."* Another approach involves searching for reference images that align with their goals, whether generated by GenAI or retrieved from human-generate sources, and uploading these images to GenAI systems, such as ChatGPT or Midjourney's 'describe' feature [4], to obtain descriptive prompts that can be used to create similar images. P11 explained, *"You can upload an image that you want, and they'll give you a description of it. [...] I tend to use that when it comes out."* To reduce the time spent on trial-and-error, designers create personal or shared repositories of result images, along with the prompts and parameters used. After refining prompts and parameters, they save the successful images for reuse and sharing with other designers (P1, P7, P9, P11, and P12).

To better address the challenges in controlling prompts, designers like P3, P4, and P7 are deepening their expertise in prompt engineering and actively participating in communities that offer training and facilitate the exchange of prompts and results. This ***'Training and Community Engagement'*** includes participation in forums, training courses, open-source websites, and social media platforms where insights and successful strategies and techniques are shared. P7 emphasizes the openness of these communities, stating, *"In general, the entire community that is trying to learn AI tools is still very open. [...] Whenever someone figures out something new, they will post it on forums, on social media platforms or YouTube."* Additionally, P2 and P3 suggested creating *"internal platforms"* within organizations to support safe experimentation with GenAI tools, particularly for corporate projects. Furthermore, P4 pointed out the

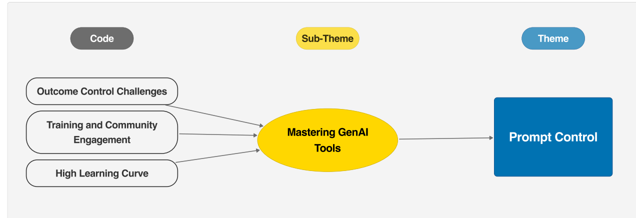

Figure 3: Thematic network diagram for Theme 3: 'Prompt Control,' with associated codes (left) and a sub-theme (middle)

[4] https://docs.midjourney.com/docs/describe-1

challenges newcomers face, captured under the ***'High Learning Curve'*** code. P4 observed, *"[Newcomers] believe they can control the outcome of [Gen]AI, but it's a very long way to get your head around the idea of what [Gen]AI is and what [Gen]AI is not for you."* Acquiring a certain level of proficiency is necessary, yet it involves a steep learning curve, underscoring the need for adequate training or effort.

4.4 Theme 4: Integrating Human Experiences into Design

The final theme investigates the significance of real-world, tangible experiences and human interactions in the design process. Our analysis revealed a sub-theme: ***'Human Experiences in Design'***. Figure 4 visually represents this theme, its sub-theme, and codes.

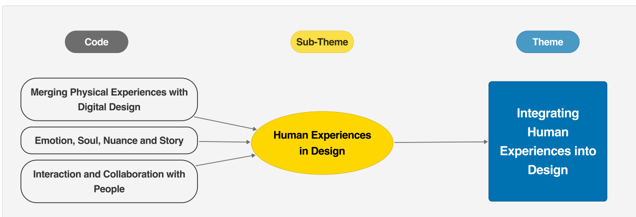

Figure 4: Thematic network diagram for Theme 4: 'Integrating Human Experiences into Design,' with associated codes (left) and a sub-theme (middle)

Human Experiences in Design. P5 discussed the broader implications of human experiences in design, stating, *"We design for people, and then people also put their own value into the product. [...] Human experience, your upbringing, how you're raised, how you think, your personality."* The code ***'Merging Physical Experiences with Digital Design'*** emerged prominently among designers, emphasizing the need to harmonize inspiration from both the physical and digital realms to craft engaging narratives. P1 emphasized this integration, stating, *"The distinction between the physical and digital realms [is important]. Ultimately, the focus should be on human-centered experiences. [...] In the world of design, one thing remains crucial, and that's storytelling. AI should be utilized as a tool to enhance this."* P7 expressed support for integrating GenAI with tangible design elements, remarking that relying solely on GenAI tools would be problematic. P7 added, *"It has to be a mixture of [Gen]AI outputs, some sketches, and some photos from other already existing products. The sketches are from your experience as a designer, and that's your value. That's why you are there."* Additionally, P10 underscored the practical aspects of such integration, suggesting a more tool-oriented approach to easily blend these elements, noting, *"It's a good idea to look at pretty paintings in museums, take photos, and use those daily experiences as sources. If you find a painting's colors or shapes interesting, you can use them as inspiration with GenAI."*

The ***'Emotion, Soul, Nuance, and Story'*** code emphasizes the importance of emotional depth in design. P8 reflected on the emotional impact of design, stating, *"Our design is also strongly related to emotion. So, you see the car and the shapes, and you have an emotion that could be negative or positive. And I'm not sure that AI is able to do that. There is no emotion. It's just code."* Echoing this sentiment, P9 stressed the power of emotional connection in influencing customer decisions, noting, *"They [customers] need to be touched emotionally in order to be convinced. And the less emotional you are, the less you can convince people to agree to something."* Regarding the lack of soul in GenAI-generated designs, P14 observed, *"What I miss in all of these [GenAI-generated] pictures is that they have no soul. Somehow, there is a certain emotion through how light shines into the car or on the exterior reflections and stuff like that. There is no real human emotion on the surface."* Expounding further, P14 underscored the significance of storytelling in design, adding, *"The story, the concept is coming out of us, the feeling, and what we want to convey in that sketch. [...] It's always about the story. Doing a nice sketch is one thing, but it got no soul without the story."* P5 shared a cautious perspective on the role of GenAI, highlighting the importance of human insight and narrative intention by saying, *"They [GenAI] might create something visually interesting to look at, but it wouldn't make sense because [...] its use wasn't justified."* P14 also emphasized the lack of emotional depth in GenAI and the importance of human emotion in the design process, explaining that GenAI functions without the emotional involvement of human designers, stating, *"This is where AI is totally without emotion. It's just doing; it's not asking, it's not arguing, it's not sad about it. When you change something, it adapts without emotion."*

The ***'Interaction and Collaboration with People'*** code explores the crucial role of collaboration and interpersonal interactions in design projects. P14 highlighted the importance of effective communication and the value of receiving constructive feedback from coworkers, which sometimes involves engaging in debates. Some designers envision GenAI tools as akin to having a colleague who provides feedback, and they foresee that the future role of GenAI tools—and AI tools more broadly—will align with this perspective. P1 described it as, *"It's like having a chat with a colleague, asking them what they think. It's interactive and helps us find inspiration. For instance, you know how you chat with coworkers about trends or things you've seen at exhibitions."* P12 was also optimistic about the potential applications, suggesting, *"Maybe that AI could be a sparring partner or a colleague that gives you inspiration, the daily inspiration of new tech, new art or new things that you haven't seen."* Notably, none of the designers interviewed agreed that existing GenAI tools adequately incorporate physical and human experiences into the digital design workflow or effectively facilitate interaction and collaboration among individuals.

5 DISCUSSION & IMPLICATIONS

Our research identified the problems that designers face when adopting GenAI image generation tools into their design workflows. The four themes offer useful insights into the design of future GenAI tools.

5.1 Supporting Multi-Modal Input Methods

One of the identified themes is the difficulty that designers, particularly visual thinkers, experience with GenAI image generation tools. These tools predominantly use text prompts [11, 35], which can be a significant barrier for designers whose ideation processes often manifest visually rather than verbally. This highlights the limitations of current GenAI image generation interfaces in accommodating the diverse cognitive styles of users. Based on our findings, we argue that supporting sketch input-centric interfaces could address this challenge effectively. Such support would enable designers to reduce the cumbersome step of translating visual ideas into textual descriptions, allowing for a more direct translation of visual concepts into digital outcomes. Sketch input aligns with the natural workflow of many designers, who often start the creative process with hand-drawn sketches. Moreover, Suwa et al. [45] noted that design sketches not only act as external memory or providers of visual cues for associating non-visual information but also create a physical environment in which design thoughts develop in real-time. Previous studies have explored sketch-based interfaces for tasks such as image retrieval [17], creating 3D object sketches from 2D sketches [25], and facilitating human-AI collaboration in painting [44] and 2D drawing, with an emphasis on real-time collaboration [37].

In line with our findings, we also recommend developing GenAI interfaces that support multiple input methods. Designers we interviewed preferred multi-modal interfaces, particularly those with visual input-centric capabilities. Qiao et al. [40] demonstrated that using image prompts alongside text prompts significantly improved subject representation in GenAI-generated images, especially for concrete subjects. This underscores the benefits of integrating various visual input methods into GenAI tools. Designers also emphasized the need for interfaces that facilitate easy input across multiple modalities, devices, and user actions. They suggested incorporating hand or finger gestures for drawing, modifying, moving, and merging image elements, and generating images on GenAI interfaces. This discussion extends beyond visual input-based interfaces to explore the potential of gesture-based input control, which remains underexplored. Further research is needed to determine how gesture-based inputs can be effectively integrated with GenAI tools supporting visual or multi-modal inputs. Furthermore, our findings suggest that multi-modal inputs should be designed for ease of selection, switching, and combination to enhance the usability and flexibility of GenAI tools in the design process. To enhance overall interaction efficiency, it is also important to consider implementing simple controls for these actions.

Notably, two designers expressed satisfaction with the current text prompt-centric GenAI interfaces. While this view was shared by only a minority of participants, it represents a valuable area for further exploration. Further research could investigate how effectively sketch input-centric interfaces support users' visual thinking and explore ways to enhance these interfaces to accommodate diverse design approaches across various design processes.

5.2 Facilitating Iterative Exploration in GenAI Interfaces

The iterative and non-linear nature of the design process underscores the necessity for GenAI image generation tools to adapt to such workflows. Currently, many GenAI tools do not adequately accommodate the typical working methods of designers [54, 55]. Our research revealed that designers fluidly navigate between different stages of their creative practices. This includes seeking inspiration, combining ideas, and iterating on designs, often without separating these activities into discrete steps. Wan et al. [49] demonstrated that incorporating features for exploration, such as the ability to mix materials, can significantly enhance creativity, making idea exploration more enjoyable and effective. To better support practical design workflows, GenAI interfaces should facilitate seamless transitions between tasks at various stages. This could include features that enable quick and easy inspiration searches [29, 48, 49], the use of multi-modal inputs [48, 54], idea merging [49], and concept expansion [54]. Additionally, allowing manipulation and iteration on GenAI-generated outputs within the same tool can enhance the creative workflow, enabling designers to refine ideas without constantly switching between different applications [48].

5.3 Interfaces for Easy Prompt Control and Sharing

The complexity of controlling prompts was identified as a key challenge in our analysis. This aligns with Oppenlaender's observations [39] in the text-to-image community, where practitioners often refine GenAI outcomes by incorporating specific 'modifiers' into their text prompts. These modifiers are crucial for achieving results that more closely match their envisioned outcomes, underlining the significance of skilled prompt formulation. Zhang et al. [53] also highlighted challenges with GenAI tools in a study involving 11 architectural design students. They particularly noted the frequent mismatch between intended and generated designs, which can be especially frustrating in precise fields like architectural design. Liu and Chilton [33] suggested design guidelines for effective prompt engineering after examining over 5,000 text-to-image generations, emphasizing the trial-and-error nature required to achieve coherent outputs. Building on this understanding, recent research has proposed interfaces aimed at facilitating user exploration of text prompts and their resulting outcomes. For instance, Chung et al. [7] adopted a traditional painting palette analogy with a slider mechanism, allowing users to navigate between two different text prompts. Their system provides intuitive control, ensuring smoother transitions and more effective user management of prompt variations.

Our analysis revealed that the difficulty in specifying precise parameters and prompts for desired outcomes complicates not only the generation process, as discussed in Theme 3 in the subsection 4.3, but also hinders collaboration within design teams, as outlined in Theme 2 in the subsection 4.2. Design teams often struggle to settle on a unified style that satisfies the majority and to share relevant prompts efficiently. To tackle these issues, we suggest developing tools that facilitate prompt management and collaboration. A shared platform where team members can access, modify, and discuss prompts and results would promote a cohesive approach to design. This shared space ensures that all members contribute to and align with the direction of the outcome. Moreover, a feature that allows team members to experiment with prompt variations, with the option to toggle between private and public access, could foster individual creativity within the context of the team's collective efforts. An intuitive interface for tracking the history of prompts, featuring visualizations and easy manipulation options, like branching from specific points, would aid in understanding the development of ideas and the decision-making process throughout the project. Moreover, designing an interface that supports collective input on a prompt formulation could enhance collaborative design efforts. By introducing user-friendly prompt management and collaboration tools, we aim to reduce the burden on designers, particularly in managing and sharing prompts during collaborative projects.

5.4 Bridging Physical Experiences and Digital Design

The integration of real-world experiences with digital GenAI processes emerged as a key theme in our study. Designers often draw inspiration from their personal experiences, such as travel, visits to exhibitions, museums, and special events. These experiences, captured in the form of photos, memos, and personal diaries, hold immense potential as prompts for GenAI tools. We propose developing interfaces that enable the seamless upload and manipulation of these materials. These interfaces could feature easy uploading and editing of personal photos or notes, with the ability to translate these inputs into digital designs that reflect the original emotional and aesthetic qualities of the physical experiences.

Furthermore, incorporating Extended Reality (XR) technologies like Augmented Reality (AR) and Mixed Reality (MR) can potentially enhance the design process [19, 22, 26, 34]. Research in the XR field has explored its role in improving creativity, covering areas like gesture-based creation and editing of virtual prototypes [22], the visualization of objects within real-world spaces [32], as well as, creating 3D models using AR [43]. Studies have also examined prototyping user interactions [50], sketch-based video prototyping [30], and using AR for high fidelity visualization [38]. However, research on integrating XR with GenAI technologies remains notably scarce. By using AR and MR, designers can interact with their physical surroundings to capture textures, colors, and patterns from the environment, which can be directly fed into the GenAI system. This approach provides an authentic source of inspiration that bridges the gap between the physical and digital realms.

5.5 Exploring GenAI from a Social Interaction Perspective

The discussion on integrating human experiences also highlighted the importance of social interaction. Designers emphasized the crucial role of communication with various stakeholders, including colleagues and user groups, throughout the design process. Some designers envisioned AI tools, beyond just GenAI image generation, that could enrich human experiences, facilitate communication with stakeholders, and promote team collaboration, thereby fostering creativity and enhancing design outcomes. Future research could explore how GenAI could incorporate or amplify social interaction and its impact on the design process. Interfaces can be designed with consideration of social dynamics between people. This domain remains relatively unexplored in both GenAI and HCI fields.

6 LIMITATIONS

Our study comes with certain limitations that need highlighting. Firstly, our thematic analysis had a methodological limitation as we relied on a single coder for theme identification and analysis from the dataset. While thematic analysis is a flexible method capable of uncovering data patterns and narratives [4, 5], using only one coder may raise concerns regarding the objectivity and reliability of the thematic interpretation. To mitigate these concerns, we followed rigorous procedures, including documenting the detailed coding process, following thematic analysis guidelines, and utilizing a 15-point checklist of criteria [4]. Additionally, we conducted four discussion sessions to review the themes identified by the main coder, ensuring their coherence, consistency, and distinctiveness from other themes, and addressed repetitive codes or themes by removing or rearranging their positions.

Furthermore, our research involved interviews with designers at a single large multinational automotive company. Although we engaged with professionals from various departments, the shared workplace might influence a common design language or ethos. Future studies should include a more expansive range of designers from diverse companies of varying scales and industries to ensure a broader understanding of design practices.

Our focus was primarily on practitioners using software-based design tools, which may overlook the nuances of working with other design methods or tools. Additionally, the geographical scope of our interviews was limited to designers working in Germany. However, our participants represented a variety of nationalities, including German, French, Australian, American, Korean, and Chinese. Expanding the geographical reach in future studies could provide invaluable insights into the cultural dimensions of design work and the adoption of GenAI tools.

Lastly, we based our findings on retrospective interviews conducted within a constrained time frame. To more thoroughly comprehend the impacts and challenges of GenAI in creative processes, future research can employ longer-term observations or more interactive methodologies, such as participatory workshops, offering a more comprehensive and detailed exploration of GenAI's integration into creative domains.

7 CONCLUSION

This paper presents the findings of a qualitative study exploring how professional designers in the automotive industry use and envision GenAI image generation tools in their daily design workflows. Through interviews with 16 designers and thematic analysis, four main challenges emerged: interfaces not well-suited for visual thinkers, limitations of interfaces in accommodating the iterative and non-linear creative process, difficulties in controlling prompts, and the need for GenAI tools to integrate tangible human experiences. Based on our findings, we proposed several design implications to improve GenAI interfaces. These include offering multimodal input methods, such as visual material-centric inputs, to better support visual thinkers; designing interfaces that cater to the iterative nature of the creative process with features for back-and-forth, non-linear exploration; and developing tools that simplify the control and sharing of outputs and prompts through intuitive and collaborative interfaces. Moreover, incorporating real-world experiences into digital workflows is crucial for enhancing creativity and design uniqueness. Further exploration of GenAI from a social interaction perspective, focusing on enhancing collaboration and its impact on the design process, is also recommended. Future work should address these identified challenges and aim to design GenAI image generation tools that meet designers' needs, ultimately improving their creative processes. Our study contributes to the field of HCI by offering empirical insights into the practical challenges designers encounter when using GenAI image generation tools in their work. By focusing on user interface and interaction challenges and proposing design implications, our research enhances the understanding of how GenAI can be better designed to enhance design workflows.

ACKNOWLEDGMENTS

We would like to thank all the participants at BMW for their time and invaluable insights on GenAI. Additionally, the authors used OpenAI's models to refine certain phrases and enhance the language for improved readability while ensuring that the original text was entirely written by the authors.

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A THEMATIC OVERVIEW OF EARLY ANALYSIS PHASE: THEMES AND CODES

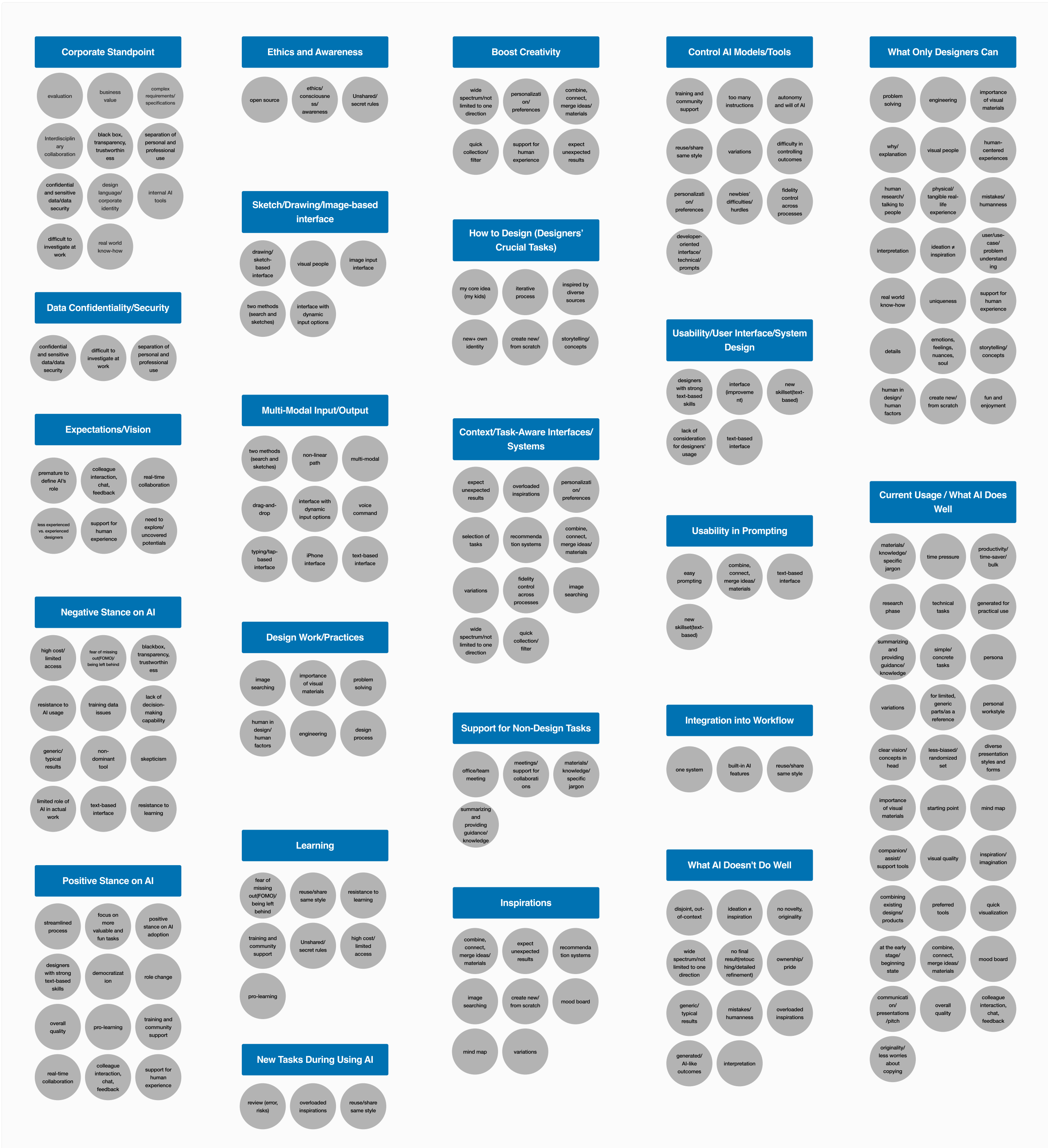

Figure 5: Overview of all themes (n=23) and codes (n=131, with some codes appearing in multiple themes) identified in the early analysis phase, specifically during the 'searching for themes' stage. This figure provides context prior to extracting four key themes through the iterative theme review process.