INTEGRATING GENERATIVE AI IN DESIGN THINKING PROCESS

A mixed-method study on how designers perceived artificial intelligence in their work

Lappeenranta–Lahti University of Technology LUT

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ABSTRACT

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The rapid integration of generative Artificial Intelligence (AI) into the design profession has outpaced scholarly understanding of its impact on the design thinking process. This study investigates how designers perceive and integrate generative AI, examining the underlying factors that drive adoption or resistance. A mixed-methods approach was employed, combining quantitative surveys and qualitative in-depth interviews with two distinct groups: designers who actively use AI and those who do not. The findings reveal a fundamental schism rooted in professional identity. AI-users predominantly view the technology as a cognitive partner that significantly expands their creative capacity, moving beyond a mere functional tool. In stark contrast, non-users perceive AI as a threat to core professional values such as authenticity and human touch, which reinforces their commitment to traditional methods. The study concludes that the decision to adopt AI in design thinking is not merely a practical choice but is deeply embedded in a designer's professional identity. For AI to be successfully integrated into the field, future systems and implementation strategies must be designed to visibly augment, rather than threaten, the humanistic principles of creativity, authenticity, and professional sovereignty that designers cherish.

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ABBREVIATIONS

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1 Introduction

In the early 2000s, pagers and cell phones dominated the world of communication. These devices were our primary tools for staying connected—until the early 2010s, when the first touchscreen smartphone, the iPhone, was introduced to the public. Apple's iPhone revolutionized the mobile phone industry, redefining how we communicate, work, and live. Almost overnight, pagers and cell phones became relics of the past (though they are still used in niche contexts, they could no longer compete with the smartphone's capabilities). Today, Apple holds a significant share of the global market and stands as one of the most influential companies in the world (Lee, 2025; Needham Mass, 2025).

Clearly, the rapid evolution of the modern world is driven by technological innovation, novel ideas, and the industrial infrastructure required for mass production. Industries that fail to adapt to this fast-paced technological evolution risk falling behind and losing their place in the market. Every product we use daily—whether it's a smartphone, a kitchen appliance, or a piece of furniture—has a story. Each one begins as an idea, undergoes a design thinking process, evolves from a prototype, and eventually becomes a successful mass-produced product. Behind every product lies the collective effort of engineers, designers, workers, and countless others who dedicate their time, skills, and resources to bring it to life.

Furthermore, product success or failure is largely determined by the ability to adapt to the rapid technological revolution defining the contemporary area. However, in this rapid change comes a critical question: *How can we integrate the latest cutting-edge technologies without losing the authenticity and human touch that make our products meaningful?* This challenge is particularly relevant in the field of industrial design, where creativity and functionality must coexist. Hence, this thesis explores how industrial design is evolving from traditional methods to integrating artificial intelligence (AI) into the creative process. Specifically, it investigates how generative AI can impact the design thinking process. Can AI enhance efficiency and creativity in ways that traditional methods cannot? Or does it risk overshadowing the human ingenuity that lies at the heart of design? By examining these questions, this study aims to shed light on the potential of AI as a co-creator in the design process, offering insights into how designers can harness its power while preserving the authenticity of their work.

1.1 Background

Generative artificial intelligence (Generative AI) traces its roots back to the early 2010s when Ian Goodfellow and his team introduced Generative Adversarial Networks (GANs) to researchers and tech enthusiasts (Goodfellow et al., 2014). GANs marked a significant breakthrough in AI, enabling machines to generate new data, such as images, that mimic real-world examples. Together with GANs, between 2015 and 2017, Google developed one of the earliest public applications of generative AI—DeepDream (Szegedy et al., 2015). This tool, which produced surreal, dream-like images, captured public attention, and demonstrated the creative potential of AI.

In 2018, OpenAI company introduced GPT-1, the first version of the Generative Pre-trained Transformer (GPT) series that has since become a foundation of modern generative AI (OpenAI, 2018). Although GPT-1 was not widely adopted by the public, it laid the groundwork for future advancements. The OpenAI continued to refine its models, launching GPT-2 in 2019 and GPT-3 in 2020 (OpenAI, 2019). The release of GPT-3 marked an important moment in the history of AI. As an advanced language model, GPT-3 enabled developers and the public to integrate its capabilities into various applications through an application programming interface (API) (OpenAI, 2020). This innovation opened new doors for research and development in generative AI, shaping the tools we use today.

Alongside the development of GPT-3 and its API integration capabilities, OpenAI introduced DALL-E in 2021 (OpenAI, 2021). DALL-E, an image generator, showcased the creative possibilities of generative AI. Users can input a detailed text description (known as a "prompt") of the image they want to create, and DALL-E generates a corresponding visual (Robert Sheldon and Sean Michael Kerner, 2025). The more precise and detailed the prompt, the more accurate the resulting image. This principle of "prompting" applies not only to DALL-E but also to other generative AI tools like Stable Diffusion or Leonardo AI (Ali Awan, Abid, 2025). While these tools offer users greater control over the output, their effectiveness depends heavily on the user's ability to craft clear and detailed prompts. The quality of the output—whether images or ideas—hinges on the user's prompting skills (Kurtis Pykes, 2025). For designers, this means generative AI can either be a powerful creative tool or a limited assistant, depending on how well they can articulate their vision. This observation led to our interest in exploring how industrial designers incorporate

generative AI into their workflows, from generating initial ideas to creating mood boards with AI-generated visuals.

Despite its rapid adoption and widespread use, the specific impact of generative AI on the design thinking process remains underexplored, particularly in the field of industrial design (Wadinambiarachchi et al., 2024). This gap in research is largely due to the fast-paced evolution of these technologies, which has outpaced scientific understanding (Lin and Liu, 2024). As generative AI continues to advance, there is a growing need for a practical and systematic approach to integrating it effectively into the design-thinking process (Guo et al., 2023). Such an approach would enable designers to work alongside AI as co-creators, maximizing its potential to enhance creativity and efficiency (Verheijden and Funk, 2023).

1.2 Research questions

Main question

The main research question of this study is to understand the impact of generative AI on the efficiency, creativity, and decision making in the industrial design. This leads to the central question ***"How can generative AI impact the design thinking process?"*** This main question aims to evaluate the impact of generative AI on the five stages in the design thinking process. In other words, the goal is to study the advantages and disadvantages in employing generative AI during the design thinking process.

Sub-questions

To break down the central question into sub-questions to gain fully understanding how innovative AI affects the design process of industrial designer, the author presents two sub-questions:

Can generative AI enhance the efficiency and creativity in the ways that traditional methods cannot?

This sub-question explores the ability and capability of generative AI as a co-creator in the design team. Additionally, this sub-question explores a better understanding how generative AI can benefit an organization or a design team when they employ innovative AI.

Hence, this sub-question leads to the second one:

How integration generative AI into the design thinking process can benefit the organization, specifically the design team and its team member?

This sub-question investigates which approaches, which methods that can be implemented to be beneficial the design thinking process and the design team.

1.3 Objectives

The aim of this study is to analyse the role of generative AI as a co-creator. Hence, to conduct this study, the author aims to break down the goal into small step:

- To evaluate the impacts of AI tools in industrial design workflow
- To conduct case studies on design thinking process with generative AI
- To measure the designers' perception of AI integration using questionnaires
- To understand the benefits of using AI in the design thinking process, quantify the improvements in productivity and quality regard to AI.

By employing this approach and collecting data from the questionnaires, these insights hold a potential in explores the capability of AI and the future actions on implemented AI in innovative and creative works.

1.4 Relevance to Working Life

This study on integrating generative AI into the design thinking process holds significant implications for industrial designers, organizations, and students. It reshapes how creativity and productivity intersect in the modern workplaces (Chan and Hu, 2023). For industrial designers, generative AI offers a transformative shift in workflow. Generative AI can automate repetitive tasks such as assisting in create mood board plan, allowing professionals to dedicate their time for high-level innovation (Georgiev, Mahmud and Islam, 2025). By acting as a collaborative partner, generative AI can push beyond our creative boundaries, generating extraordinary design variation that inspire fresh solutions (McGuire, De Cremer and Van De Cruys, 2024). As AI proficiency becomes an increasingly sought-after skill,

designers who master these tools gain a competitive edge in an evolving job market (Rana, Verhoeven and Sharma, 2025).

Meanwhile in businesses and industry, the integration of AI translates to resources saving such as cost and time savings, particularly in research and development. Rapid AI-driven ideation and virtual testing accelerate product development cycles, enabling companies to respond quickly to market trends and consumer demands. Furthermore, the ability of AI in optimizing materials and reducing waste align with the growing trend in sustainable design, offering both economic and environmental benefits (Verdecchia, Sallou and Cruz, 2023; Bibri and Huang, 2025; Xue et al., 2025). Companies and organization that adopt AI-enhanced design processes can stay ahead of competitors while meeting the expectations of an eco-conscious market.

From the perspective of students and educators, this research highlights the need to future-proof design education by incorporating AI tools into the curricula (Karataş, Eriçok and Tanrikulu, 2025). By familiarizing themselves with AI at an early state, students can bridge the game between academic training and industry expectations (UPCEA, 2025), entering the workforce with a skill set that matches the job market's demands (Chu and Ashraf, 2025). Generative AI also democratizes design, enabling students with limited technical expertise to visualize and refine ideas effortlessly (Nikki Muncey, 2025). However, the study also emphasizes the importance of balancing AI with human judgement (Eleni Meletiadou, 2025), preparing the next generation of designers to navigate ethical considerations such as the originality and bias in AI generated work.

Finally, this research provides insights for professional seeking to optimize their workflows, businesses aim to enhance innovation and sustainability, and educators adapting to advance technology. By considering AI as a co-creative tool not as a replacement, the research empowers stakeholders across the design eco-system to harness its potential strategically – ensuring that human ingenuity remains at the heart of the design process, even technology redefines its boundaries.

1.5 The relationship to existing knowledge

At the time of this study, the use of generative AI has been studied widely, and many studies concluding that AI positively facilitates creativity (O'Toole and Horvát, 2024). Moreover, in the article "AI improves Employee Productivity by 66%", Jakob Nielsen once again reinforces the benefits of using AI in business, demonstrating how it enhances productivity - specifically the less-skilled workers (Jakob Nielsen, 2023). His research, spanning multiple industries, yielded consistent findings: 66% increase in throughput, improved output quality, and a narrowed skill gap between high- and low-performing employees. Crucially, Nielsen asserts that AI will not replace humans but rather augment their capabilities. This aligns with the vision of the computer pioneer J.C. Licklider, whose an influential paper "Man-Computer Symbiosis" by (Licklider, 1960), envisioned a future that humans and computer would cooperatively working together side by side. The intellectual groundwork for this investigation was laid by foundational texts such as Licklider's "Man-Computer Symbiosis" and the design principles articulated by Jakob Nielsen. Their work inspired a critical examination of AI's role in design thinking. Consequently, irrespective of the acknowledged potential and limitations of generative AI, the advent of an AI-augmented future is rendered undeniable. And that is the starting point of this study, if GenAI has proven its positive impact on many different industries, how will GenAI leave a mark on the industrial design field, especially how GenAI effects on the design thinking process?

Additionally, many case studies in various industries (from packaging, marketing, architecture, engineering) widely utilized AI in their projects such as Heinz ketchup created the first-ever ad campaign Heinz A.I. Ketchup visualized by Dall-E 2 (COTW, 2022), or the iconic Nutella label has an artistic makeover in the project Eurostampa's Envelope 8 by Bria AI (Packaging suppliers global, 2024). The AI implement goes beyond packaging and marketing industry. In architecture and engineering industries, Autodesk Forma and AFRY boldly utilized AI in their projects. AFRY is one of Europe's largest engineering firms, in their task developing a residential complex in the Fjällbogatan neighborhood, Gothenburg, Sweden (Team, 2024). AFRY used Forma – an AI powered cloud-based tool to simulate real world external impacts such as wind, noise, or solar shading to speed up the decision-making process and comply to the local regulation (Team, 2024; Balaji, 2025). Similarly, ARCO Architecture company – one of the largest architect firms in Finland, using Forma to

optimize the building's design for their eight-story student housing complex in Malmi, Helsinki, Finland (Tan, 2023).

The integration of AI into the design thinking process and across industries marks a paradigm shift in how we approach innovation (Kaplan, 2024). From boosting productivity and democratizing skills in business to enabling rapid prototyping in marketing and optimizing sustainable architectural solutions (Bibri and Huang, 2025), AI proves to be a powerful collaborator rather than a replacement for human ingenuity. As evidenced by real-world applications in packaging, engineering, and beyond, AI's ability to process vast datasets, simulate scenarios, and generate novel ideas complements human creativity, leading to faster, smarter, and more inclusive outcomes (Georgiev, Mahmud and Islam, 2025; Neural Concept, 2025). The future of design—and indeed, many industries—lies in human-AI symbiosis, where technology amplifies our potential while preserving the irreplaceable value of human insight. Embracing this partnership will be key to driving progress in an increasingly complex and competitive world.

1.6 Methodology

This research aims to study the evolving relationship between industrial design and generative AI by investigating how AI can serve as a co-creator in the design thinking process. To achieve this goal, the research will follow these steps. First, the author evaluates the impact of AI tools on the industrial design workflows, examining how they influence each stage of the process – from initial ideation to prototyping, and identifying the most practical applications of tools like text-to-image generators or AI-assisted sketching.

Next, the study conducts case studies analysing real-world examples of designers integrating AI into their creative processes, highlighting successes, challenges, and unexpected outcomes to provide actionable insights for the field. Additionally, the research will measure the designers' perception of AI integration through questionnaires and interviews, gathering qualitative data on their attitudes, concerns, and levels of adaptability toward AI adoption.

Finally, the study quantifies the benefits of AI in the design thinking process, assessing improvements in productivity (such as time savings and iteration speed) and output quality (such as creativity and precision), while comparing AI-assisted workflows with traditional

methods to determine advantages and limitations. By combining these approaches – workflow analysis, case studies and designer feedback, this study provide a comprehensive understanding of generative AI's potential in industrial design, offering insights into its current capabilities and future applications. Eventually, the findings help bridge the gap between technological innovation and human-centered design, proposing new strategies for designers to leverage AI as a collaborative partner rather than a tool, thereby shaping the future of creative workflows.

2 Theoretical Framework

The historical development of the Design Thinking process is explored in this chapter, alongside an analysis of generative AI's role in the design domain. Particular attention is paid to the mechanisms through which AI is integrated into the creative process.

2.1 Design thinking process

The Design Thinking process is an approach that focus on human, iterative problem-solving approach that emphasizes empathy, creativity and experimentation. This process had a long history, rooted from the early of 1950s and 1960s (Dam and Siang, 2022), people started to apply scientific methodology and processes to understand every aspect of design. In the mid-1960s, Horst Rittel mentioned the term “wicked problem” to describe a problem that is multidimensional and complex. To tackle the “wicked problem”, the design practitioners needed to have collaborative methodology to understand human’s needs, motivation and behaviour.

In the 1970s, Herbert A. Simon, a cognitive scientist and Nobel Prize laureate, was the first mentioned The Theory of Design in his book, The Sciences of the Artificial (1969). In the book, he proposed many ideas such as the Psychology of Thinking, or the Science of Design (Simon, 1996). These ideas later are considered as the foundation principles of design thinking.

In 1982, Nigel Cross introduced his third paper “Designerly ways of knowing” in which he discussed the approaches that designers solve problem different from non-design related disciplinaries such as sciences and humanities. In his paper, Design thinking was characterized by four principal attributes: the conception and realization of novelty, immersion within material culture, the application of language modelling, and a distinct mode of knowing (Cross, 1982). In his research paper, Nigel Cross described the design process studies from Bryan Lawson on design behaviour, in which focused on problem-solving strategies between designers and scientists. Lawson concluded that scientists applied problem-focused approaches, meanwhile designers were solution-focused (Cross, 1982).

The “Designerly ways of knowing” shed light on the foundation of design thinking – the topic that many scientists and engineers did not pay attention at the time the paper was published. In 1987, the book “Design Thinking” published by Peter Rowe, which described how architectural designers approached their tasks through an inquisitive view (Dam and Siang, 2022). In his book “Design Thinking”, Peter Rowe aimed to create a general picture of design thinking, in which this principle focused on how designers inventing and creating building and urban artifacts (Rowe, 1991).

The progress of design thinking is a journey through various of specialization fields over decades (see Figure 1). The specialists, the thinkers in those fields, explored the process of cognitive thinking how they approach a problem. They all come to the final principle - design thinking, and slowly shed a light on the concept of design thinking.

From 1991 to the present, IDEO found in 1991 by David M Kelly, which is one of four leading institutes lead the lights in design thinking (Yun, 2024). IDEO values the design thinking mindset, approaches, and skills which they applied to many fields (Design Shanghai, 2023). They aim to teach people to use design thinking in daily lives, businesses, and organizations. At the present, the design thinking mindset is growing rapidly due to its benefits if one knows how to apply it (Franziska Kraft, 2024). As Don Norman stated in his renowned book “The Design of everyday things”, design thinking has been practiced by all great innovators, whether they are artists, scientists, engineers, or businesspeople (Norman, 2013). According to Don Norman, two of the most powerful tools of design thinking are human-centered design and the double-diamond diverge-converge model of design (Norman, 2013).

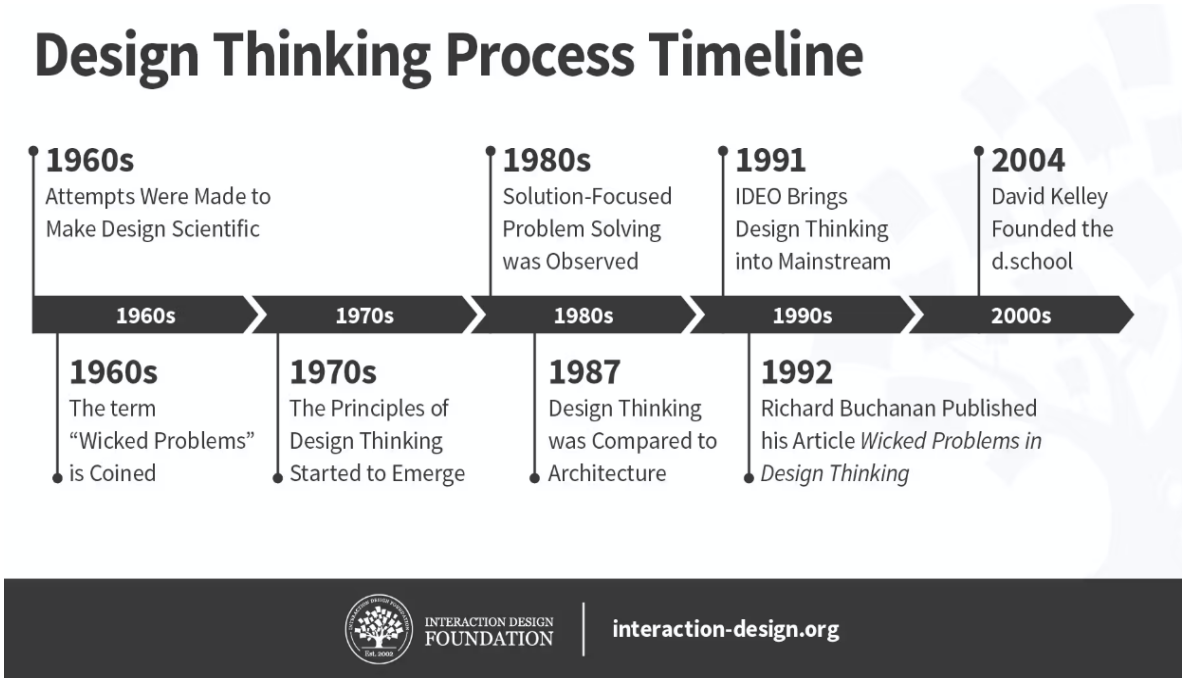

Figure 1. Design Thinking Process Timeline (Dam and Siang, 2022)

2.1.1 The Double-Diamond Model of Design

The British Design Council first introduced the double-diamond as double-diamond design process model in 2005 (see Figure 2). The double-diamond model aims to two component of design – finding the right problem and meeting human needs and capabilities. Hence, the double-diamond model has two phases: finding the right problem and finding the right solution - satisfy human needs and capabilities. Each phase includes the diverge and converge process (see Figure 3). In the first phase, the diverge-converge process includes "discover" and "define", in which the designers focus on the problems, finding the right problem to solve. In the second phase, the diverge-converge process includes "develop" and "deliver", in which the designers make progress and start to converge upon a solution. This diverge-converge process can be repeated many times until the designers properly determining the right problem to solve and come up with the best way to solve it.

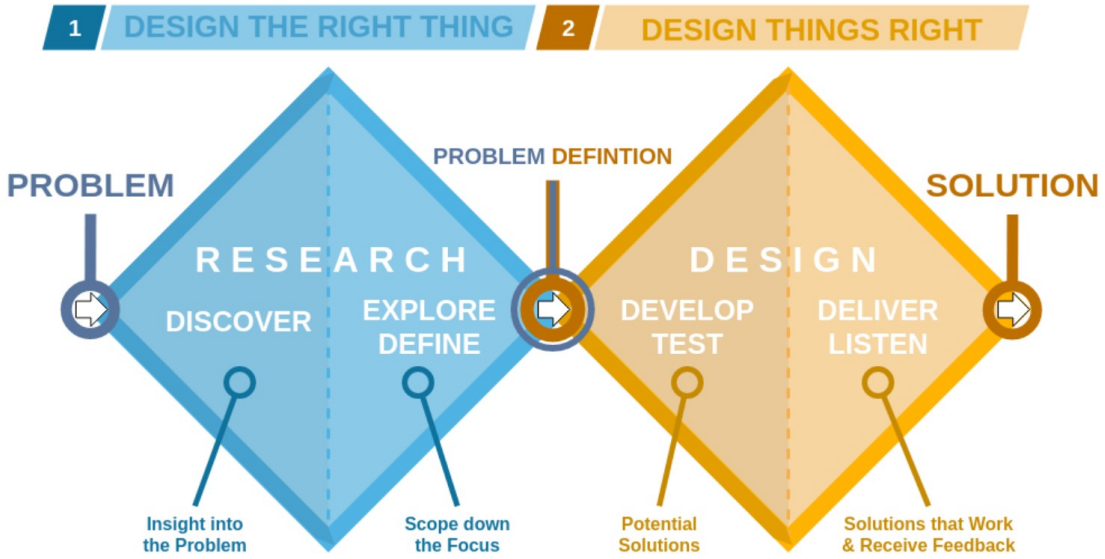

Figure 2. Double Diamond model (Davis-Owusu, 2023)

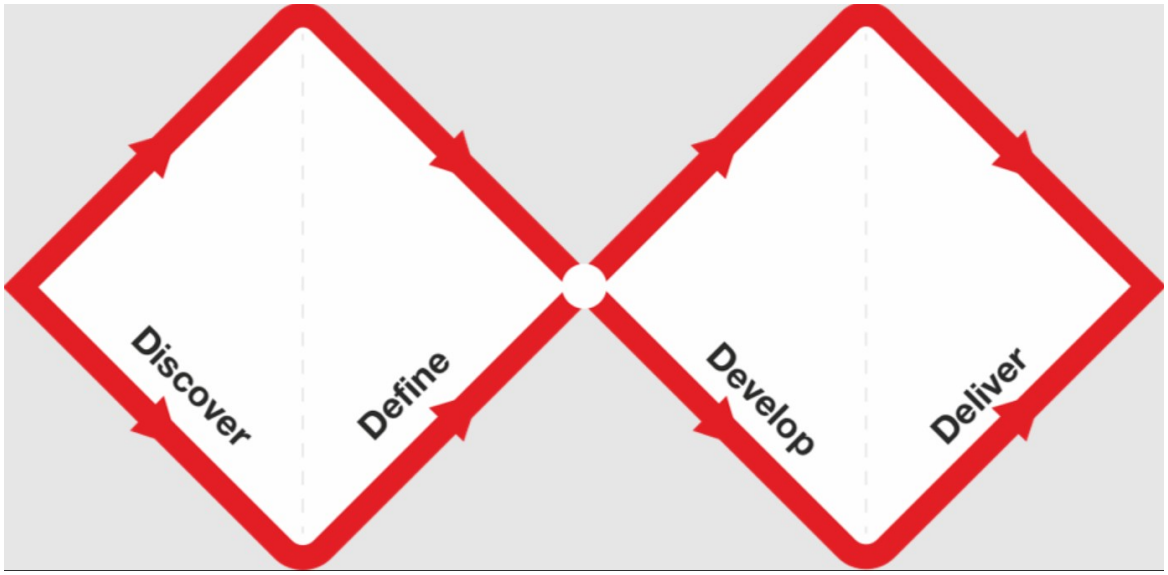

Figure 3. Double Diamond by the Design Council (Design Council, 2025)

2.1.2 The Human-Centered Design Process

In the double-diamond model describes two phases in design: finding the right problem and satisfying human needs (Design Council, 2025). In the human-centered design (HCD) process shows how to execute the double-diamond approach, which was illustrated in Figure 4. The HCD process takes place within the double-diamond model, and it includes four

phases: Observation, Idea generation (ideation), Prototyping, and Testing (Design Council, 2025; ISO 9241-210, 2025). These four phases are repeated over and over until the designers get closer to the desired solution. Let's explore each phase individually in the HCD process.

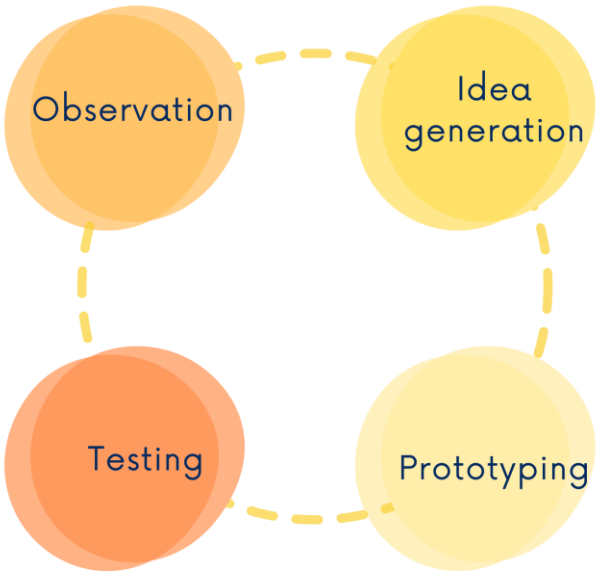

Figure 4. Human-Centered Design Process, Adopted from Don Norman (Norman, 2013)

Observation

The designers conduct research on the customer, on the people who will use the products. This research is different from the scientist conduct research in the laboratories; it aims to gain deep understand of the potential consumers in their normal lives, in their natural environments. The designers gain the insights of their consumers, their interests, their motives, their true needs. Sometimes, the potential consumers may not know their true needs, or motives. That's why the designers must follow their consumers even to the shower if necessary (Norman, 2013), because we – designers want to understand the real situation the consumers encounter, not our pure assumptions. According to Don Norman, this technique is called *applied ethnography*, which is employed from anthropology – a field studies of humans, past and present. Nevertheless, when the design research is conducted, it supports the double-diamond approach. The observation activities gain deep understanding of the true needs of human – this is the first diamond, finding the right problem. After understanding the right problem, finding the appropriate solution also requires deep understanding of the

consumers behaviours, how the consumers experience in their activities and their capabilities.

Idea Generation (Ideation)

After obtaining the deep understanding in the assigned problem, the next step for the design team is propose potential solutions. This activity is called *idea generation*, or *ideation*. Ideation is critical because it involved creativity. The aim is to generate as many ideas as possible, and the idea should be creative without any constraints.

According to Don Norman in his book The Design of Everyday Things, there are three main rules while executing Ideation

- Generate numerous ideas: the design team needs to create as many ideas as possible.
- Be creative without any constraints: any ideas are welcome in this phase, no matter how crazy it is. Avoiding criticizing ideas or avoid premature dismissal of ideas. Any abnormal idea contains highly creative insights that can be useful in the final decision.
- Question everything. There is no stupid question during this stage. When we take a simple question seriously, we may find the obvious solution while discovering that stupid question.

Prototyping

How do the design team know whether an idea is reasonable? The only way to know is to test it – prototyping that idea. It can be a quick prototype, a mock-up. It can be a sketch with pencil, or it can be built by foam and cardboard. If there is a mock-up model, it is easy to test the idea, and to understand the human activities.

When the design team test their ideas with prototyping, the aim is to ensure that the problem is well understood (Norman, 2013).

Testing

In this phase, we gather a small group of target population – whom the product is intended. The research team should observe the target attendant, see how they react to the prototype. It can be in single tester at a time or a group of people. It is recommended to have video record while observing the target attendant with the prototype.

After the study is over, gathering more detail information about the people's thought processes by tracing back their interactions, and questioning them. This is when the video recording is important. However, how many people should be studied? In his article, Jakob Nielsen, a renowned usability expert in the field of human-computer interaction, emphasized the number five (five users). Jakob Nielsen explained that studying five individually is enough for the test. After the fifth user, the designer is wasting time to observe the same finding repeatedly without learning anything new (Jakob Nielsen, 2000).

2.2 Generative AI in design

Astonishingly as it grows rapidly within the few years, the first well-known generative AI image model was introduced to the public was Dall-E launched by open AI in January 2021 (OpenAI, 2021). Generative AI (GenAI) is a type of artificial intelligent that can create new content such as images, text, music, and even 3D models, based on what it has learned from existing data (information that human created and fed to the databased of AI). GenAI can be considered as a super-smart assistant in generating logos, posters, or website designs. It can suggest the colour schemes and layouts, create various designs within seconds. The question is, How GenAI can work in design with its capabilities?

GenAI image is trained on thousands or even millions of existing designs, it learns the patterns, styles, and even the latest trends. The users, or designers input a prompt – a text that describe what you want in the desired images. Then GenAI generates multi design variation immediately, and the users can pick the image or adjust the prompt until the users reach the desired image. For example, the earliest version of Dall-E generated the image which was illustrated in Figure 5, in which the input prompt was "a grumpy cat having fun eating ice cream".

As a result, during the learning journey while interacting and employing GenAI images, the author learned that the more details in the prompt, the more precise and better image result GenAI generated. At the moment this research is written, there are plenty of GenAI image available such as Dall-E, MidJourney, Stable Diffusion, DeepDream, and many more.

As GenAI image get evolved through time, the user interaction in each GenAI images keep improving. The result from different GenAI image can be a logo, or images for social media

(Canva AI) or UI/UX design tasks (Figma AI). Some GenAI image offers more than photos or images, it can assist in improving the prompts or create different result based on an original image (Leonardo AI). The potential in GenAI image is undeniably helpful. It is time efficiency; it can boost creativity and provide various styles. And the most prominent capability in GenAI is easy for beginners to use, no advanced design skills needed.

However, no matter how useful the GenAI images offer to human. There are some limitations that designers or users easily recognize while employing GenAI images in their work. For example, users cannot fully rely on the outputs of GenAI images. The results always need to be reviewed or refined before proceeding to the next step. Next, the output sometimes involved abnormal details or off-brand designs. Moreover, some GenAI images output may involve in legal restrictions or copyright issues. Hence, it is critical to review or supervise the output from GenAI images instead of fully rely on the GenAI.

Figure 5. AI image from Dall-E (2022), prompt "a grumpy cat having fun eating ice cream"

2.3 Integrating AI in creative process

The potential of GenAI when integrating in the creative and design thinking process is undeniable. Designers can incorporate GenAI into each activity of the design thinking process: empathize, define, ideate, prototype, and testing (Goonetilleke and Au, 2020).

Empathize (research and users' insights)

As many authors, designers, and experts said, one of the foremost stages in the design thinking process is empathize with the users. Being a designer means to deeply understand the users, who will use the products, the services. A deep understand of the users leads the ideation process into delivering richer insights and finer tuned products and services (Campbell, 2022). Once the designers understand the users deeply, it is easy to define the users' needs, problems, or the insights. In the Empathize stage, AI tools such as ChatGPT (for interview scripts), MonkeyLearn (for sentiment analysis) or Hotjar (for user behaviour tracking) can analyse enormous data to reveal the user insights.

Define (the problem)

In the Define stage, the designers need to refine the problems and insights. Using AI tools such as Miro, Notion, or ChatGPT to assist the brainstorming process, or powerful AI tool as Tableau AI analytics can be used to spot trends in user behaviours. Once the datasets from user behaviours is analysed, the designers can spot the main problems and gather useful insights before coming to the ideation stage.

Ideation (generating solutions)

During the ideation activities, mood board and rapid concept creation take critical roles in creating new ideas. Employing AI in generating rapid concept, generating images, are significantly helpful in this stage. To generate rapid concepts or mood boards, generative AI images such as MidJourney, Dall-E or Stable Infusion are extremely helpful. Additionally, digital service designers can use ChatGPT, DeepSeek or Jasper AI to assist brainwriting in creating digital contents. Additionally, GenAI is proven to be efficient in generate abstract ideas, boost creativities (Berg, 2024). When interacting with GenAI, the designers need to provide a specific request in the desired results, the more details in the prompting, the more accurate of the results GenAI generates.

Prototype (Building and Visualizing Ideas)

After accelerating the creative exploration with AI in the ideation stage, prototyping stage speeds up in creating mock-ups, sketches, or images such as employing AI tool to generate 3D models and textures in game industry – Kaedim or NVIDIA Canvas for video editing or architectural visualization.

The roles of AI in prototyping do not stop at 3D models, videos, or images. It goes far beyond the traditional methods. In digital services design, AI tools such as Figma AI, or Galileo AI can assist UI/UX designers sketch a rough idea into a high-quality wireframe.

Testing (User Feedbacks and Iteration)

The way AI integrating in the testing activities can accelerate the process of analysing user interactions and feedbacks. For example, Optimizely AI or Google Optimize are two powerful to predicts which digital products has better performance in various platform. Meanwhile, Hotjar can detect effortlessly the struggle of users while they're using a prototype. This is invaluable function because AI tool can predict the best-performing design seamlessly.

3 Research methods

This research was conducted using a mixed-methods methodology, whereby methodological triangulation was implemented through the combination of questionnaire and interview data. The adoption of this approach was motivated by its capacity to enhance validity, facilitate a more comprehensive analysis, and reduce the potential for bias.

3.1 Quantitative method, gathering feedbacks via questionnaires

To collect the data, two different tailored questionnaires were sent to the participants. Each questionnaire has at least 11 - 12 questions, aligned with 5 stages of the Design Thinking process. Additionally, each questionnaire includes 2 open questions, in which one question discusses the impact of each method on the Design Thinking process. In the Questionnaire A (target to group A – AI users), the aim is to analyse AI role in each stage of the Design Thinking process. Meanwhile, Questionnaire B (target group B – non-AI users) explores the manual or human-driven methods in the same stages.

Both Questionnaires can be found in the Appendices section.

3.2 Qualitative method, semi-structure interviews

To conduct the semi-structure interviews, two different tailored interview questions were prepared for each group. Each interviews forms have 12 questions totally, 10 questions aligned with 5 stages of Design thinking process (2 questions each stage). Furthermore, each forms includes 2 open questions, in which searching for the opinions on ethical issues while using AI (group A – AI users). Meanwhile, open question in the interviews of group B discuss the benefits or limitations of following traditional methods – without using AI in the Design Thinking process.

Both forms of the interview questions can be found in the Appendices section.

3.3 Study setup and Evaluation criteria

Participants were recruited from professional networks and design communities, including LinkedIn with eligibility contingent upon demonstrated design experience. Data were collected using a triangulation framework, combining digital questionnaires distributed via Microsoft Forms with semi-structured interviews. The questionnaires incorporated open-ended questions to capture nuanced participant approached, and informed consent was obtained for the use of anonymized data.

While the primary analytical focus on the qualitative interview data, the quantitative survey data were instrumental in enhancing the study's validity. The triangulation of methods served to mitigate the inherent bias of single-method studies, provide comprehensive insights, and reveal underlying patterns or contradictions within the dataset. Furthermore, participant responses were evaluated against four established criteria: efficiency, creativity, user-centricity, and the mitigation of bias and ethical concerns in AI application.

3.4 Sample

The study targeted designers and engineers who involve in design thinking process in their professional works - products design or services design. The research employs qualitative comparative case study approach, which analysing two group of participants: group A – designers who actively integrate AI tools into their Design thinking process, group B – designers who follow traditional (non-AI) Design thinking process. The group allocation for each group as following: in group A, the participants must have used AI tools in more than 2 projects. In group B – the non-AI users, the participants do not rely on AI in their Design Thinking workflow. Although group B (non-AI users) do not fully rely on AI in their professional work, they are fully aware of AI tools and gave themselves chances to expose to the AI tools.

Most of the participants were taken from the researcher's network. The participants were provided information about the study and voluntarily attended the study. Following the initial sampling, a snowball sampling approach was used. The research depended on the contacts provided by her network, who may be interested in the study and willing to participant in the research (Rapley, 2014). This allowed the researcher to recruit more

participants, including those who might come from diverse background and expose themselves to different level of practices in their Design Thinking.

A total of 5 participants were recruited for the interviews, of which three were AI-users and two were non-AI users (see Table 2). Although the total participants of the research were 9 participants, only 5 participants voluntarily agreed to attend the interviews.

Table 1. Demographics and characteristics of participants

Participant	**Group**	**Years of Experiences**	**Professionals**	**Gender**
Expert 1 _ E1	AI users – A	4	Software engineer	Female
Expert 2 _ E2	AI users – A	5	Industrial engineer	Male
Expert 3 _ E3	AI users – A	2	Website developer	Female
Expert 4 _ E4	Non-AI users – B	15	Mechanical engineer	Male
Expert 5 _ E5	Non-AI users – B	3	3D designer	Female

3.5 Instruments

This study employs a mixed-methods approach, combining quantitative questionnaires with qualitative interviews to achieve methodological triangulation (John W. Creswell and Vicki L. Plano Clark, 2018). The questionnaires were used to establish general patterns and frequencies across the sample, while the subsequent interviews provided depth and context to these statistical trends. This approach aligns with Greene, Caracelli and Graham's (1989) (Greene, Caracelli and Graham, 1989) concept of complementarity, where different methods are used to elucidate overlapping but distinct facets of the same phenomenon.

3.5.1 Questionnaires

Data collection began with a Likert-scale questionnaire designed to gauge participant perceptions. Two versions were administered: one for AI users (group A) – Appendix 3, and another for non-AI users (group B) – Appendix 4. Both questionnaires targeted four key metrics: efficiency, creativity user-centricity, and a fourth metric concerning ethics (focus on bias for Group A and risks/satisfaction for Group B). Responses were captured on a four-

point scale (Strongly Agree to Strongly Disagree) to facilitate analysis. This quantitative data was intended for later triangulation with qualitative interview data. Prior to deployment, the instrument was refined based on feedback from experienced faculty advisors in research and industrial design to ensure clarity and adjust leading questions.

3.5.2 Semi-structured interview protocol

This study employed a semi-structured interview methodology. This approach ensured that data collection remained anchored to set of predetermined, open-ended questions while providing the flexibility to probe emergent themes in depth. Hence, the interviewer was able to adopt the sequence of topics and pursue follow-up questions based on participant responses, thereby facilitating a deeper exploration of significant insights before returning to the core interview protocol. This method allows a richer and more complete insights into the participants' views and experiences with the assessments (Adeoye-Olatunde and Olenik, 2021). Furthermore, the open-ended questions and dynamic interactions allow the researchers to clarify the reasons and investigate related factors with the participants, thereby uncovering profound insights into underlying values and opinions that are frequently difficult to access through other means (Hirsjärvi and Hurme, 2022).

The interview questions were modified for two groups of participants accordingly to their integration of AI into their Design Thinking process. Each interview involved 10 questions, aligns with 5 stages of Design Thinking process: Empathize, Define, Ideation, Prototype, and Testing. Additionally, there are 2 follow-up questions in the interview, asked their opinions on the ethical considerations when using AI in their design process, and their opinion on any concerns that the participants did not have a chance to mention during the whole interview.

The interview commenced with introductory questions designed to establish rapport, focusing on participants' professional backgrounds, including their career history, years of experience, and field of experience. This approach enables the researcher to create a friendly and comfortable atmosphere to the participants, hence they are willing to open and share their inner thoughts with the researcher, to obtain authentic and deep insights for the study.

3.6 Procedure

The data collecting process involved sending questionnaires and conducting interviews occurred between 2nd August 2025 and 27th August 2025, the period when all participants had finished their summer break and they had time for filling the Likert questionnaires and participated in the interviews. Participants first completed the questionnaires actively. Subsequently, those who voluntarily agreed to be interviewed were contacted by the researcher to schedule and conduct the sessions, following the granting of their consent.

As the participants live in many different locations, while the researcher is in Helsinki (Finland), the interviews were conducted online on Microsoft Teams Meeting. While interviewing, the researcher switched on her video camera to create an environment similar to a real conversation. However, most of the participants attended the interview without video camera due to their personal choice. All the audio recordings of the interviews were taken with the consent of the participants.

The interviews mainly conducted in English, only one participant was interviewed in Vietnamese. Each interview took between 30 minutes to an hour. All the audio recordings of the interviews, which conducted in English, were transcribed by using an online software Revoldiv (revoldiv.com). The interview conducted in Vietnamese was transcribed by using an AI transcribe tool – TurboScribe (turboscribe.ai) then translated into English. During the interviews, notes were taken in each interview as recommended to identify gaps and asking follow-up questions on the spot (Fraenkel, Wallen and Hyun, 2012).

3.7 Ethical and privacy considerations

Potential participants were recruited via social media network group, mainly for designers, architectures, and digital artists. An informational poster detailed the study's purpose, procedures, data collection methods, and confidentiality measures, was mentioned. Prior to obtaining consent, individuals were informed of the interview recording process and their right to withdraw from the study at any time. Participation was contingent upon the receipt of signed consent agreement.

Immediately preceding each interview, the study's purpose and the intended use of the finding were reiterated, and participants were given an opportunity to ask questions. Separate consent was obtained for audio recording and the use of third-party transcription software. To ensure anonymity, all identifiers were replaced with participant codes in the transcripts and audio files.

4 Analytical methods

Methodology triangulation was implemented to construct a robust, nuanced, and compelling dimensional understanding of the research topic. The quantitative data derived from questionnaires and the qualitative data obtained from interviews were analysed separately yet concurrently. The former was evaluated statistically using Microsoft Excel, while the latter was subjected to a detailed thematic analysis. This approach ensured that each dataset was interpreted through its appropriate analytical lens before a synthesized understanding was developed.

4.1 Quantitative research

Questionnaire's data were analysed using Microsoft Excel. Independent samples t-test were employed to assess differences in responses between experts. For each statement, p-value were calculated to evaluate the degree of consensus among the participants.

4.2 Qualitative research

The interview data collected for this study were subjected to thematic analysis. This approach was selected for its capacity to facilitate the systematic organization and interpretation of complex qualitative datasets (Braun and Clarke, 2021). Thematic analysis provides a robust suite of conceptual tools and procedural guidelines, rendering it particularly efficacious for the examination of unstructured raw data, such as interview transcripts. Its application enables the distillation of voluminous textual material into a manageable framework of salient themes, the identification of underlying patterns of similarity and divergence, and the construction of a structured interpretation of salient meanings.

In accordance with the established framework proposed by Braun and Clarke (2021), the analytical procedure was rigorously followed. The subsequent section delineates the specific stages of this iterative process, see Table 2.

Table 2. Phases of thematic analysis (Braun and Clarke, 2021)

Phase 1	Familiarizing yourself with the dataset
Phase 2	Coding
Phase 3	Generating initial themes
Phase 4	Developing and reviewing themes
Phase 5	Refining, defining and naming themes
Phase 6	Writing up

4.2.1 Familiarization

The data transcription process was initiated utilizing two digital tools: TurboScribe and Revoldiv. The initial transcripts were subsequently refined through a meticulous process against the original audio recordings to correct inaccuracies and insert appropriate punctuation. Following this, the corrected transcripts were exported to Microsoft Word, where participants were assigned anonymized numerical codes. A further iterative review was conducted on hard copies to identify and rectify any residual errors. Concurrently, analytical annotations were made to facilitate the researcher's immersion in the data and to document the key concepts articulated by each participant.

4.2.2 Coding

The initial coding phase was conducted using Taguette software to systematically organize the data into meaningful categories (Tuckett, 2005). An inductive coding approach was adopted, whereby an initial list of codes was generated from salient segments of the transcripts (Naeem et al., 2023). In this first cycle of coding, as recommended by Braun & Clarke (2021), the process remained open to as many potential patterns as possible to ensure no significant insights were pre-emptively excluded. This resulted in a substantial and emergent set of codes. Subsequently, these initial codes were reviewed and aggregated into broader, coherent categories based on thematic similarity.

4.2.3 Generating initial themes

During the third phase of analysis, the generated codes were synthesized into potential themes by examining their interrelationships, including points of convergence, divergence, and overlap (Ahmed et al., 2025). Following the generation of multiple potential themes, a rigorous refinement process was undertaken. Candidate themes were systematically evaluated based on their capacity to coherently capture the dataset and directly address the research questions (Braun and Clarke, 2021). Upon this identification, all relevant coded data extracts were collated and assembled within their respective thematic categories to facilitate a deeper analysis.

4.2.4 Developing and reviewing themes

To conceptualize the broader patterns within the dataset, an initial thematic map was constructed (Braun and Clarke, 2021). The candidate themes were identified through a rigorous review of coded data, with selection criteria based on both prevalence – recurrence across multiple transcripts – and the substantive significance of the ideas expressed. Codes and themes that occurred infrequently and lacked analytical value were set aside to ensure a reliable representation of the entire dataset for readers.

4.2.5 Refining, defining and naming themes

In this phase, the themes refinement involved a critical review of the candidate themes to ensure internal coherence and external distinctiveness. This was achieved through an iterative process of re-reading the dataset, redefining thematic boundaries, and reallocating codes where necessary (Braun and Clarke, 2021). Double-coding was employed as a strategic measure to verify the clarity and distinctiveness of the evolving thematic structure. This cyclical process of analysis continued until a robust and analytical satisfying thematic framework was established, culminating in the identification of the overarching themes and sub-themes presented in the figure below, see Figure 6.

4.2.6 Writing up

The analytical process culminated in the production of a thematic write-up, constituting a synthesized representation of the data both withing and across the established themes (Braun and Clarke, 2021). A thematic table was first constructed, delineating each theme alongside its description and most illustrative data extracts. This instrument served to consolidate a comprehensive understanding of the thematic structure, thereby providing a coherent foundation for the detailed analysis and discussion presented in the subsequent chapter.

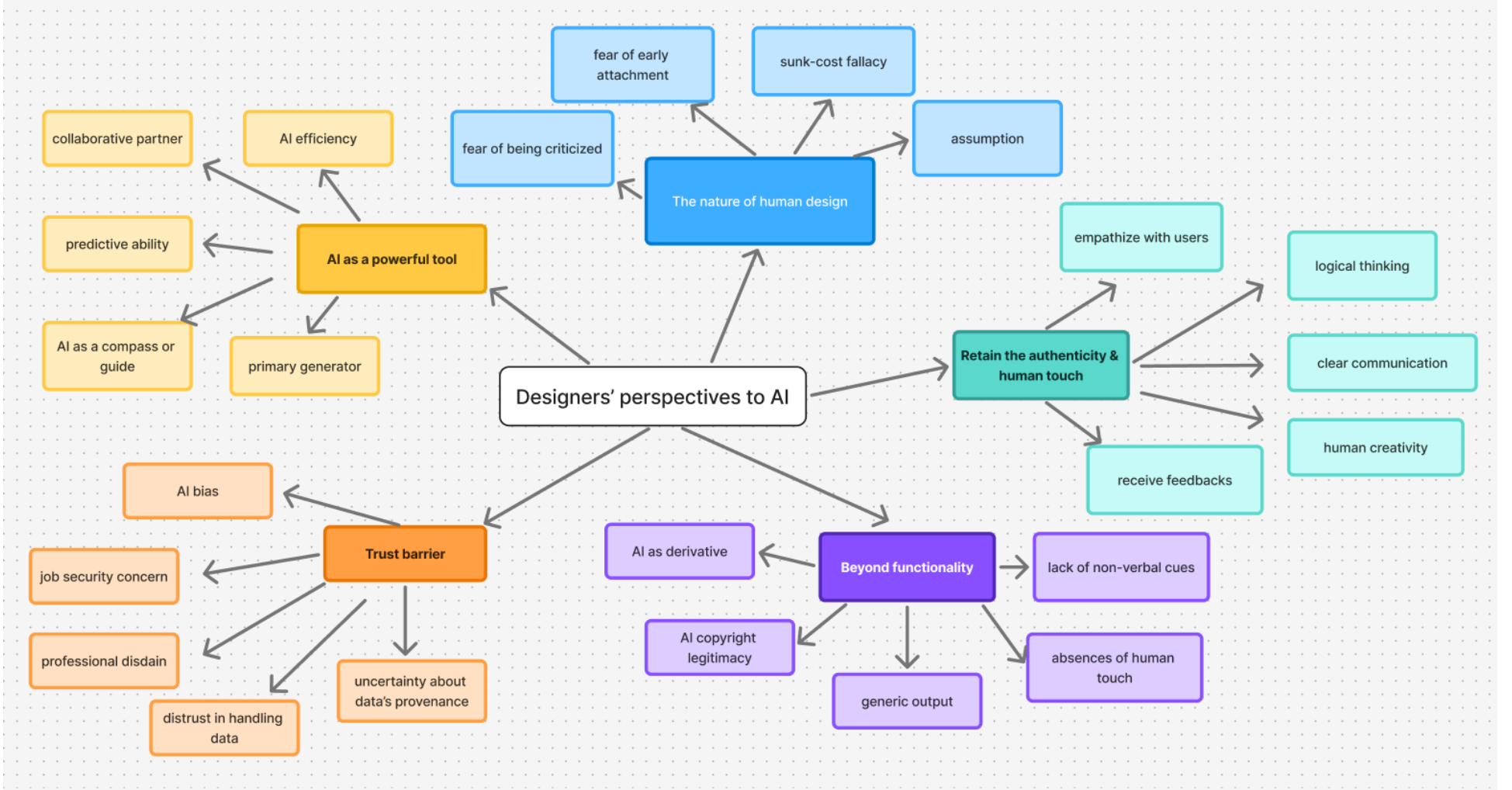

Figure 6. Concept map of all the themes

5 Results

This chapter presents a separate interpretation of the quantitative and qualitative datasets. The quantitative results were evaluated through a comparative analysis between the two participant groups. In contrast, the qualitative findings were derived from the emergent themes within the interview responses across both cohorts. This analytical approach was instrumental in revealing meaningful divergence and generating rich insights, thereby illuminating distinct facets of the research problem from multiple perspectives.

5.1 Quantitative results from Questionnaires

In group A, the statistical analysis in *Table 3* revealed strong, statistically significant consensus on several key benefits of AI integration within the design-thinking process. The statistical results in group A can be seen below.

Table 3. Statistical results of Group A

Statements	**STDEV**	**t-value**	**p-value**
Statement 1	1.06	2.82	0.03
Statement 2	0.53	7.78	0.0002
Statement 3	0.48	9.30	0.000008
Statement 4	1.06	2.83	0.03
Statement 5	0.53	7.07	0.0004
Statement 6	1.13	1.33	0.23
Statement 7	0.97	1.61	0.28
Statement 8	0.89	2.52	0.04
Statement 9	0.53	7.78	0.0002
Statement 10	1.39	0.81	0.44
Statement 11	0.53	7.07	0.0004

Participants in group A (AI users) reported that AI significantly enhances ideation by helping them generate novel ideas they would not have conceived independently (Statement 3, $p <$

0.001, t = 9.30) and broadens the range of design directions they explore (Statement 5, $p < 0.001$, t = 7.07). Furthermore, AI was found to substantially improve operational efficiency by shortening the time spent on routine tasks (Statement 4, p = 0.03, t = 2.83) and reducing the overall cost of prototyping (Statement 2, $p < 0.001$, t = 7.78). This integration follows a collaborative model, as designers significantly combine AI outputs with their own concepts to create novel solutions. Critically, this adoption does not appear to compromise methodological rigor, respondents test AI-assisted prototypes as frequently as non-AI prototypes (Statement 8, p = 0.045, t = 2.52). A strong proactive ethical stance was also evident, with a clear consensus on checking AI outputs for potential bias before stakeholder review (Statement 9, $p < 0.001$, t = 7.78). These positive experiences culminate in a highly significant agreement that the overall integration of AI is beneficial (Statement 11, $p < 0.001$, t = 7.07).

Conversely, the analysis identified areas where no significant consensus was established, pointing the potential gaps in practice or perceived value. Notably, participants in group A did not consistently report that AI allows for prototypes to be tailored more closely to user needs and contexts (Statement 7, p = 0.289, t = 1.16). The process for integrating user feedback also appeared less systematic; there was no significant agreement that real user feedback is consistently gathered as a gatekeeping mechanism before selecting AI-generated concepts (Statement 6, p = 0.231, t = 1.33). Most notably, the practice of formally documenting and discussing broader ethical risks, such as fairness and privacy, was not found to be a standardized part of projects (Statement 10, p = 0.448, t = 0.81). This contrasts sharply with the proactive checking for bias, suggesting that while immediate, visible risks are managed, more systemic ethical documentation is not yet a common practice. These non-significant findings highlight a critical divergence between adoption of AI for efficiency and ideation and its application for user-centric refinement and comprehensive ethical governance.

Meanwhile, in group B, the non-AI design thinking group, the analysis baseline reveals a process characterized by widespread ambivalence and a lack of strong, consensus-driven strengths in *Table 4* below.

Table 4. Statistical results of Group B

Statements	STDEV	t-value	p-value
Statement 1	0.70	2.12	0.28
Statement 2	0	N/A	1
Statement 3	2.12	0.23	0.85
Statement 4	0	N/A	1
Statement 5	0	N/A	1
Statement 6	1.41	0	1
Statement 7	0	N/A	1
Statement 8	0	N/A	1
Statement 9	2.12	0.23	0.85
Statement 10	1.41	0	1
Statement 11	0.70	2.12	0.28
Statement 12	0.70	2.12	0.28

On a majority of dimensions – including cost-effectiveness of prototyping (Statement 2), breadth of ideation (Statement 5), user-centric practices like tailoring prototypes (Statement 7) and frequent testing (Statement 8), and the synthesis of diverse inspirations (Statement 4) – the participant responses clustered perfectly at a neutral point, indicating no strong collective sentiment. Furthermore, several critical areas exhibited significant internal disagreement, as evidenced by high standard deviations. Most notably, the group was sharply divided on their ability to generate novel ideas (Statement 3) and on their proactive checking of outputs for bias (Statement 9). This pattern suggests that, in the absence of AI, the design process is perceived as neither systematically excellent nor systematically flawed but is highly variable and dependent on individual practitioner habits and skills.

The baseline results establish a clear pre-existing context against which the impact of AI integration can be measured. The absence of significant consensus on overall satisfaction (Statement 12), efficiency in routine tasks (Statement 1), and confidence in minimizing harm (Statement 1) despite a slight positive trend, highlights latent inefficiencies and uncertainties in the current workflow. Crucially, the significant disparities in ideation novelty and bias checking point to fundamental, unmet needs within the traditional process. These baseline

findings are essential for contextualizing the positive effects of AI; they demonstrate that AI tools are not being introduced into an optimizing system but are instead addressing specific, measurable gaps in ideation capacity, procedural consistency, and ethical assurance. The neutral consensus on user-feedback gates (Statement 6) and ethical documentation (Statement 10) further identifies these as endemic areas of procedural weakness, not new problems created by AI.

Note that, both primary results from the Questionnaires can be seen from the Figure 7 (group A) and the Figure 8 (group B).

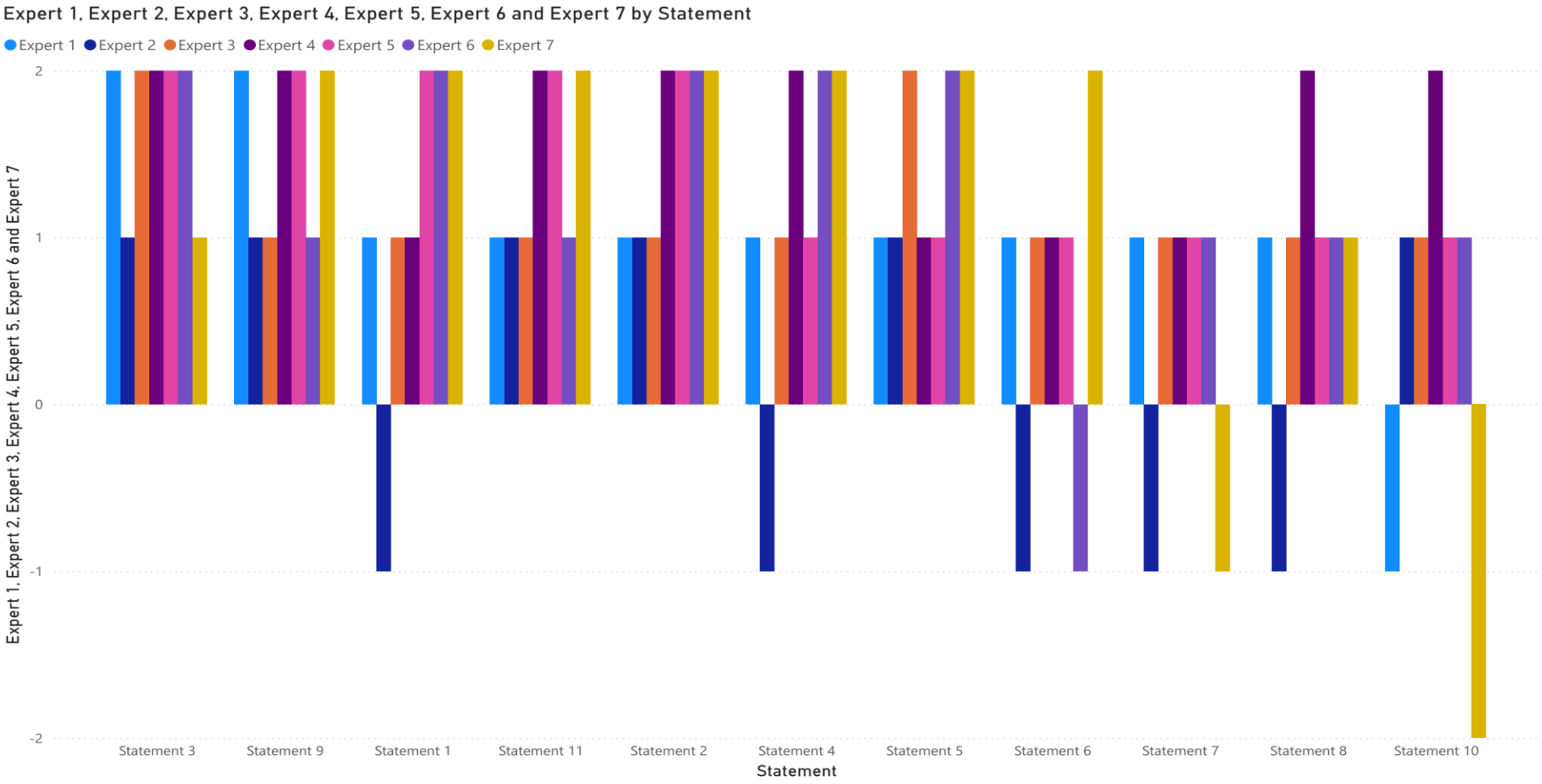

Figure 7. Primary results from Questionnaires, group A

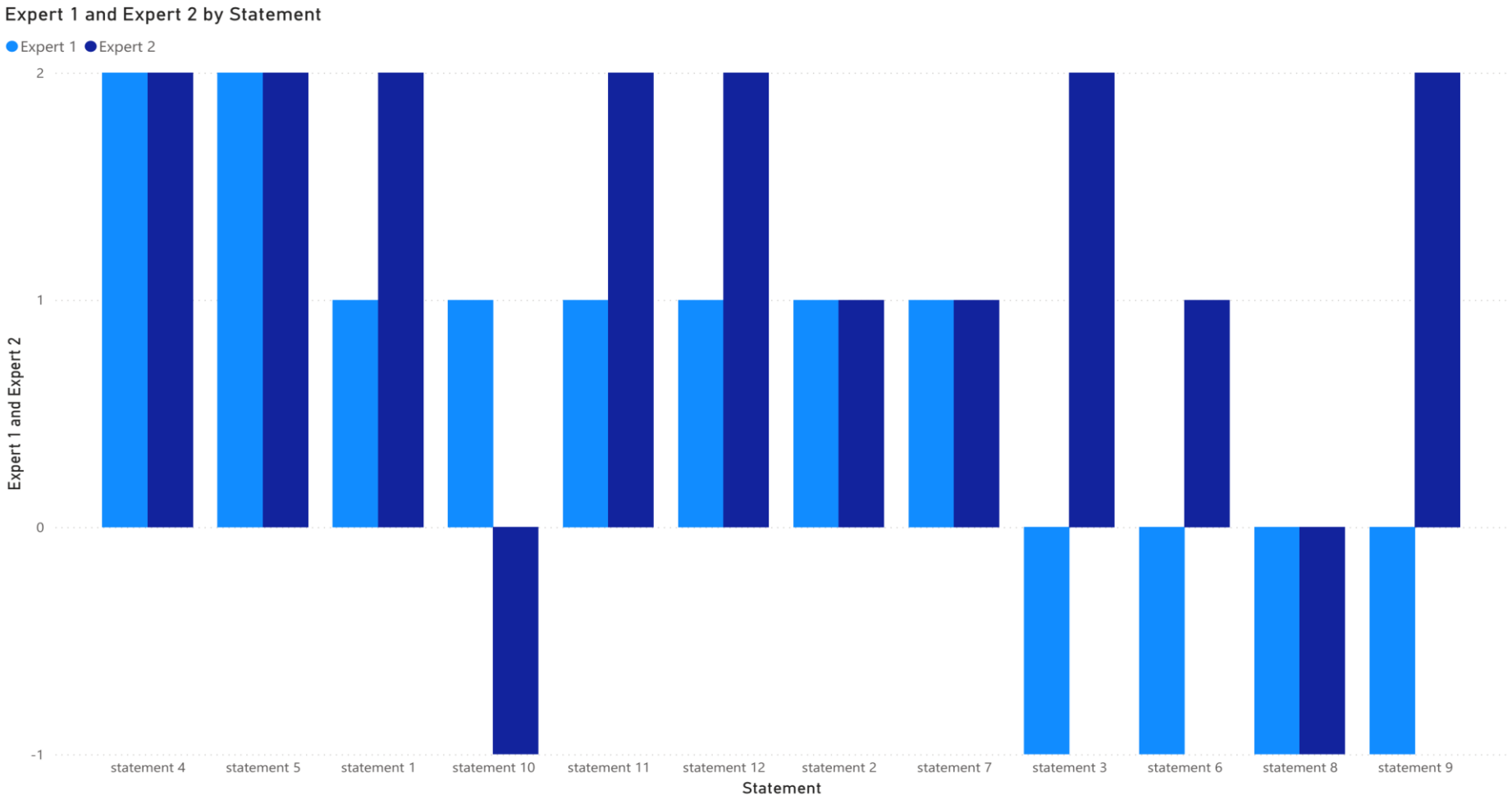

Figure 8. Primary results from Questionnaires, group B

5.2 Qualitative results from Thematic Analysis

The finding from the Thematic Analysis includes 5 themes: AI as a powerful tool, Beyond functionality, Trust barrier, Retain the authenticity & human touch and The nature of human design. The researcher first analyses the distribution of each theme to understand the general pattern of the data before diving in discussing the results of each theme later.

5.2.1 Overall themes

A summary of the thematic analysis, detailing the number of codes and their relative percentage within each theme, is provided in Table 5 below.

Table 5. Distribution of all codes according to themes

Themes	**No. Of codes**	**Percentages**
AI as a powerful tool	62	33%
Beyond functionality	24	13%
Trust barrier	25	13%
Retain the authenticity & human touch	70	37%
The nature of human design	9	4%

In general, the distribution of codes mainly focuses on two themes: “AI as a powerful tool” and “Retain the authenticity & human touch” with the most codes categorized under the theme “Retain the authenticity & human touch”. This suggested that the theme is significant and possibly the most concern amongst the designers.

Next, an analysis of the relationship between two groups and the identifies themes was conducted using Taguette and Excel. The distribution of percentages code of two group according to themes is illustrated in Table 6, can be seen below.

According to the data from Table 6, the patterns amongst group A (AI users) showed a large portion of codes (31%) amongst all codes were under the “AI as a powerful tool” theme, while the largest portion of codes (32%) amongst group B (non-AI users) were under the

theme “Retain the authenticity & human touch” theme. This reveals a sharp divergence in perspective. As AI users primarily consider AI as a powerful tool, while non-users express significant concern about the authenticity of human touch in their design. Additionally, a significant finding is that AI users themselves report a higher level of concern regarding trust barriers associated with AI.

Table 6. The distribution of two groups according to themes

Themes	**Group A**	**Group B**
AI as a powerful tool	31%	1.6%
Beyond functionality	7.6%	5%
Trust barrier	9.1%	4%
Retain the authenticity & human touch	5.1%	32%
The nature of human touch	0%	4.8%

5.2.2 AI as a powerful tool

In this theme, the word cloud (see Figure 9) included high-frequency words such as AI, primary generator, compass, guide, finding patters, predictive ability. This indicates that AI was related to ideas to give instructions and guidance, generate ideas, and thinking amongst all designers.

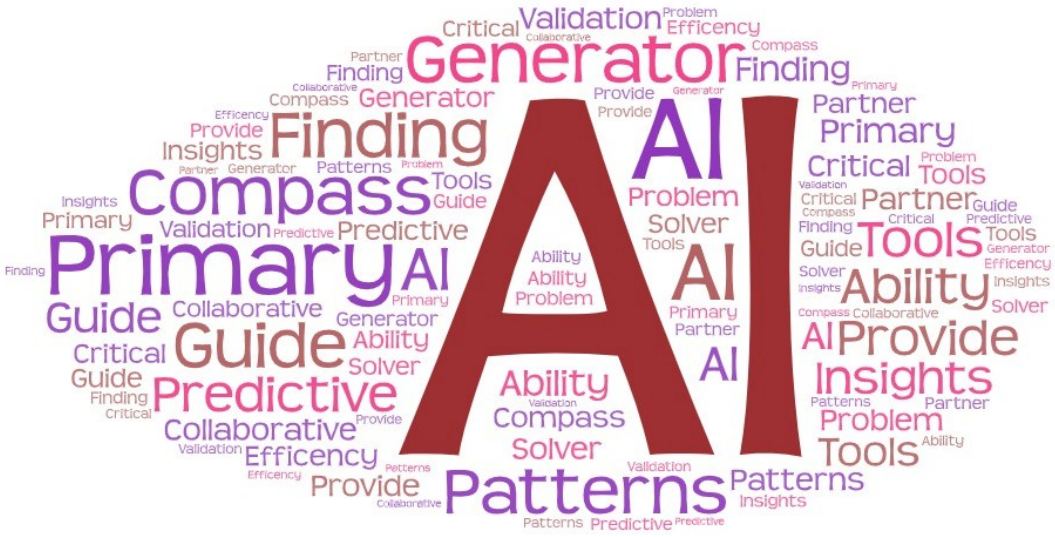

Figure 9. Word cloud for theme "AI as a powerful tool"

Based on the code distribution in Table 7, the detailed analysis of the theme “AI as a powerful tool” reveals a strong contrast in perception between group A (AI users) and group B (Non-AI users). Group A demonstrated a more nuanced and comprehensive understanding, accounting for 100% of the mention in 7 out of 10 specific codes such as *AI as a compass or guide*, *predictive ability*, and *collaborative partner*.

The most commonly cited code was *primary generator* (n = 15). While group A dominated this category at 86.7%, this code is the only category with significant input from group B (non-AI users) at 13.3%. The second most cited code is *AI efficiency*, was the only other code where non-AI users contributed 33.3% This suggests that designers in group B (non-AI users) primarily perceive AI in its most basic functional term such as a generator and efficiency tool, meanwhile designers in group A (AI users) appreciate a wide spectrum of advanced and supportive roles that AI can play.

Table 7. Codes distribution in theme "AI as a powerful tool"

Code	**% Group A**	**% Group B**
Primary generator	86.7	13.3
AI as a compass or guide	100	0
Finding the patterns	100	0
AI predictive ability	100	0
AI tools	100	0
Provide insights	100	0
AI as a collaborative partner	100	0
Critical validation	100	0
AI as a problem solver	100	0
AI efficiency	66.7	33.3

5.2.3 Beyond functionality

The theme “Beyond functionality” discusses the limitations and qualitative aspects of AI, moving beyond its basic utilities. According to the code distribution in Table 8, the key pattern found in this theme is the group B (Non-AI users) focuses on human-centric and

experiential shortcomings, meanwhile group A (AI users) focuses on technical and legal limitations.

Table 8. Codes distribution in theme "Beyond functionality"

Codes	**% Group A**	**% Group B**
Absences of human touch	0	100
AI as derivative	100	0
AI copyright legitimacy	100	0
AI struggle with technical specificity	100	0
Generic output	0	100
Lack of authenticity	33.3	66.7
Lack of non-verbal cues	100	0
Lack of precision/accuracy	66.7	33.3
Unsatisfied output	33.3	66.7

The theme reveals a pronounced contrast between two different group, described by their experiential familiar with AI. The group B (Non-AI users) articulated criticisms that were overwhelmingly human-centric and experiential in nature. This was most evident in their exclusive identification of the code *Absences of human touch* (100% mentioned) and *generic output* (100%). Furthermore, group B constituted the majority of response citing *a lack of authenticity* (66.7%) and *unsatisfied output* (66.7%), underscoring that their primary reservations lie with AI's inability to replicate or satisfy human qualitative standards.

Conversely, group A (AI users) demonstrated a more nuance critique, grounded in technical and ethical considerations arising from direct engagement with AI. Group A was sole contributors to several distinct codes, including concerns about *AI copyright legitimacy* (100%) and the *derivative* nature of AI content (100%), *struggle with technical specificity* (100%), and *lack of non-verbal cues* (100%). While both groups mentioned a *lack of precision/accuracy* (66.7%), designers in group A were dominant voice on this more practical limitation. This pattern indicated that direct usage shifts the focus of criticism from broad, humanistic apprehension to specific, operational challenges related to integration, quality control and intellectual property.

5.2.4 Trust barrier

The theme "Trust barrier" uncovered a profound qualitative divergence in the nature of distrust between group A (AI users) and group B (Non-AI users) towards AI, in which the former group expressing a more complex and operationalized set of concerns. This pattern of the theme reflected in the distribution codes in Table 9 below.

Table 9. Codes distribution in theme "Trust barrier"

Codes	**% Group A**	**% Group B**
Authenticity concerns	0	100
Awarenss of AI bias	100	0
Confidential concerns	100	0
Distrust in data handling	100	0
Distrust in predictive ability	100	0
Distrust of AI's objectivity	100	0
Intellectual concern	100	0
Job security concern	28.6	71.4
Non-transparent data practices	100	0
Non-use in core works	100	0
Professional disdain	50	50
Risk awareness	100	0
Uncertainty about data's provenance	100	0

Group A articulated a multifaceted distrust rooted in the technical and ethical architecture of AI systems. This group was a sole source of concerns regarding *uncertainty about data's provenance* (100% mentioned), *non-transparent data practices* (100%), *distrust in data handling* (100%) and *confidential concerns* (100%). All these codes highlighted acute apprehension about data provenance. Furthermore, group A demonstrated a sophisticated critique of AI's core functionality, exclusively citing *distrust in predictive ability* (100%) of AI, *distrust of AI's objectivity* (100%), and awareness of AI bias (100%), which they directed linked to *risk awareness* (100%) and a conscious decision for *non-use in core works* (100%).

In strong contrast, the trust barrier in group B (Non-AI users) was characterized by two primary code yet significant, anxieties: an overwhelming preoccupation with *job security* (71.4%) and a distinct *authenticity concern* (100%) which they uniquely cited. The only point of convergence was *professional disdain*, which was shared equally (50% each group). This pattern indicated that for group A (AI users), the trust barrier is an active, internalized risk management calculus based on technical flaws and ethical misgivings, whereas for group B (non-AI users), it manifests as more externalized fear of professional displacement and a loss of authentic human output.

5.2.5 Retain the authenticity & human touch

The theme “Retain to Authenticity & Human touch” in Table 10 reveals a strong and fundamental division between two groups, with group A articulating a greatly more detailed, nuanced, and prescriptive vision of indispensable human capabilities. Meanwhile in group B (non-AI users), this theme was not only a general principle but also a detailed taxonomy of specific, irreplaceable human functions. They dominated discussion across a wide spectrum of activities, most notably in the action of *receiving feedbacks* (75%). Critically, group B was main contributors to a suit of advanced cognitive and empathetic skills, exclusively citing *human creativity* (100%), *logical thinking* (100%), the ability to *empathize with users* (100%) and *questioning the problem* (100%). Their perspective extended to the entire design process, from *testing prototype* (100%) and *clear communication* (100%), to *finalizing the design* (100%). Thereby, the perspectives of group B (non-AI users) framed authenticity as a holistic, process-wide human endeavour.

In strong contrast, the responses from group A (AI users) on this theme were relatively limited and abstract. Their contributions were largely confined to high-level concepts such as *retention of human agency* (100%) – a concern they alone mentioned – and shared, but less frequent acknowledgements of the need for *human synthesis* (33.3%) and *guarding human creativity* (25%). This dramatic disparity demonstrates that group B (non-AI users), human touch constitutes a rich, practical framework of concrete skills they deem vital, whereas for group A, it appears to be a more circumscribed, often philosophical, consideration within their AI-integrated workflow.

Table 10. Distribution of codes in the theme "Retain the authenticity & human touch"

Codes	**% Group A**	**% Group B**
Brainstorm	25	75
Clear to communication	0	100
Efficiency	50	50
Empathize to users	0	100
Facilitating & Interpreting	0	100
Finalize the design	0	100
Guarding human creativity	25	75
Human creativity	0	100
Human kindness	0	100
Human synthesis as essential	33.3	66.7
Intutional	25	75
Logical thinking	0	100
Moodboard	0	100
Questioning the problems	0	100
Receiving feedbacks	8.3	91.7
Retention of human agency	100	0
Testing prototype	0	100
Trial & error strategy	0	100
Uncovering hidden needs	0	100

5.2.6 The nature of human design

The theme “The nature of human design” unveiled a critical finding: this entire conceptual category was exclusively articulated by group B (non-AI users), with no contribution from their counterpart – group A (see Table 11). The data indicates that group B possess a distinct and psychological nuanced understanding of the design process, one that is acutely aware of its inherent human vulnerabilities and cognitive bias. Specifically, group B (non-AI users) framed the design endeavour as being fraught with internal psychological challenges, including the *fear of being criticized* (100%) and the *fear of early attachment to one idea* (100%). Furthermore, they demonstrated an awareness of detrimental cognitive patterns that can hinder objective decision-making, explicitly identifying the *sunk-cost fallacy*

(100%) as a pitfall. Their perspective also encompassed a pragmatic acknowledgement of potential failure points in the process, such as the root of unchallenged *assumptions* (100%) and the possibility that ideas may *fail in testing* (100%). The complete absence of these codes from the group A (AI users) suggests a fundamental difference in how the two groups conceptualize the design process. For group B, the nature of human design is intrinsically linked to a complex interplay of emotions, bias and risk – the messy, psychological substrate of creativity. The silence from group A (AI users) on this theme implies that their perspective on design may be more focused on operational efficiency or solution-oriented generation, potentially viewing these psychological dimensions as secondary or mitigated through their use of technology.

Table 11. Distribution of codes in the theme "The nature of human design"

Codes	**% Group A**	**% Group B**
Assumption	0	100
Fail in testing idea	0	100
Fear of being criticized	0	100
Fear of early attachment to one idea	0	100
Sunk-cost fallacy	0	100

6 Discussion

6.1 Quantitative Analysis (Questionnaires Data)

The comparative analysis between group A (AI users) and group B (non-AI users), reveals a pronounced divergence in designer perceptions, underscoring AI's significant impact on the design-thinking workflow. The most striking findings pertain to creative efficacy and process efficiency. Group A reported a highly significant consensus that AI augments their creativity, both by generating novel ideas ($p < 0.001$) and broadening their exploration of design directions ($p < 0.001$). This stands in direct contrast to group B, which exhibited significant internal disagreement and no consensus on their ability to generate novel ideas, indicating a key area of vulnerability in the traditional process. Similarly, where group A strongly agreed that AI reduces prototyping costs and shortens routine task time, group B demonstrated uniform ambivalence toward the cost-effectiveness and speed of their own methods. This suggests AI directly addresses perceived inefficiencies in the traditional design cycle. Furthermore, the data illuminates critical differences in procedural rigor and ethical awareness. A pivotal finding is that both groups maintain a commitment to user validation; group A tests AI-assisted prototypes as frequently as non-AI users ($p = 0.045$), mirroring the neutral but universally consistent testing frequency in group B. this indicates that the core principle of user-centricity is preserved despite the integration of new technology. In the ethical domain, however, a notable divergence emerges. Group A demonstrates a robust, proactive practice of checking AI outputs for bias ($p < 0.001$). Conversely, group B showed major internal disagreement on checking their own outputs for bias, revealing a lack of standardized ethical scrutiny in the traditional workflow. This suggests that the introduction of AI has not diminished ethical vigilance but has instead institutionalized a specific, critical check that was previously inconsistent. A shared challenge is evident in the lack of consensus in both groups on formally documenting broader ethical risks, pointing to a systemic gap in ethical governance beyond the scope of any single tool.

Ultimately, the aggregate sentiment validates the transformative potential of AI integration. Group A revealed a strong, significant agreement on the overall benefit of AI ($p < 0.001$), which reflects a positive assessment of its net impact. In contrast, group B's perception of

their traditional process is best characterized as one of functional adequacy, with only non-significant trends toward satisfaction and no strong consensus on any major strength. The evidence posits that, for these practitioners, AI integration has effectively augmented the design process. Creating a workflow perceived as more creative, efficient, and systematically rigorous in key ethical checks, while steadfastly upholding the user-validation protocols fundamental to design-thinking.

6.2 Qualitative Analysis (Interviews Data)

The findings from Qualitative research reveal a profound and multi-layered divergence in how designers in group A and group B perceive artificial intelligence in their design thinking process. The data does not simply indicate different levels of adoption but exposes fundamentally distinct paradigms through which the two groups view the nature of work, creativity, and the role of technology. This discussion synthesizes the five core themes to argue that the central tension is between a tool-oriented paradigm embraced by group A and a human-centric paradigm defended by group B.

The most compelling narrative emerging from the data is the inverse relationship between the themes “AI as a powerful tool” and “Retain the authenticity & human touch”. Group A exhibited a sophisticated, granular understanding of AI’s utility, describing it as a “compass”, “predictive engine” and “collaborative partner”.

“I use AI as this like diverging methodology that if I have a problem or need a solution, I ask AI like, hey, how can this be handled?” – Expert 1

“It’s really great because it saves me time that I would normally need to Google like how to use a software and find specific YouTube videos” – Expert 1

“I believe it’s very capable of giving you feedback on what potential problems in manufacturing or large scale” – Expert 2 on the predictive ability of AI

This suggests that for users, AI has transcended being a simple generator and has become and integrated cognitive partner that enhances their strategic capabilities. Conversely, group B articulated an extensive and prescriptive taxonomy of the “human touch”, exclusively mentioned codes like, “intuitional”, “human creativity”, “empathy”, “logical thinking”, and “questioning the problem”.

"The biggest advantage is I retain my logical thinking skill because I don't outsource it" – Expert 5

"I put, put myself on their position, and think, how do they remove this part?" – Expert 5

"I questioned, what is the best solution? If there is a problem, what is that? I think about the problem… not just try to improve the first idea or anything, not think about that idea at all, but just try to take a completely different approach to the problem." – Expert 4

This is not merely a preference but a deeply held belief system that defines their professional identity. The near-total mutual exclusivity of these themes indicates that the two groups are operating within different epistemological frameworks. For group A designers, value is derived from a synthesis of human and intelligence, while for group B designers, value is intrinsically and exclusively human.

Additionally, the nature of each group's criticisms further illuminates their underlying paradigms. Group A designers demonstrated an operationalized critique of AI's limitations. Their concerns, categorized under the theme "Beyond functionality" and "Trust barrier" were specific, technical, and born from direct experience revealing in the codes: "AI copyright legitimacy", "non-transparent data practices", "awareness of AI bias", and "uncertainty about data's provenance".

"That is really questionable if it's borrowed from other people as their content sort of stolen by AI and then modified or not." – Expert 1

"The database AI using is not reliable anymore. I don't input too much personal information" – Expert 3.

"I really don't like how biased AI is, that it can invent all the arguments to support the theory it wants to elevate and just kind of skip all the bad parts… like it can tailor the reasons to fit its own agenda and not be very like, what is the word? Reliable, I think." – Expert 1.

These are not mere complaints but a reflection of a core value: the imperative for reliable, accurate, and applicable output in their work. This indicates a posture of critical engagement – they accept AI as a tool but are actively managing its risks and flaws within their workflow. This perception is directly tethered to their "Trust Barrier" concerns, which are not about fear, but about verifiable provenance and ethical accountability. Issues like "uncertainty about data's provenance" "non-transparent data practices" and "AI copyright

legitimacy" are operational risks that threaten the integrity of the final design product and the designer's professional liability. In essence, their dual critique forms a coherent system: they cannot leverage AI as a powerful tool ("Functionality") unless they can trust its inputs and processes ("Trust"), leading to a viewpoint of critical, managed integration.

In contrast, group B non-AI users' criticisms were more existential and human-centric. Their worldview centered on professional identity and sovereignty. Their primary trust issue was not data provenance but "job security", and their core functional concern was the "absences of human touch", "generic output", and "lack of authenticity". This underscores their primary value: the preservation of unique human qualities – creativity, empathy, and nuanced judgement – as a definitive source of value in design. This value is inextricably linked to "Trust Barrier", which is characterized not by operational risks, but by existential threats to their professional role and self-concept.

"It lacked aesthetic value and felt offensive… while people might say "the image itself has no errors, it lacks soul and thought" – Expert 5.

The dominant concern of "job security" and the uniquely cited "authenticity concern" are not a tool's failure, but about resisting the potential obsolescence of the very human skills they cherish. Thus, for non-AI designers, the connection between the themes is defensive. The functionality of AI is inherently suspect because it operates in a domain ("generic output") that they fundamentally distrust, as it threatens the "human touch" that constitutes their professional identity. Therefore, to non-AI designers, their trust barrier is, a firewall to protect their core value of human supremacy from being swallowed by the potent machine.

Within group B, a critical finding that consolidates the human-centric paradigm of non-users is the exclusive emergence of the theme "The nature of human design" from their group. By identifying vulnerabilities like the "fear of being criticized", the "sunk-cost fallacy" and reliance on "assumptions", non-AI designers are not merely listing flaws but are implicitly arguing that the entirety of the human design process – including its psychological delicateness, is essential to authentic creativity.

"It won't work if the boss is conservative and criticized others during the meeting." – Expert 5

"I received a lot of criticize when I start my career, and I have a lot of crazy ideas. Do not be afraid to show your design, whatever in your mind. Because if you are afraid, you're restricted yourself a lot." – Expert 4

"It's very, very important that when you are creating something new, you don't necessarily stick with, like it's like a sunk-cost fallacy, like when you start investing into your first idea, and then a new idea comes along, you just come up with it, then it's very hard to move from that idea you've already been doing into that" – Expert 4.

This perspective frames design as a deeply human, introspective, and emotionally charged endeavor. The complete absence of this theme among designers in group A is telling that their framework may view these psychological dimensions as inefficiencies to be mitigated or as secondary to the goal of instrumental problem-solving. This represents a fundamental philosophical divide on the very essence of creative work: one side sees the human psyche as the core of creativity, while the other sees it as a variable in a problem-solving equation.

6.3 Triangulation summary

The integration of quantitative survey data with rich qualitative themes reveals a consistent and compelling narrative: the distinction between AI-using designers and non-AI-using designers is not merely a binary of tool adoption but represents a fundamental divergence in professional identity, workflow optimization and the very definition of value in design thinking process. The summary of these dataset strengthens the validity of the findings, demonstrating that the measured attitudes (quantitative) are deeply rooted in the underlying beliefs and experiences (qualitative) of each group.

First, the quantitative data from group A paints a picture of designers who perceive AI as a significant enhancer of their workflow. Statistically strong agreement ($p < 0.05$) with statement that AI "shortens time", "reduces cost", and help them generate novel ideas that they "would have not thought of on my own" (Statement 1, 2, 3). These statements are powerfully explained by the qualitative theme "AI as a powerful tool". The qualitative data moves beyond these general benefits to reveal how this augmentation occurs: AI acts as a "compass or guide", and a "collaborative" agent, providing insights that broaden their exploration (Statement 5, $p = 0.0004$). This indicates that AI is not just a time-saver but a cognitive partner that expands their creative capacity.

Furthermore, the significant quantitative agreement on combining AI outputs with their own concepts (Statement 4, p = 0.03) aligns with the qualitative finding that designers in group A critically manage AI's limitation. Their operationalized concerns about AI being "derivative", its struggle with "technical specificity" and "lack of precision" reflect sharply in the theme "Beyond Functionality". The designers remain the central synthesizing agent, a concept qualitatively captured as "The retention of human agency".

Most notably, the high significance of checking AI outputs for bias (Statement 9, p = 0.0002) is given profound context by the "Trust Barrier" theme. Users' qualitative concerns about "uncertainty about data's provenance", "non-transparent data practices", and "awareness of AI bias" demonstrate that their qualitative behaviour is driven by a sophisticated, experienced-based distrust of AI's objectivity. Their trust barrier is not a deterrent to use but a defined set of risks that must be actively managed, leading to documented ethical risk discussions (Statement 10). In essence, the qualitative data shows what they do, and the qualitative data explains why they do it: they are critically engaged augmenters, not passive users.

In stark contrast, the quantitative data of group B reveals a cohort that is highly satisfied with their existing, non-AI involved process. The non-significant p-values (approaching 1.0) for most statements indicate no strong deviation from neutrality, suggesting contentment but not necessarily superior performance in metrics like cost, tailoring, or testing. Their significant satisfaction lies in the overall workflow (Statement 12, p = 0.28). this quantitative satisfaction is fundamentally rooted in the qualitative data.

The overwhelming qualitative theme for group B was "Retain the authenticity & human touch", which functions as their core professional philosophy. Their quantitative confidence in generating novel ideas (Statement 3) and creating original solutions (Statement 4) is qualitatively defined by an exclusive reliance on "human creativity", "intuition", "logical thinking", and "empathy". They perceive their process not just as a method, but as a human endeavour. This is further crystallized by the theme "The nature of human design", where they uniquely acknowledge the "fear of being criticised" and the "sunk-cost fallacy". For them, these human vulnerabilities are not inefficiencies to be eliminated but intrinsic parts of the authentic creative struggle.

The primary quantitative concern for group B, hinted at in their data, is ethical risk and minimizing harm (Statement 11, p = 0.28). The "Trust Barrier" theme explains that this is

not about data bias, but about the existential threat of “job security” and the “authenticity concerns” associated with AI-generated output. Their distrust is not of a tool’s functionality, but of a technology’s impact on their professional value and the integrity of their work. Therefore, their satisfaction with their current process is a direct result of its alignment with a human-centric paradigm that preserves their sovereignty, creativity and professional identity.

To sum up, the convergence of these datasets reveals two self-reinforcing, coherent ecosystems of practice: group A’s ecosystem in augmented workflow, and group B’s ecosystem in human-sovereign workflow. In group A, designers use AI to achieve quantitative gains in efficiency and ideational scope. This practice is enabled by a qualitative mindset that views AI as a powerful, yet flawed tool. The limitations of AI necessitate their critical, integrating role, which in turn requires them to actively manage ethical risks, creating a cycle of critical augmentation. Meanwhile, in group B, designers derive quantitative satisfaction from a process that qualitatively preserves human authenticity. Their identify is built on a rich taxonomy of human skills they deem irreplaceable. Introducing AI is perceived not as an enhancement, but as a violation of their ecosystem, introducing “generic outputs” and threatening their professional value, thereby reinforcing their satisfactory with their AI-free process.

In conclusion, the methodology triangulation analysis demonstrates that the choice to adopt or reject AI in design thinking process is not a simple calculation of efficiency. It is a decision deeply embedded in the designer’s professional identity. For AI advocates, this suggests that convincing group B requires more than demonstrating superior speed or novelty. It requires addressing the core humanistic values of authenticity, creativity, professional sovereignty, and designing AI systems that visibly augment rather than threaten these fundamental principles.

6.4 Limitations and future work

As a small-scale exploratory study, several limitations must be acknowledged. The first concerns participant selection, which relied on a self-selecting sample that may possess certain characteristics, thereby limiting its representativeness of the broader design community. Furthermore, as the interviewees were predominantly designers based in

Finland, the findings may not be fully generalizable to contexts in other geographical or cultural settings.

Another limitation pertains to the professional scope of the sample. Although participants included designers from both service and product domains, key professions such as architecture, management consulting, and innovative institutions that heavily utilize design thinking were not represented. The snowball sampling method, initiated from the researcher's network, may not have captured the full spectrum of relevant professions. Moreover, the sample was largely composed of mid-level designers. Consequently, the perspectives of senior decision-makers were absent, meaning the interview data may not fully reflect the strategic considerations present in the final stages of the design thinking process.

Additionally, although methodological triangulation was employed in the study, this approach is expensive and time-consuming. Triangulation requires significant resources and expertise in two distinct methodological domains. Thus, it is important to note that triangulation does not automatically confer validity; both the survey instrument and the interview protocol were carefully designed and piloted to ensure their rigor within their respective paradigms. The potential for participant burden was mitigated by ensuring interview participation was voluntary and separate from the anonymous survey.

In light of these limitations, the limitations inherent in this exploratory study provide a clear and valuable roadmap for subsequent research. To build upon these findings, future investigations could design to address the specific constraints identified here, thereby enhancing the scope, generalizability, and analytical depth of the field.

To mitigate the biases associated with self-selection and snowball sampling, a more stratified and randomized recruitment strategy is recommended. Participants could be systematically selected from diverse professional registries and international design associations to construct a cohort that is more representative of the global design community. The Finnish context examined here should be complemented by cross-cultural comparative studies, where identical research protocols are administered across different geographical regions to disentangle universal trends from culturally specific phenomena.

Moreover, the professional scope of this inquiry should be deliberately expanded. Future studies would benefit from the targeted inclusion of architects, management consultants, and professionals from R&D-intensive institutions. By incorporating these voices, a more

holistic understanding of design thinking's application across the broader ecosystem of creative and strategic professions can be developed.

Furthermore, the perspective gap left by the absence of senior executives could be filled. Subsequent research should specifically be directed at engaging C-suite level decision-makers and senior design leaders. This would illuminate the strategic, financial, and organizational dynamics that influence the large-scale adoption of AI, providing a critical top-down perspective to complement the ground-level insights generated here.

Finally, the methodological path paved by this study can be extended. The resource-intensive nature of triangulation, as experienced in this study, could be addressed in a larger-scale study with dedicated funding, allowing for an even more robust longitudinal or multi-method design. The survey instrument and interview protocol developed and piloted here can be refined and validated further, serving as a foundation for more extensive quantitative studies or more nuanced qualitative inquiries. Ultimately, these recommended directions are not merely corrective but are conceived as a constructive progression toward a more comprehensive and authoritative body of knowledge.

7 Conclusion

This research has explored the integration of Artificial Intelligence into the design thinking process, employing a mixed-methods approach to compare the practices of designers utilizing AI (group A) with those who do not (Group B). The findings confirm that the research objectives have been met, revealing that the adoption of AI is not merely a calculated decision but is profoundly entangled with a designer's professional identity. This study, therefore, moves beyond the prevailing discourse in the literature, which often focuses on the technical efficacy of AI tools, to illuminate the underlying socio-cultural and philosophical tensions driving adoption resistance.

The research yielded a consistent narrative through methodological triangulation. Quantitatively, while group A demonstrated significant consensus on the benefits of AI, group B's satisfaction with traditional methods was best characterized as a sentiment of functional adequacy, lacking strong statistical endorsement. Qualitatively, a profound philosophical schism was uncovered. Group A conceptualized creativity as a variable withing a problem-solving equation, leveraging AI for quantitative gains in efficiency within a cycle of critical augmentation. In stark contrast, group B anchors creativity in the human psyche, viewing their process as an act of authentic expression. To group B, AI integration is perceived not as an enhancement but as a violation of their core professional values, thereby reinforcing their commitment to traditional methods.

These findings constitute the primary theoretical contribution of this research: the bifurcation between AI-adopting and non-adopting designers represents a fundamental divergence in professional identity, workflow philosophy, and the very definition of value in design. This challenges earlier studies that frame adoption barriers primarily in terms of cost of learning curves, instead positing that resistance is a defensible stance rooted in a human-centric professional ethos.

The practical and societal implications are significant. For practitioners and technology advocates these results indicate that persuading traditionalists requires more than demonstrating efficiency; it necessitates a fundamental address of humanistic values like authenticity and professional sovereignty. AI systems must be designed to visibly augment, rather than threaten these principles. On a wider scale, this research highlights a critical

societal conversation about the future of creative work, emphasizing the need for educational and professional frameworks that prepare designers for evolving, synergistic roles partnering with computational intelligence.

It is crucial to acknowledge the limitations of this study. As an exploratory investigation, its generalizability is constrained by a self-selecting sample predominately composed of mid-level designers within the Finnish context. Consequently, the perspectives of senior strategic leaders and specific creative professions like architecture were not captured. Subsequent studies could deliberately include C-suite executives and architects to understand strategic adoption drivers. Furthermore, replicating this protocol in different cultural and professional contexts would be invaluable to disentangle universal trends from locally specific phenomena. Longitudinal research tracking identity evolution as designers engage with AI could also yield critical insights into the dynamics of this professional transformation.

In conclusion, this study argues that the integration of AI into design thinking process is redefining, not replacing, the role of the human designer. The challenge for the field is to navigate this identity shift, fostering a collaborative paradigm where human empathy and strategic vision are powerfully combined with algorithmic capability.

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Appendix 1. Interview questions to group A (AI users)

Design Thinking with AI

Empathize

1. How do you use AI (e.g., sentiment analysis, chatbots, NLP) to gather and analyse user needs, behaviours, or pain points?
2. Describe a time AI helped uncover insights about users that traditional research methods might have missed.

Define

3. How does AI assist in synthesizing large datasets (e.g., user interviews, surveys) to define the core problem statement?
4. Have you used AI-powered tools (e.g., clustering algorithms, topic modelling) to identify patterns in user needs? If so, how?

Ideate

5. Do you leverage AI (e.g., generative AI like ChatGPT, DALL·E, or brainstorming tools) to enhance creativity or generate unconventional ideas?
6. How does AI help in prioritizing or refining ideas from brainstorming sessions?

Prototype

7. What AI tools (e.g., Figma's AI features, AutoML, synthetic data) do you use to rapidly create or test prototypes?
8. How does AI enable you to personalize or adapt prototypes for different user segments?

Testing

9. How do you use AI (e.g., A/B testing algorithms, usability analytics, computer vision) to evaluate user interactions with prototypes?
10. Can AI predict user adoption or friction points before full-scale implementation? Share an example.

Follow up questions

11. What ethical considerations do you address when using AI in design thinking (e.g., bias, privacy, over-reliance on automation)?
12. If you have any stories or opinions to share. Here is your chance. We welcome and value all the opinions and feedback!

Appendix 2. Interview questions to group B (Non-AI users)

Understanding Design Thinking process

Empathize

1. What methods do you use to understand user needs (e.g., interviews, observations, shadowing)? How do you ensure deep empathy without AI-driven data analysis?
2. Describe a time when direct user interaction revealed an unexpected insight that shaped your project.

Define

3. How do you synthesize qualitative research (e.g., affinity mapping, personas) to define the core problem without AI-assisted pattern recognition?
4. What challenges do you face when manually interpreting user data, and how do you overcome them?

Ideate

5. What brainstorming techniques (e.g., mind mapping, SCAMPER, Crazy 8s) do you use to generate ideas without AI-generated suggestions?
6. How do you encourage unconventional thinking when ideating in a team setting?

Prototype

7. What low fidelity prototyping methods (e.g., paper sketches, role-playing, physical models) do you prefer, and why?
8. How do you decide which ideas to prototype when resources (time/materials) are limited?

Testing

9. How do you gather and interpret user feedback on prototypes without AI-powered analytics (e.g., manual observation, note-taking)?
10. Describe a time when user testing led you to revisit an earlier stage of the process. How did you pivot?

Follow up questions

11. In your experience, what are the biggest advantages (or limitations) of *not* using AI in the Design Thinking process?
12. If you have any stories or opinions to share. Here is your chance. We welcome and value all the opinions and feedback!

Appendix 3. Likert Questionnaire to group A (AI users)

(Strongly Disagree, Disagree, Agree, Strongly Agree)

1. AI shortens the time I spend on routine design-thinking tasks.
2. Using AI reduces the overall cost (time, money, effort) of prototyping.
3. AI helps me generate ideas I would not have thought of on my own.
4. I frequently combine AI outputs with my own concepts to create novel solutions.
5. Using AI broadens the range of design directions I explore during ideation.
6. I gather real user feedback before deciding which AI-generated concepts to keep.
7. AI allows me to tailor prototypes more closely to user needs and contexts.
8. I test AI-assisted prototypes with users as often as I test non-AI prototypes.
9. I check AI outputs for potential bias before showing them to stakeholders.
10. I document and discuss ethical risks (e.g., fairness, privacy) arising from AI use in my projects.
11. Overall, integrating AI into my design-thinking process is beneficial.

Appendix 4. Likert Questionnaire to group B (Non-AI users)

(Strongly Disagree, Disagree, Agree, Strongly Agree)

1. I complete routine design-thinking tasks quickly.
2. My current process keeps prototyping costs (time, money, effort) low.
3. I consistently generate ideas that feel novel to me and my team.
4. I combine diverse sources of inspiration to create original solutions.
5. I explore a wide range of design directions during ideation.
6. I gather real user feedback before deciding which concepts to keep.
7. I tailor prototypes closely to user needs and contexts.
8. I test prototypes with users at every appropriate opportunity.
9. I check my own outputs for potential bias before presenting them to stakeholders.
10. I document and discuss ethical risks (e.g., fairness, privacy) in my projects.
11. I feel confident that my current process minimizes unintended harm to users.
12. Overall, I am satisfied with my current non-AI design-thinking workflow.