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Towards Fostering Human Ownership in GenAI-Assisted Design

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ABSTRACT: GenAI has significant potential to transform the design process, driving efficiency and innovation from ideation to testing. However, its integration into professional design workflows faces a gap: designers often lack control over outcomes due to inconsistent results, limited transparency, and unpredictability. This paper introduces a framework to foster human ownership in GenAI-assisted design. Developed through a mixed- methods approach—including a survey of 21 designers and a workshop with 12 experts from product design and architecture—the framework identifies strategies to enhance ownership. It organizes these strategies into *source*, *interaction*, and *outcome*, and maps them across four design phases: *define*, *ideate*, *deliver*, and *test*. This framework offers actionable insights for responsibly integrating GenAI tools in design practices.

KEYWORDS: artificial intelligence, ethics, design methodology, human-centered design, generative AI

1. Introduction

Generative AI (GenAI) has demonstrated immense potential across all phases of the design process, offering transformative capabilities that enhance efficiency and creativity. From the earliest phases, designers can leverage GenAI to define design problems, identify user needs, and create design requirements (Ataei et al., 2024). In the conceptual design phase, GenAI amplifies creativity and helps break fixation, enabling designers to incorporate textual and visual inspiration to generate design ideas (Wang et al., 2024). In the delivery phase, GenAI enhances modeling workflows by automating 2D drawing and 3D modeling (Sanghi et al., 2023; Xu et al., 2024a). In the testing phase, it has the potential to inter- pret simulation results, and suggest iterative improvements, creating a feedback loop that strengthens the design process (Elrefaie et al., 2024).

Despite its potential, integrating GenAI into practical design workflows presents significant challenges. Designers often struggle with a lack of control over AI-driven processes (Wang et al., 2024; Damen et al., 2024). First, GenAI frequently produces inconsistent and unexplained outputs, lacking the reliability and transparency of traditional tools (Ganguli et al., 2022; Sun et al., 2024). Second, biases and hallucinations in AI-generated results raise concerns about quality and reliability, undermining trust and contributing to hesitancy in adopting GenAI in professional contexts (Zhou et al., 2024; Ferrara, 2023). Biases are systematic errors that favor certain groups or reinforce stereotypes, while hallucinations occur when AI generates misleading information that seems credible but lacks factual basis.

To address these challenges, ensuring psychological ownership—the sense of control, involvement, and authorship over outcomes—is critical for human-centered AI practice (see Section 2.3 Human Ownership in the Use of GenAI for details). Improved psychological ownership in the use of GenAI enables users to utilize the technology more productively and safely (Xu et al., 2024b). It also enhances sense of control by driving deeper interaction with GenAI tools, allowing designers to explore advanced fea- tures and unlock innovative applications (Shneiderman, 2020). Furthermore, it builds trust, positioning GenAI as a collaborative partner and strengthening confidence in human-AI co-creation.

The gap between GenAI's transformative potential and designers' perceived lack of control remains a key issue. To bridge this, we introduce a framework to foster psychological ownership in GenAI- driven design. Developed through a mixed-methods approach, the framework combines insights from a survey of 21 professional designers and a structured workshop with 12 experts from product design, manufacturing, and architecture-engineering-construction (AEC) fields. These methods identified key design tasks where AI provides value and strategies to enhance human ownership.

The framework organizes strategies for enhancing ownership into three dimensions—*source* (the data AI learns from), *interaction* (designers' interactions with AI), and *outcome* (the output of human-AI co-creation)—and maps these dimensions across four design phases (Figure 1): *define* (identifying user types, problems, and needs), *ideate* (exploring concepts and variations), *deliver* (developing detailed solutions), and *test* (evaluating solutions through simulation and prototyping). This mapping highlights how different aspects of ownership are emphasized across design phases, offering actionable strategies for design professionals and researchers.

The framework serves as a practical guide for integrating GenAI responsibly into design workflows. For design professionals, it offers actionable strategies for detailed design tasks and a structured approach to evaluating AI tools through the lens of human ownership. For researchers and developers, the framework identifies critical areas for improvement, offering a roadmap to address challenges related to control, transparency, and trust.

2. Related Work

2.1. The Use of GenAI in Design

Regarding how engineers and designers use the GenAI tools, researchers have examined strategies involving three levels of engagement with GenAI: *selective delegation, intimate co-design, and minimal use* (Ma et al., 2024), as well as various use cases, and opportunities to further augment designers (Thoring et al., 2023). However, since the adoption of the GenAI tools in design industries is still in its early phases, there is limited understanding of how professionals incorporate the tools into various design processes and their perceptions of its benefits and limitations.

2.2. Challenges of GenAI

While GenAI is being rapidly integrated into industry due to its potential, its unique operational mechanisms have raised controversies and concerns about ethical and trustworthy implementation. Researchers pointed out that, unlike conventional AI, GenAI creates output based on prompts (Sun et al., 2024), challenging traditional notions of authorship and ownership (Bozkurt, 2024). The concept of authorship is closely tied to originality and creativity (McCutcheon, 2013; Montal and Reich, 2017). Given that GenAI is trained with diverse data and algorithmically remixes them to produce outputs (Bartlett and Camba, 2024), debates have arisen about AI's role as a tool or a co-author (Bozkurt, 2024), along with ethical concerns regarding data use without consent or compensation to original creators (Bartlett and Camba, 2024). In addition, autonomous and generative aspects of AI, including autonomous decision making abilities (Diakopoulos, 2014), uncertainties driven by algorithms (Montal and Reich, 2017), limited controllability and customizability (Sun et al., 2024), and unpredictability (Ganguli et al., 2022) were mentioned as factors increasing risks related to reliability.

To address these challenges, researchers have emphasized the need for explainable AI (XAI) in mitigating the black-box nature of AI systems and have explored specific approaches for GenAI. For instance, Weisz et al. (2023) underscored the importance of building calibrated trust by clearly communicating system limitations, and Sun et al. (2022) identified different categories of explainability requirements in GenAI applications for coding. In addition, regulatory and policy frameworks, such as the EU AI Act (European Union, 2025) and Assessment List for Trustworthy Artificial Intelligence (ALTAI) for Self-Assessment (European Union, 2021) are being developed to enforce ethical AI practices in various industries.

2.3. Human Ownership in the Use of GenAI

The concept of ownership has been examined from legal and psychological perspectives (Wilpert, 1991; Pierce et al., 2003; Etzioni, 1991). Legal ownership relies on external validation through copyright and property laws, whereas psychological ownership arises from individuals bonding with artifacts and perceiving them as “theirs” (Wilpert, 1991; Wang et al., 2006; Beggan, 1992). In Human-Compter-Interaction (HCI), studies show a sense of ownership can extend to digital possessions (Kuzminykh and Cauchard, 2020; Brown et al., 2001; Gruning and Lindley, 2016; Gruning, 2017), relevant to GenAI outputs. However, the investigation on psychological ownership in human-AI co-creation are still scarce (Xu et al., 2024b), in contrast to the active societal discussions on the legal boundaries of GenAI-created output ownership.

Our approach to human ownership adopts a psychological standpoint, focusing on a user’s sense of control, which is linked to human agency, self-efficacy, and involvement. Human agency and control over AI systems have been emphasized in human-centered AI practice (Shneiderman, 2022) as well as the design principles for GenAI applications (Weisz et al., 2023). Furthermore, (Shneiderman, 2020) contends that the integration of high levels of human control and computer automation enhance human performance while ensuring reliability and trustworthiness in human-centered AI. The sense of control and self-efficacy (demonstrating the ability to successfully complete a task and exert control over the target (Xu et al., 2024b)) were identified as linked factors contributing to psychological ownership (Wang et al., 2006; Odom et al., 2012). (Xu et al., 2024b) further highlighted that a user’s sense of control over human-AI co-creation is tied to their perception of contribution, which in turn affects their sense of involvement of the co-creation process. Studies suggest that increased user involvement and control in GenAI-assisted writing—such as crafting longer prompt (Joshi and Vogel, 2024), or accepting suggestion lists (Lehmann et al., 2022; Lee et al., 2022)–improves users’ sense of ownership and authorship over the output. However, strategies to foster human ownership in the use of GenAI for design remain in the early phase of development. To address this, we hope to develop strategies by integrating the insights gathered from professional designers.

3. Methods

This study employs a mixed-methods approach, combining a survey of professional product designers and a structured in-person workshop with 12 experts from product design, manufacturing, and architecture-engineering-construction (AEC) fields.

3.1. Survey

The survey was conducted in May 2024 using (Qualtrics, 2024), an online survey platform. Participants were recruited through the Autodesk customer network based on their experience using design tools, including car design, industrial design, and mechanical engineering. Among the 61 participants, 21 reported prior experience with GenAI in design. This analysis focuses on these 21 participants to ensure insights are grounded in practical, real-world usage. Over three-quarters of the participants had more than 10 years of design experience.

Participants were asked to reflect on a specific project where they had used GenAI and respond to survey questions based on that experience. The survey included questions such as “What kind of design project did you use the generative AI tools for?”, During which design process did you use the generative AI tools?”, and “How useful do you think the generative AI tools are for each design process?”. This approach ensured that responses were based on concrete practices rather than hypothetical scenarios. The survey explored the design tasks where GenAI was used and overall experiences with GenAI integration.

3.2. Workshop

The in-person workshop took place in October 2024 as part of an industry-focused design-and-make conference in the United States. Twelve design professionals participated in the one-hour session, including six experts from product design and manufacturing and six from the AEC sector. All participants had over 10 years of experience in their respective fields and had previously used GenAI in design.

Participants were divided into four groups, each corresponding to a distinct phase of the design process: *define*, *ideate* , *deliver* , and *test* (see Figure 1). The group assignments were based on participants’ professional expertise, enabling them to contribute insights grounded in their practical experiences. The distribution included three participants in *define*, three in *ideate*, four in *deliver*, and two in *test*, with one facilitator assigned to each group.

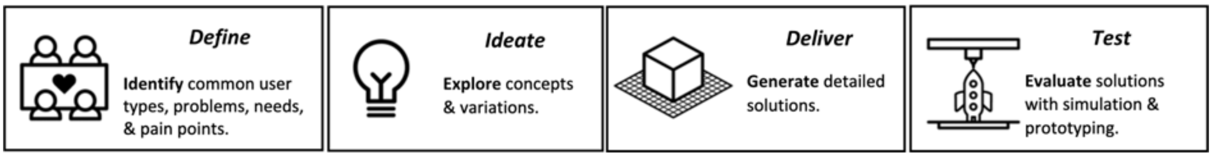


Figure 1: The four design phases used in the workshop: designers were grouped into *define*, *ideate*, *deliver*, and *test*, representing the progression from early to late phases of the design process

The workshop began with an introductory session on psychological ownership (Section 2.3), the four design phases (Figure 1), current applications of GenAI in design (Section 2.1), and associated risks (Section 2.2). The remainder of the workshop consisted of two activities:

Design Task Ideation: Each group collaboratively identified design tasks within their assigned phase where GenAI could provide value. Participants discussed how GenAI could enhance these tasks and proposed multiple ideas.
Ownership Strategy Development: Groups developed strategies to ensure psychological ownership in GenAI-assisted design, addressing issues such as control, trust, and accountability in human-AI co-creation.

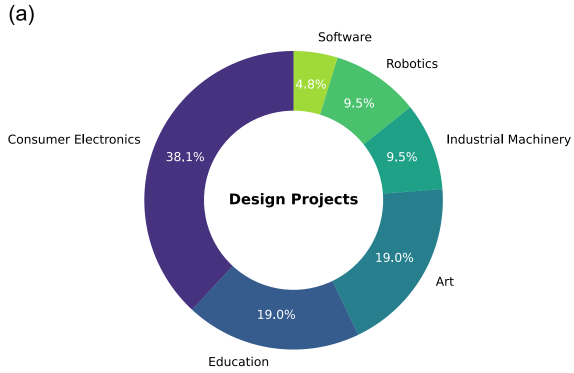
The outputs from these activities were documented in Google Slides, allowing for real-time note-taking and review. Two researchers conducted a thematic analysis of the collected data, employing a structured approach to identify patterns and themes. They independently reviewed the documented ideas and strategies, coding the data to capture key concepts such as *"Translate requirements into plans," "Task automation,"* and *"Explainability."* Similar codes were grouped into broader themes, which were iteratively refined for clarity and alignment with the study's objectives. Discrepancies between researchers were resolved through discussion, ensuring robust and reliable analysis.

4. Findings and Discussion

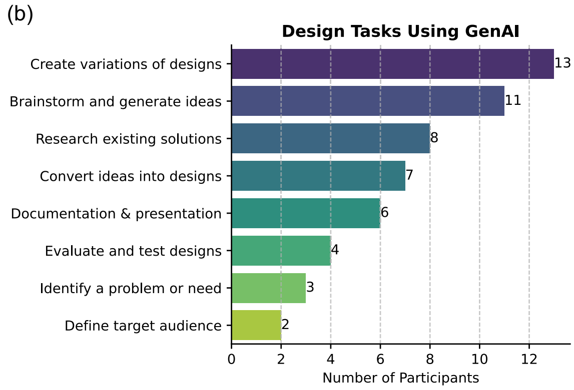
This section presents findings from the survey and workshop, following a structured progression: starting with how GenAI supports designers in current practices (Section 4.1), then identifying potential design tasks where GenAI assistance is most valuable (Section 4.2), and finally exploring strategies to ensure human ownership in GenAI-assisted design (Section 4.3).

4.1. Survey Results on GenAI-Assisted Design Practices

Among the 21 survey participants who reported using GenAI in their design practices, each reflected on a specific project where they integrated GenAI tools. The distribution of these projects is shown in Figure 2 (a). Over one-third of participants used GenAI for consumer electronics design, with 19% applying it to education and another 19% to art. The remaining projects spanned industrial machinery, robotics, and software.
Participants elaborated on how GenAI supported their projects. One participant described using ChatGPT for problem-solving in mechanical engineering and manufacturing, sharing: *"I used ChatGPT for ME and manufacturing. For instance, I was having trouble with a CNC lathe drilling operation not retracting from its hole."* Another highlighted its utility in sourcing, stating: *"I use it primarily to suggest manufacturers of parts and modules that perform a function."* Other designers utilized GenAI for concept generation, with one participant in automotive design using it to *"create visualizations for a client,"* while another leveraged it for *"concept visualization and image generation to provide context for a product."*
Regarding tool usage, more than half (n = 14) of participants used ChatGPT, while one-third used DALL-E and another third used MidJourney. Nearly half (45%) of participants combined tools, most commonly pairing ChatGPT with an image-generation tool. ChatGPT was used more frequently, with half of its users engaging daily or monthly, while image-generation tools were used less often, typically monthly or rarely.
When asked about design tasks where GenAI was used, results (Figure 2(b)) showed a strong focus on those related to the *ideate* phase. Over half the participants used GenAI to create design variations (n = 13) and brainstorm ideas (n = 11). Use in the *define* phase was minimal, with only two participants



Design project categories using GenAI.



Design tasks using GenAI.

Figure 2: Survey participants reported on projects where they used GenAI and identified the design tasks GenAI assisted with

using it to define a target audience and three to identify a problem or user need. GenAI was also rarely employed for evaluating and testing designs (n = 4). Most participants (n = 17) reported using GenAI across multiple tasks.

The perceived usefulness of GenAI aligned with its frequency of use. Over 65% of participants found tasks like converting ideas into designs and generating variations to be useful or very useful. One designer explained: *"Concept visualization. It transforms text into images quickly and often finds new paths to follow."* However, GenAI was perceived as less useful for tasks such as defining a target audience or identifying problems, with limitations cited such as *"a lack of contextual awareness"* and *"hallucinations of completely fabricated information."*

In summary, designers use both LLMs and image-generation tools across a variety of production, educational, and research projects. According to the survey, GenAI is most commonly used in the *ideate* phase, assisting with idea conversion and generating variations for rapid iteration. However, it is less frequently applied to complex problem-solving that requires contextual understanding or technical expertise. The primary use of GenAI for ideation likely stems from the current capabilities of commercial tools, which are optimized for conceptual design. To address this imbalance, a follow-up workshop explored GenAI's potential across all design phases and identified strategies to foster human ownership in AI-assisted tasks.

Designers emphasized the importance of treating GenAI as an assistive tool rather than a primary solution, with one participant noting: *"Some people don't use AI as a tool; they use it to generate final products. That's an error because AI is not a designer. AI is a tool."*

4.2. Potential GenAI-Assisted Design Tasks

To explore valuable design tasks across all phases, workshop participants were divided into groups corresponding to the *define*, *ideate*, *deliver*, and *test* phases. Each group was tasked with generating ideas for valuable GenAI-assisted design tasks in their assigned phase. A thematic analysis of these ideas revealed six key themes, as illustrated in Figure 3:

1. **Provide guidance** (n = 8): Participants emphasized the need for GenAI to guide the design process. For instance, one participant suggested, *"Recommend next steps,"* while another wanted GenAI to *"Create bullet points for user profiles and develop streamlined interview questions."*
2. **Generate design solutions based on requirements** (n = 7): Requirements were highlighted as critical. One participant stated, *"Train the AI based on companies' unique standards, styles, and processes,"* while another suggested, *"Based on test data, it could generate a new solution."*
3. **Search and synthesize knowledge** (n = 5): Designers sought GenAI assistance in looking up existing knowledge—*"First find what has already been done"*—and summarizing information, such as *"Summarize specifications."* They also wanted AI to combine multiple sources of information, for example, *"Pair customer interview data with usage data."*
4. **Automate processes** (n = 3): Participants emphasized the importance of reducing repetitive tasks, summed up as *"Anything to reduce clicks."*

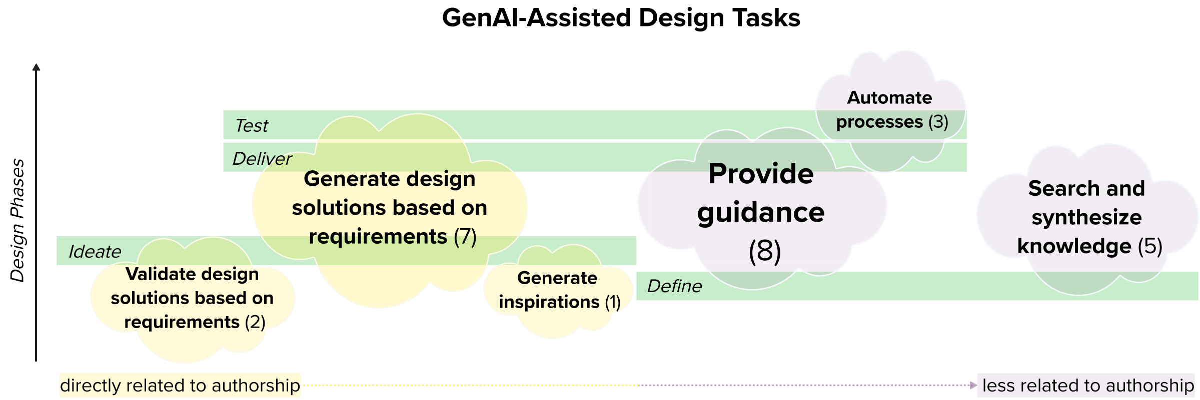


Figure 3: GenAI-Assisted Design Task Themes. The numbers in brackets indicate the number of task ideas generated by workshop participants for each theme. Themes directly tied to design authorship are highlighted in yellow, while those less related are highlighted in gray. *Provide guidance* and *generate design solutions based on requirements* are the most prominent themes spanning early to late design phases

5. **Validate design solutions based on requirements** ($n = 2$): Designers wanted GenAI to validate outcomes against established standards, with one participant suggesting, *"Memorize code books and check that requirements are satisfied."*
6. **Generate inspiration** ($n = 1$): One participant suggested using GenAI to *"Look at all existing products and morph something to inspire."*

The six themes can be categorized based on their connection to the final design output. Tasks directly influencing the final design include *generate design solutions based on requirements*, *validate design solutions based on requirements*, and *generate inspiration*. Tasks less directly related to the final design include *provide guidance*, *search and synthesize knowledge*, and *automate processes*, as shown in Figure 3.

Mapping these themes against the design phases where the ideas originated reveals interesting patterns. In the *ideate* phase, all tasks are directly tied to authorship, emphasizing creativity and solution generation. In contrast, tasks in the *define* phase are less related to authorship, focusing on gathering and organizing contextual information. In the *deliver* and *test* phases, designers seek GenAI assistance for both tasks directly and indirectly connected to authorship, highlighting the varied needs in these phases. The two most prominent themes, *provide guidance* and *generate design solutions based on requirements*, span the entire design process, from early phases like *define* and *ideate* to late phases such as *deliver* and *test*. This underscores the importance of considering design context when developing GenAI tools, ensuring that information captured in earlier phases can be reused and built upon in later phases to support iterative design effectively.

4.3. Strategies to Foster Human Ownership

From the second part of the workshop (see Section 3.2 Workshop), six key strategies to foster psychological ownership (see detailed definition in Section 2.3 Human Ownership in the Use of GenAI) emerged, as illustrated in Figure 4:

1. **Coach AI** ($n = 4$): Participants emphasized the need for GenAI to not only understand their industry but also their specific needs. One participant suggested, *"What if you could teach AI* your industry, your terminology? Understand your users and your own research needs." They also expressed the importance of iterative improvement, stating, *"Teaching the AI. Feeding the information to the AI to explain why its choices might be wrong (another form of collaborative work)."*
2. **Ensure explainability** ($n = 3$): Several participants expressed concerns about GenAI functioning as a black box and emphasized the need for explainable AI. One participant stated, *"Ask the AI to explain its answer to catch mistakes. Clear Box AI where the program can explain how it got to its solution."*

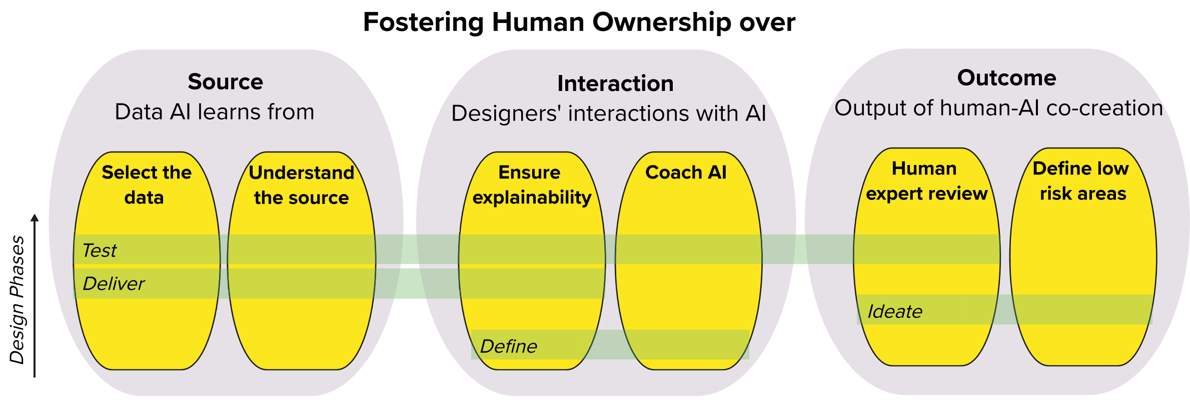


Figure 4: Ownership Framework. The framework illustrating strategies for fostering human ownership in the use of GenAI for design. It organizes ownership into three dimensions—*source*, *process*, and *outcome*—and maps these strategies across four design phases: *define*, *ideate*, *deliver*, and *test*

3. **Human expert review** (n = 3): Participants highlighted the importance of human oversight to ensure accountability and trust. One participant noted, *"Would I feel like the outputs were mine? I think if we reviewed it, we would trust it and take ownership—stamp and seal—liable (legal, ethical) for it. We still oversee AI."* Another suggested incorporating diverse perspectives, saying, *"Collaborative work. Outside perspectives from other disciplines allowing people to provide feedback."*
4. **Define low-risk areas** (n = 3): Participants recognized that some design tasks involve lower risks and are more suited for GenAI, with one stating, "*Hallucination could actually be desirable in some cases for creativity—conceptual phase.*"
5. **Understand the source** (n = 2): Trust in GenAI can be built by understanding the sources of the data it was trained on. One participant remarked, *"Spec review: Which references in the spec did you read to give us this report? Give you the links and you can jump to those and verify."*
6. **Select the data** (n = 1): One participant went further, advocating for control over the data GenAI learns from, saying, *"Control of data that it learns from."*

These six strategies were grouped into three dimensions: ownership over the *source* (data GenAI learns from), *interaction* (interactions with AI), and *outcome* (outputs of GenAI co-creation). When mapping these strategies against the four design phases, a pattern emerges. In the early *define* phase, designers prioritize control over interaction, reflecting the need for collaborative engagement. Conversely, in the *ideate* phase, designers focus on control over outcomes, as tasks in this phase are closely tied to authorship (see Section 4.2 for details).

As the design process progresses into later phases, such as *deliver* and *test*, designers seek greater control over all three dimensions, including the *source*. This reflects the increasing need for trust in GenAI, particularly as designers bear responsibility for the outputs of AI co-creation.

The ownership framework can also serve as a tool to assess the readiness of integrating GenAI into different design phases. For example, as discussed in Section 4.1 Survey Results on GenAI-Assisted Design Practices, designers predominantly use GenAI in the *ideate* phase. This aligns with the framework, where designers leverage strategies such as *defining low-risk areas* to manage outcomes in ideation. However, the remaining five strategies highlight areas where current GenAI applications require significant improvements to fully integrate into professional design workflows.

5. Limitation and Future Work

While this study introduces a framework for enhancing psychological ownership in GenAI-assisted design, several limitations and opportunities for future research remain.

The study relies on self-reported data from surveys and workshops, which may introduce subjectivity. While these qualitative insights provide valuable perspectives from design professionals, incorporating observational studies and longitudinal data could strengthen the reliability of the findings. Future research could track designers' interactions with GenAI tools over extended periods to assess how ownership, trust, and usability evolve in practice.

Another potential direction is to conduct case studies exploring the application of the strategies to foster human ownership in potential GenAI-assisted design tasks across various design phases based on a real-world design scenario. Based on the current capability of the technology, the application of GenAI is primarily concentrated in ideation phase; however, case studies would help us identify more concrete applications in other design phases while enhancing user's ownership of the GenAI use. Furthermore, it would allow us to investigate more detailed directions of the application of the strategies based on the context of the design scenario. Regarding the design scenario, we can consider interdisciplinary collaboration contexts, including interactions between designers and the use of multiple GenAI agents.

6. Conclusion

The ownership framework (Figure 4) outlines strategies to foster human ownership in GenAI-assisted design, developed from insights shared by design professionals. Constructed through an analysis of current GenAI-assisted design practices (Section 4.1) and potential design tasks (Section 4.2), the framework is grounded in survey findings and a structured workshop (Section 3). It enhances ownership across three key dimensions: *source* (the data AI learns from), *interaction* (designers' engagement with AI), and *outcome* (the results of AI co-creation). By mapping these strategies across design phases, we observe that as the process moves from early to late phases, designers increasingly seek greater control and trust in all dimensions.

Designers are increasingly embracing the transformative potential of GenAI, integrating it into various phases of real-world design practices. Our findings reveal varying levels of adoption across different design phases, with the *ideate* phase being the most common area of application, reflecting the current capabilities of the technology. However, participants expressed a strong interest in expanding the applications to all design phases and exploring a wider variety of GenAI-assisted design tasks, both directly or indirectly related to authorship. Enhancing ownership—sense of control, involvement, and author-ship—over the use of GenAI in these tasks is essential for supporting all design phases and ensuring more effective and safe adoption.

The framework also highlights actionable research and development opportunities, such as ensuring explainability, enabling AI coaching, integrating human expert reviews, and providing mechanisms to understand and control the data GenAI learns from. By emphasizing the importance of psychological ownership, this framework represents a significant step toward the responsible and effective integration of GenAI into design. It underscores the need for human-centric approaches, enabling innovative yet accountable design practices.

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