GENERATIVE AI IN THE UX/UI DESIGN PROCESS: DEFINING KEY CONSIDERATIONS FOR DESIGNER-CENTERED TOOLS

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ABSTRACT

GENERATIVE AI IN THE UX/UI DESIGN PROCESS: DEFINING KEY CONSIDERATIONS FOR DESIGNER-CENTERED TOOLS

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Today, artificial intelligence (AI) tools are rapidly evolving and at the same time being heavily integrated into the workflows of UX/UI designers. This integration accelerates design processes while re-shaping it. This transformation increases the need for AI solutions that understand designers' needs and support creative production. This thesis aims to understand the considerations for designer-focused AI-enhanced support tools for UX/UI design. The thesis involves a two-stage user research project consisting of semi-structured interviews with UX/UI designers and a co-design workshop. The findings from the literature review and semi-structured interviews reveals the expectations of UX/UI designers from an AI-enhanced support tool, and these expectations plays a decisive role in forming the co-design workshop. The workshop's outcomes allows for the identification of key design considerations of AI-enhanced UX/UI tools that adapt to designers' work practices and needs. The findings indicate that UX/UI designers integrate AI tools selectively at different stages of the design process, including research support, data analysis, idea generation, UI and visual asset production, and prototyping. Also, use of these tools in UX/UI design workfloes leads to shifts in workflow, such as increased

efficiency, enhanced communication, and the expansion of designers' competencies and roles. The co-design workshop further articulates these patterns by translating designers' experiences and expectations into design considerations for AI-Enhanced CSTs for UX/UI designers. These considerartions includes project-based workflow structures, mechanisms for selectively incorporating insights, customizable guidance tailored to different experience levels, non-disruptive feedback integration, and features supporting decision and version traceability.

Keywords: UX/UI Design, Generative Artificial Intelligence, Creativity, Creativity Support Tools

ÖZ

UX/UI TASARIM SÜRECİNDE ÜRETKEN YAPAY ZEKA: TASARIMCI ODAKLI ARAÇLAR İÇİN TEMEL UNSURLARIN BELİRLENMESİ

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Günümüzde hızla gelişen yapay zeka araçları, UX/UI tasarımcıları tarafından iş akışlarına yoğun biçimde entegre edilmektedir. Bu durum tasarım süreçlerini hızlandırırken bu süreçlerin doğasında da değişimlere yol açmaktadır. Bu değişimler, tasarımcıların ihtiyaçlarını anlayan ve yaratıcı üretimi destekleyen yapay zeka çözümlerine yönelik gereksinimi artırmaktadır. Bu tez, UX/UI tasarım süreçlerinde kullanılmak üzere tasarımcı odaklı bir yapay zeka aracı tasarlanırken dikkate alınması gereken unsurları anlamayı hedeflemektedir. Tez kapsamında UX/UI tasarımcılarıyla gerçekleştirilen yarı yapılandırılmış görüşmeler ve bir birlikte tasarım çalıştayından oluşan iki aşamalı kullanıcı araştırması gerçekleştirilmiştir. Literatür taraması ve yarı yapılandırılmış görüşmelerden elde edilen bulgular, UX/UI tasarımcılarının yapay zekâ destekli bir destek aracından beklentilerini ortaya koymuş ve bu beklentiler, ortak tasarım atölyesinin şekillenmesinde belirleyici bir rol oynamıştır. Atölyenin sonuçları, tasarımcıların çalışma pratiklerine ve ihtiyaçlarına uyum sağlayan yapay zekâ destekli UX/UI araçlarının temel tasarım hususlarının belirlenmesine olanak sağlamıştır. Bulgular, UX/UI tasarımcılarının yapay zekâ araçlarını tasarım sürecinin farklı aşamalarında, araştırma desteği, veri

analizi, fikir üretimi, UI ve görsel varlık üretimi ve prototipleme dahil olmak üzere, seçici olarak entegre ettiklerini göstermektedir. Ayrıca, bu araçların UX/UI tasarım iş akışlarında kullanımı, verimliliğin artması, iletişimin gelişmesi ve tasarımcıların yetkinliklerinin ve rollerinin genişlemesi gibi iş akışında değişikliklere yol açmaktadır. Ortak tasarım atölyesi, tasarımcıların deneyimlerini ve beklentilerini, UX/UI tasarımcıları için yapay zekâ destekli ortak tasarım araçlarına yönelik, farklı deneyim seviyelerine göre uyarlanmış özelleştirilebilir rehberlik, kesintisiz geri bildirim entegrasyonu gibi tasarım önerilerine dönüştürerek bu kalıpları daha da detaylandırmıştır.

Anahtar Kelimeler: UX/UI Tasarımı, Üretken Yapay Zeka, Yaratıcılık, Yaratıcılık Destek Araçları

To my family…

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LIST OF ABBREVIATIONS

ABBREVIATIONS

AI – Artificial Intelligence

GAI – Generative AI

UI – User Interface

UX – User Experience

CST – Creativity Support Tool

CSI – Creativity Support Index

CHAPTER 1

INTRODUCTION

Today, Generative AI tools are increasingly used in UX/UI design processes to enhance workflows, boost productivity, and expand creative processes. This collaboration, however, raises several significant issues, including how designers can work with AI tools more efficiently, what new abilities they will require, and how to preserve the uniqueness of the final design.

The use of artificial intelligence tools is rapidly expanding in UX/UI design as well as in many other creative industries and design fields. The emergence of artificial intelligence as a technology has opened up numerous research opportunities for its application in UX/UI design processes. Among the current research topics, the most common ones are how designers integrate generative AI tools into their design processes and the challenges and opportunities they face when working with these tools (Stige et al., 2024).

Designers increasingly reckon AI related features as a common approach when developing design activities. Although currently viewing AI systems as virtual assistants, they suggest that they would be open to working collaboratively with intelligent technologies (Bertão & Joo, 2021). UX/UI Designers are integrating generative AI tools into various stages of their design process, such as inspiration and idea generation, automating repetitive tasks, accelerating and supporting user research, and increasing overall efficiency and productivity to improve workflows and achieve better results (Adeleye, 2023). Designers provide creativity, domain expertise, and a user-centered approach, whereas AI provides data-driven insights, design options, and task automation. However, recent examples regarding AI-integration to design include loss of control over AI-generated output, biases in AI

algorithms, and the necessity for designers to learn new skills. These considerations remain important in developing new tools and methodologies.

With the creation of design tools, on the other hand, designers have some responsibilities such as establishing a healthy collaboration between AI and themselves. They have to guide AI tools and align the AI outputs to meet their objectives. They also need to learn new skills in the process, such as prompt engineering and iteratively refining the ideas obtained through AI. This means that the skill set expected for designers is growing day by day, and these expectations signify a need to alter our approach to the relationship between design and AI. Since artificial intelligence continues to develop rapidly daily, it is an inevitable prediction that academic studies on this subject will have difficulty keeping up with the pace of developing technology, especially considering the breakthrough innovations of generative AI in recent years. In this case, it is important to support the subject with comments and insights from designers who are already using artificial intelligence effectively in practice.

This study investigates how generative AI and human creativity interact, especially in UX/UI design workflows. Its main goal is to understand how designers incorporate these technologies into their workflows and how upcoming technologies and resources might enhance human-AI collaboration. By examining present practices, obstacles, and opportunities, this study aims to help define the key considerations for the creation of designer-centered AI-enhanced tools that help designers make the most of AI's capabilities without losing their creative control.

While AI tools are increasingly embedded in UX design workflows, their influence on creativity, control, and collaboration remains underexplored (Fu et al., 2024; Khan et al., 2025). Existing tools often prioritize automation over designer agency, disrupting creative flow and clashing with designers' established habits. Moreover, the UI of these tools is frequently opaque and misaligned with human-centered design principles. This study addresses this gap by investigating how AI tools impact UX designers' creative processes.

Artificial intelligence in design has recently emerged as a rapidly growing and highly debated research area, with several recent master's theses examining its role in design processes and UX/UI practice, particularly in relation to creativity, efficiency, and process integration (Arda, 2024; Kılıç, 2025; Salimi, 2026; Sözen, 2024; Vakili, 2025). This research not only explores designer expectations, also aims to offer considerations for AI-enhanced and designer centered creativity support tools.

1.1 Aim and Objectives

This research aims to understand how UX/UI designers integrate AI tools into their design processes, the challenges they face, the strategies they adopt, and the resulting practices. The research also aims to reveal needs and usage scenarios based on designers' industry experiences and expectations, thereby contributing to the design of future AI-enabled UX/UI design tools that are more user-centric. These aims planned to be attained through following objectives;

- Understanding how UX/UI designers integrate AI tools into their design processes,
- Identifying the current and perceived challenges designers face when using AI-powered tools,
- Understanding the strategies and practices designers have developed to overcome these challenges,
- Understanding the role and use cases of generative AI tools in the UX/UI design process,
- Analyzing the AI tools currently used most frequently by designers and the extent to which these tools are integrated into their workflows,
- Identifying the needs and use cases of designers based on their industry experience and expectations,

1.2 Research Questions

RQ1: How do UX/UI designers integrate AI tools into their UI design processes?

-What are the distinct roles played by designers and the AI Tools they use?

-What are the challenges and opportunities encountered and perceived by UX/UI designers when incorporating AI tools into their design workflows?

-How do designers strategize and control the generation of ideas by AI tools to align with their design goals and vision?

RQ2: What are the main design considerations for AI-assisted design tools to support designers' creativity and UX/UI design processes in the development of digital products?

1.3 Scope of the Study

This research focuses on the integration of generative AI tools in professional UX/UI design workflows and the implications of this integration for tools that are designer-centric. In this study, UX and UI are addressed together, as they form an inseparable process in today's digital product development, including user research and problem definition to ideation, prototyping, and interface design. Rather than focusing on specific design stages, the study examines how AI tools are used across the workflow, specifically how designers interact with these tools and how these tools influence the workflow.

The term UX/UI designer is used as an umbrella concept to refer to designers who are involved in any phase of the digital product design process. Accordingly, the participant group consists of professional UX/UI designers with industry experience, without restricting participation to a specific seniority level or industry sector.

The scope of the research is limited to generative AI tools currently used in UX/UI design practice (as of November 2025). This study does not aim to evaluate AI

systems from a technical or performance-oriented perspective; instead, it concentrates on designers' experiences and perceptions when working with these tools.

Empirical data is collected through semi-structured interviews and a co-design workshop. The scope of the findings is therefore interpretive and qualitative, aiming to inform the design of future AI-enabled UX/UI tools.

1.4 Structure of the Study

This thesis consists of five chapters. The chapters are as follows:

The first chapter *Introduction* lays out the subject matter of the research as well as its goal and scope. In this chapter, the motivation of the research is explained in the context of growing use of AI-supported tools in UX/UI design processes. Further along these lines, the position of this research and its main questions are defined in regards to how it relates to the literatures of design, human-computer interaction and creativity.

The second chapter *Literature* Review establishes the theoretical framework of the research. This chapter deals with the historical evolution of artificial intelligence and the current generative and agentic models. Also, it examines the literature of creativity theories and creativity support tools. Additionally, it touches upon the current academic and grey literature on AI-support tools in UX/UI design processes.

The third chapter *Methodology* explains the research design and the methodological process. In this chapter, the structure of the two-phased user research design is presented; moreover, the semi-structured interviews and process of the co-design workshop are detailed. The sampling of the study, data-gathering and analysis methods are also presented in this chapter.

The fourth chapter *Findings* contains an analysis of the data gathered via the semi-structured interviews and co-design workshop. It exhibits the interactions between

UX/UI designers and AI-supported tools, what kind of problems the designers run into when using these tools and the expectations of designers through a thematic analysis.

The fifth and final chapter *Conclusion* is where the research questions are revisited and findings of the study are interpreted. The findings regarding the AI-support tools for UX/UI design processes are summarized and limitations of this research and suggestions related to what can be done in future researches are also discussed in this chapter.

CHAPTER 2

LITERATURE REVIEW

Defining criteria of an AI-powered UX/UI tool, requires first understanding the concepts of *Artificial Intelligence (AI)* and *Creativity,* since these tools can be considered creativity support tools. These concepts are complex and have historically been addressed in various ways across different disciplines. Rapid advances in generative and agentic AI models, particularly in recent years, have raised the question of whether these technologies can be creative or should only support human creativity, necessitating an examination of these two concepts. Therefore, this review first clarifies the background of the Generative and Agentic AI models that used increasingly to enhance modern UX/UI design tools. Then it examines how creativity is defined, how it is supported, and the principles under which this support should be designed. Finally, by examining current research on UX/UI practice, AI-enhanced UX/UI design and the structure of existing tools, this review aims to understand the necessary conceptual groundwork to be able to answer the question "What to consider when designing an AI-enhanced UX/UI tool that focuses on designers' needs?"

2.1 AI

There is no single, universally accepted definition of artificial intelligence (AI). Most definitions describe artificial intelligence as a machine’s ability to perform tasks that generally require human intelligence. With each technological development in the field of AI, this concept has significantly evolved.

Haenlein and Kaplan (2019) point out that the origins of artificial intelligence can be traced to both cultural and scientific milestones. From mythology to philosophy, the

concept of granting intelligence to non-human objects and the effort to formulate intelligence are the oldest indicators of humanity's desire to understand and contextualize intelligence.

For example, in ancient Greek mythology, Hephaestus forges automatons, human-like statues made of gold and bronze that are intelligent and can be taught how to do things (Macedo, 2025; McCorduck & Cfe, 2004). These artificial beings capable of movement and perception can be considered an early example of the concept of an "intelligent machine."

On the other hand, in philosophy, Aristotle's work on formal logic established the foundation for the idea that reasoning could be mechanized. Aristotle's propositional logic later inspired the algorithms used in Newell and Simon's General Problem Solver (1959) system (Russell & Norvig, 2021). In the 17th and 18th centuries, Descartes's *Meditations on First Philosophy* and Leibniz's *Monadology* can be cited as other early philosophical examples of the concept. Both philosophers explored the idea of a universal language of thought and the possibility of creating thinking machines. Descartes' ideas on mind-body duality and consciousness, especially, shed light on the relationship between human and machine intelligence (Macedo, 2025).

In addition, Programmable Computing Machines developed by Charles Babbage and Ada Lovelace in the 19th century are considered to be one of the earliest and most important examples that helped develop the fields of artificial intelligence and computer science (McCorduck & Cfe, 2004; Russell & Norvig, 2021).

Towards the 1950s, Isaac Asimov's short story *"Runaround"* (1942) introduced the "Three Laws of Robotics," opening up discussions about the ethical dimensions of machine behavior and influencing subsequent generations of AI and robotics research (Haenlein & Kaplan, 2019). Around the same time, as part of their neurophysiology study McCulloch and Pitts (1943) claimed that "Because of the "all-or-none" character of nervous activity, neural events and the relations among them can be treated by means of propositional logic" (p.115). This study became a

conceptual inspiration for later machine learning and artificial neural network research.

A few years later, Alan Turing's (1950) paper, Computing Machinery and Intelligence, laid the theoretical foundation for the concept of machine intelligence and proposed the Turing Test as a measure of artificial thinking. In 1956, the term "artificial intelligence" was introduced by John McCarthy and his colleagues in their proposal for the Dartmouth Summer Research Project on Artificial Intelligence (McCarthy et al., 2006).

Today, after almost 70 years of the term's first appearance, there is still no universal answer to the question: "What is artificial intelligence?" Over the decades, researchers have approached AI from different perspectives, emphasizing different aspects. Early descriptions, such as Minsky's (1968) work in the 1960s, framed AI as the effort to build machines capable of performing tasks that would require intelligence in humans. Later, this view expanded by outlining intelligence in terms of perception, reasoning, learning, communication, and action within complex environments (Nilson, 1998).

Russell and Norvig's (2010) approach classifies Artificial Intelligence on four cognitive and behavioral axes:

> Thinking humanly: modeling the cognitive processes of the human mind (e.g., cognitive science, neural networks).
>
> Acting humanly: passing the Turing Test by imitating human behavior.
>
> Thinking rationally: applying formal logic and reasoning, as in symbolic AI.
>
> Acting rationally: designing autonomous agents that pursue goals optimally.

At first glance, the axes above might be inferred as a sharp distinction between "thinking/reasoning systems" and "acting systems". That is not the case as there is no crystal clear division; on the contrary, researchers generally treat these two dimensions as complementary elements (Bringsjord and Govindarajulu, 2025).

However, despite continuous references made to human intelligence while trying to come up with an encompassing definition, McCarthy (2007) states that "it [AI] is the science and engineering of making intelligent machines, especially intelligent computer programs. It is related to the similar task of using computers to understand human intelligence, but AI does not have to confine itself to methods that are biologically observable." (p. 2).

More recent definitions, like those of Heinlein and Kaplan (2019), focus on AI's ability to interpret data, learn from it, and adaptively use this learning to achieve specific goals. Additionally, there are also some approaches that try to encapsulate the concept of AI via its capacity and scope. These approaches lay out three basic levels exemplifying AI capacity (Haenlein & Kaplan, 2019):

> *Narrow AI:* A majority of current public systems fall into this category; they perform specific tasks like visual recognition, language processing, and image generation with extreme accuracy.
>
> *Artificial General Intelligence (AGI):* Being a subject-matter of many sci-fi scenarios, an AGI is assumed to possess human-like cognitive flexibility. However, its conceptualization or realization is still merely theoretical.
>
> *Superintelligence:* This refers to a possible future scenario that surpasses human intelligence in every domain.

2.1.1 History and Evolution of AI

Having presented varied and continuously changing perspectives on AI, this section focuses on the development of AI-related concepts and the established milestones in the evolution of AI. As such, this study examines what terms such as symbolic AI, generative AI, and deep learning come to mean as well as explore how such tools have been utilized.

The Dartmouth Summer Research Project on Artificial Intelligence, mentioned in the previous chapter, that took place in 1956, has played a significant role not only in the conceptualization of AI but also its evolution. Following the Dartmouth Project, Allan Newell and Herbert Simon (1956) developed a device they named the *Logic Theory Machine*. It had a simple purpose: proving mathematical theorems laid out in *Principia Mathematica* (1910) by Whitehead and Russell. Later, they went on and engineered another machine called the *General Problem Solver* (Newell et al., 1959). It was more complicated than the Logic Theory Machine, which was intentionally built to replicate how humans approach and attempt to solve logical and other problems (Kaplan, 2024, p.20).

Nowadays, these early machines are called Symbolic AI or, rather humorously, “Good Old-Fashioned AI (GOFAI)” (Boden, 2016). It is possible to sum up these devices as a model of human intelligence through logical inference rules and symbolic representations. During this period, human thinking was explained through abstract and rational models, and symbol processes and rule-based systems were adopted as the primary means of simulating logical thinking and problem solving (Mayer, 2024).

Pioneers such as Marvin Minsky and John McCarthy viewed the human mind as a total of data processes and aimed to transfer these processes to computers through formal rules. This approach identified intelligence with the capacity for "rational thought" and "rule-based problem solving" (Luger, 2025). The expert systems, developed in the late 1970s and early 1980s, are the most prominent products of symbolic artificial intelligence. These systems attempted to solve complex problems by encoding the knowledge of human experts in a particular field into a set of computational rules (Macedo, 2025).

Later, efforts to overcome the limitations of the symbolic approach led to the emergence of a new direction of thought called connectionism. Researchers such as David Rumelhart and Geoffrey Hinton proposed that intelligence arises not from a centralized symbolic representation, but from distributed networks of simple

interconnected units (Sun, 2014). This understanding was inspired by the structure of the human brain and defined learning as a process that draws inference from data patterns rather than following explicitly-stated rules.

In 1986, Rina Dechter used the term "deep learning" for the first time to describe these multilayered and more complex network structures (Luger, 2025). However, due to the limited amount of data and computational power at the time, the deep learning approach failed to find widespread application. In the 1990s, however, the increasing amount of data and computational capacity led to a radical shift in artificial intelligence research. The field transitioned from rule-based systems to data-driven learning (machine-learning/statistical AI) methods (Mitchell, 1997). To better understand what this transition meant, we can look at Deep Blue, which was a milestone to exemplify what AI machines could achieve (Kaplan, 2024). Deep Blue was developed by IBM to play chess in 1996, and it introduced the concept of AI to the public in a spectacular manner by beating Gary Kasparov, who was the world chess champion back then.

In addition to the sensation created by Deep Blue, researchers and engineers have made great progress in terms of data-readability in the late 1990s. They developed computer-readable training data in huge chunks, which made a big impact in machine-learning. Also, since the 1990s, machines' capacity to store and process data hugely improved, easing and bettering the machine-learning processes (Kaplan, 2024). Now there are different machine-learning systems directly extracting patterns from data, without predefined rules (Alnuaimi & Albaldawi, 2024):

Supervised learning allows the model to be trained using examples whose correct outputs are known.

Unsupervised learning discovers hidden structures and relationships in unlabeled data.

Reinforced learning is based on the system optimizing its behavior through rewards or punishments.

In addition to these developments since the 1990s, Big Data came into play. The statistical databases of online networks fastened the machine-learning processes simply because of the sheer magnitude of available information. As a result, the applicability of artificial intelligence widened to spheres like medicine, finance, and engineering.

In the late 2000s and early 2010s, the Deep Learning approach entered a new and almost explosive phase. Deep Neural Networks gained the capacity to learn meaningful representations from raw data, leading to major advances in computer vision, speech recognition, and natural language processing. These developments paved the way for AI to become a system that not only analyzes information but also produces it. For instance, AlexNet's success in ImageNet in 2012 can be considered as a symbol of the deep-learning revolution. Google's AlphaGo (developed by the DeepMind program) is another great example to what deep-learning has come to as it beat the World Go champion (Kaplan, 2024).

The transition from classical AI to generative models and agentic systems has been a significant leap forward in AI's capabilities. While classical AI focuses on decision-making, classification, and prediction, these new technologies have the capacity to directly generate content and autonomously execute user goals. This is creating a significant transformation, particularly in the design field today. The following sections will detail why these two technology lines are important to this research and how they are redefining UX/UI design practices.

2.1.2 Generative AI

Generative AI (GAI) encompasses artificial intelligence systems that can generate different types of media, such as text, images, or video. These systems can generate new and original data with similar properties by learning patterns and structural relationships in training data (Sengar et al., 2024). Nah et al. (2023, p. 277) define Generative AI as "an example of highly promising unsupervised machine learning".

Generative AI represents the transformation of early AI from data analysis-focused discriminative tasks to more complex and creative production processes (Banh & Strobel, 2023). The difference between the processes of two models can be seen in Figure 2.1.

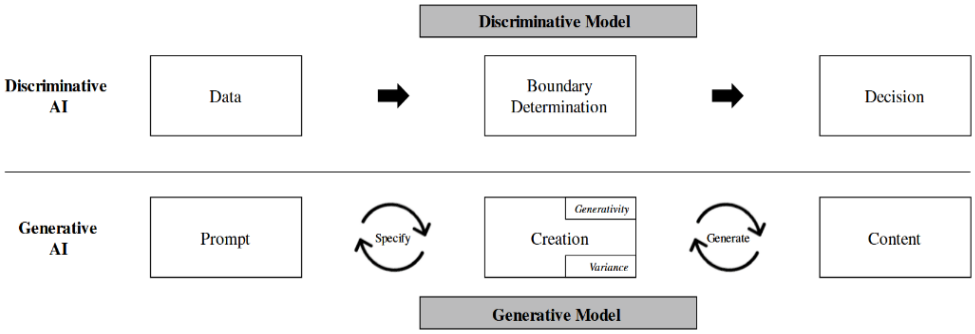


Figure 2.1 Procedural differences between generative and discriminative AI (Banh & Strobel, 2023, p.5).

The deep generative models (DGMs) that form the core of Generative AI systems are as follows:

Generative Adversarial Networks (GANs): A GAN is a system in which two artificial intelligence models, one generating fake data (Generator) and the other attempting to distinguish between real and fake data (Discriminator), compete against each other and become progressively better (Goodfellow et al., 2014).

Variational Autoencoders (VAEs): These are probabilistic models that represent and reconstruct data in a low-dimensional latent space (Feuerriegel et al., 2024; Kingma & Welling, 2022).

Diffusion Probabilistic Models (DMs): These are models that gradually add noise to data and then reverse-learn this process to generate high-quality synthetic samples. Ho et al. (2020) demonstrated that diffusion models can produce high-quality samples by effectively training them.

The development of these models played a fundamental role in the evolution of artificial intelligence from task-focused systems to general-purpose architectures

such as Transformer models which, thanks to its attention mechanism, enabled scalable learning across different data types (Vaswani et al. 2017).

In the 2020s, as a result of rapid developments in the field, foundation models, which have existed for a long time and are used in deep learning have come to the forefront of AI-related thinking and research again (Bommasani et al., 2022). Simply put, foundation models are large, general-purpose models that are pre-trained on very large datasets and can be fine-tuned for different tasks (Gupta et al., 2025). While basic generative architectures such as GAN, VAE and Diffusion enable data generation in specific tasks, foundation models have generalized this capacity into a structure that can handle multiple tasks and data types in the same setting.

Not every foundation model is essentially generative, but most of the advanced generative systems of our day are based on the foundation model structure. In the case of generative AI two different models fall under this category :

Large Language Models (LLMs): These are language-focused foundation models. They are pre-trained on large text datasets. Examples: GPT-3, GPT-4, PaLM, LLaMA, Claude.

Large Vision Models (LVMs): These are the equivalent of foundation models in the visual domain. Visual-text pre-training (e.g., CLIP, ALIGN) and some diffusion models (Stable Diffusion, Imagen) fall into this group.

The six main modalities of Generative AI are categorized as text, image, video, code, audio, and specialized domain applications.

Text (X-to-Text): Natural Language Processing (NLP)-based applications rely on LLMs. Systems such as ChatGPT, Meena, and Xiaoice are used in areas such as content generation, summarization, customer support, and research assistance.

Visual (X-to-Image): Systems based on GAN and Diffusion models (Stable Diffusion, DALL·E 2, Midjourney) enable the generation of images from text. They are used in fields such as design, marketing, fashion, and medicine.

Video (X-to-Video): Generate moving images from text or images. Platforms like Synthesia produce virtual avatars and automated video generation for educational and promotional content.

Code (X-to-Code): Models that generate source code from natural language (Codex, AlphaCode, CodeBERT) accelerate software development. Tools like GitHub Copilot provide error detection and automatic code completion support.

Audio (X-to-Audio): Generate human-like speech or music from text or audio input. VALL-E, MusicLM, and Jukebox stand out in this field.

(X-to-Modality): Generative AI is also used in specialized fields such as biotechnology (AlphaFold, OpenBioML), 3D modeling (DreamFusion, GET3D), knowledge graph generation (K-BERT), handwriting synthesis, traffic simulation, and error detection.

These models generate the same output type as their input type (e.g., text-to-text or image-to-image generation) are referred to as unimodal models. Systems that can process different inputs such as text, image, and audio together through the combination of LLM and LVM (e.g., text-to-image, code-to-text, or image-to-text) are classified as multimodal models (Gupta et al., 2025).

2.1.3 Agentic AI

Agentic AI is defined as the next big thing in artificial intelligence, and it refers to autonomous systems that use advanced reasoning and iterative planning processes to autonomously solve complex, multi-stage problems (Pounds, 2024). Such systems operate in four fundamental stages: perceive, reason, act, and learn. They gather data from their environment, come up with certain goal-oriented plans, interact with external tools to perform specific tasks, and continuously learn from the results of all these actions.

With the launch of ChatGPT in 2022, the field of AI evolved from basic generative systems to more autonomous and much more task-oriented ones (Sapkota et al., 2025). This transformation began with systems that are defined as AI agents, and by late 2023, we had entered the era of Agentic AI, where multi-agent systems work together. This new framework is built on deep learning, reinforcement learning, and foundation models. It has gained features such as contextual awareness, continuous learning, and emergent autonomy. Generative AI agents can also form the components of agentic AI. Sapkota et al. (2025) have analyzed AI agents, Generative AI, Agentic AI, and Generative Agent in detail in their conceptual taxonomy study. Their study provides a good reference to better understand the distinction between these concepts, shown in Figure 2.2

Conceptual Dimension	Generative AI	AI Agent	Agentic AI	Generative Agent (Inferred)
Initiation Type	Prompt-triggered by user or input	Prompt or goal-triggered with tool use	Goal-initiated or orchestrated task	Prompt or system-level trigger
Goal Flexibility	(None) fixed per prompt	(Low) executes specific goal	(High) decomposes and adapts goals	(Low) guided by subtask goal
Temporal Continuity	Stateless, single-session output	Short-term continuity within task	Persistent across workflow stages	Context-limited to subtask
Learning/Adaptation	Static (pretrained)	(Might in future) Tool selection strategies may evolve	(Yes) Learns from outcomes	Typically static; limited adaptation
Memory Use	No memory or short context window	Optional memory or tool cache	Shared episodic/task memory	Subtask-level or contextual memory
Coordination Strategy	None (single-step process)	Isolated task execution	Hierarchical or decentralized coordination	Receives instructions from system
Key Role	Content generator	Tool-based task executor	Collaborative workflow orchestrator	Subtask-level modular generator

Figure 2.2 Distinction Between Generative AI, Agentic AI, and AI Agents (Sapkota et al., 2025, p.10).

Murugesan (2025) emphasizes that what distinguishes agentic AI from traditional AI is its proactive, adaptive, and goal-oriented behavior. Systems no longer simply react to inputs; rather, with their improved chaining capabilities, they can transform a single request into a multi-step process, break down complex tasks into smaller sub-goals, and continuously optimize their approach. This transforms agentic AI from a simple tool into an active collaborator for humanity.

This trend is also evident in the industry. For example, Adobe states that it aims to develop agentic systems that accompany users like a “creative partner” at every stage

of the creation process (Greenfield, 2025), which can have and is already having drastic effects on how humans do create.

Today, recent developments in agentic AI are redefining the human-machine relationship in design processes. While traditional generative AI tools are largely limited to single-step production, agentic systems are capable of simultaneously intervening in the early, middle, and late stages of problem-solving processes. In a field like UX/UI design, issues such as user agency, explainability, and control become even more critical. Furthermore, the role of agentic AI in creative processes provides a foundation for the design principles of tools that aim to support those processes. Therefore, concepts of generative AI and Agentic AI offer a new collaboration model that intersects with creativity research, creativity support tools (CSTs), and human-AI collaboration literature. This intersection forms the basis for the discussion of how creativity theories and CST principles can be adapted to UX/UI design tools, which will be discussed in the next section.

2.2 Creativity

The idea of human creativity can be traced back to early notions of divine inspiration, imagination, and aesthetics. It began to be studied as a distinct psychological and methodological subject only in the second half of the 19th century.

Over the years, the concept of creativity has been addressed in the literature with numerous definitions and theoretical approaches, and it is studied through interrelated concepts rather than as an independent phenomenon. Csikszentmihalyi (2014) states that definitions and theories of creativity are often presented in an intertwined manner. He argues that there is no single, unified psychological theory of creativity; they noted that concepts such as imagination, resourcefulness, innovation, intuition, invention, discovery, and originality are often used interchangeably with creativity (Csikszentmihalyi, 2013).

From a cognitive perspective, creativity is often associated with divergent thinking, based on generating a variety of ideas (Guilford, 1967). Another approach to creativity emphasizes that, in addition to the element of novelty, it should also include criteria of relevance, value, or social benefit (Davis, 1999). According to Davis, creativity is also characterized as a problem-finding activity rather than problem-solving (1999). Due to this complex nature and the difficulty of finding a single definition, creativity has been studied under various dimensions for years (Runco, 2004).

Understanding creativity through these different perspectives is essential as AI-supported design tools increasingly intervene in early-stage ideation, problem framing, and evaluation which are areas associated with creativity.

This section discusses the fundamental approaches and process models of the concept of creativity based on different definitions to offer a basis for understanding how AI might assist different aspects of creative work. Then, early perspectives on artificial intelligence and computer-supported creative processes will be examined, linking it to Creativity Support Tools (CSTs) and finally to the discussion of contemporary approaches to human-AI co-creation.

2.2.1 Understanding Creativity

Wallas (1926) developed one of the first models to explain the thinking process systematically. Drawing on Helmholtz's observations of the formation of new ideas, he describes the process in four stages:

> ...The first, in time, I shall call Preparation, the stage during which the problem was investigated... in all directions"; the second, the stage during which he was not consciously thinking about the problem, which I shall call Incubation; the third, consisting of the appearance of the "happy idea" together with the psychological events which immediately preceded and

> accompanied that appearance, I shall call Illumination. And I shall add a fourth stage of Verification, which Helmholtz does not mention here. (p. 80)

This model of Wallas (1926), consisting of the stages of preparation, incubation, illumination, and verification, explains the mental process from problem recognition to the elaboration of a solution. This model later became the basis for many other models developed to explain the creative process.

The widespread study of the cognitive processes encompassing creativity dates back to Guilford's (1950) call, in which he emphasized the importance of creativity and the need for further study of the subject. Guilford's study primarily focused on the characteristics of creative individuals, but he also discussed creative behavior in the context of idea generation. The distinction between convergent and divergent thinking he introduced with his Structure of Intellect (SOI) model profoundly influenced creativity research (O'Quin & Besemer, 2020). According to Guilford, in divergent thinking the individual explores numerous possibilities rather than finding a single correct answer; the diversity of responses produced constitutes the fundamental characteristic of the process associated with creativity (1967). Therefore, Guilford viewed the abilities encompassed by divergent thinking as the most decisive elements of creative thinking and innovative problem solving. This approach was developed by researchers in later years and formed the basis for subsequent creativity theories (Sternberg & Grigorenko, 2001). For example, Torrance (1988) resembles the creativity process to the scientific method, comprising four key steps: sensing problems or gaps, formulating hypotheses, testing and modifying them, and communicating results, and places a stronger emphasis on problem finding. Torrance's model also shares similarities with Wallas' (1926, p.80) long-standing four-stage model: "Preparation, Incubation, Illumination, and Verification". Guilford and Torrance describe and assess creativity through underlying cognitive dimensions. These dimensions are often considered central characteristics of the creative process (Almeida et al., 2008):

1. Fluency: The production/number of relevant ideas.

2. Flexibility: The production of different ideational categories or shifts in responses/approaches.

3. Originality: The production of unusual, novel, or statistically infrequent ideas.

4. Elaboration: Persistency on introducing details or the number of details used to extend a response. (p.54).

As another approach to study creativity, Rhodes (1961) sought to unify diverse definitions by identifying four core aspects of creativity: Person, Process, Product, and Press (environment). Barron (1969) later reinforced this framework, suggesting that creative achievement emerges through the interaction of these four aspects. Cropley et al. (2021, p.4) summarize these four aspects as follows: " In simple terms, our ability to generate creative outputs (Product) is a function of how we think (Process), who we are (Person) and where we work (Press)."

This 4P view also showed parallels with the process-oriented models developed in the same period, such as Osborn and Parnes' (Osborn, 1963; Parnes, 1977) Creative Problem Solving (CPS) model, which views creativity as a process consisting of specific stages. This model consists of problem definition, idea generation, solution selection, and implementation. The model, was later developed by Treffinger and Isaksen (2005), and reframed as a circular, open-ended structure with discovery and evaluation processes (Figure 2.3).

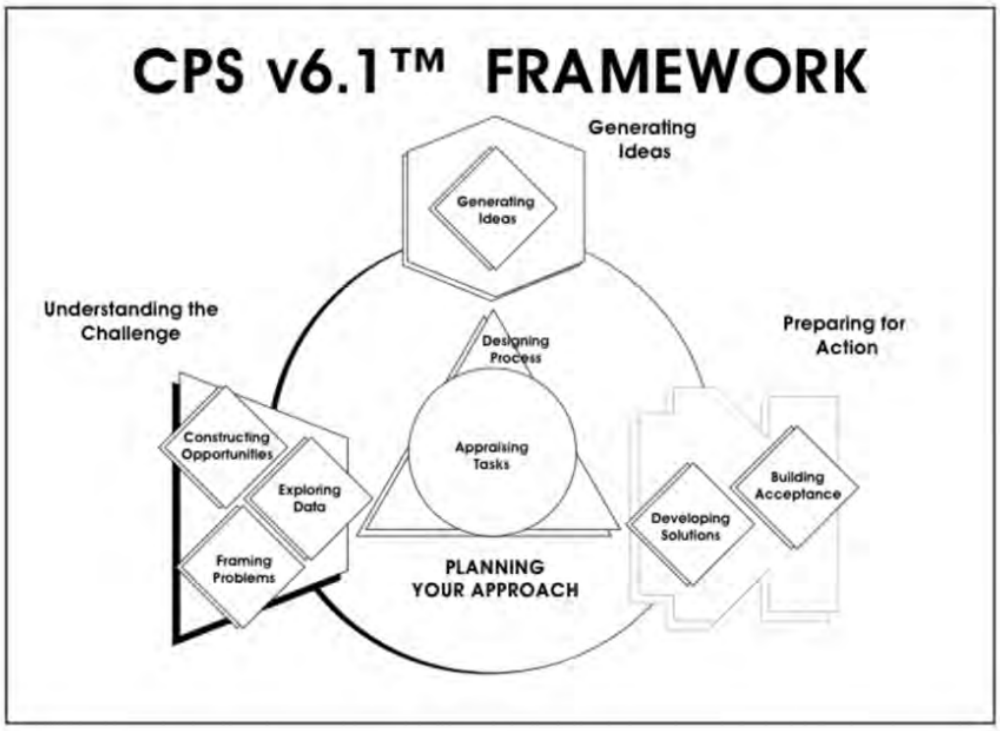


Figure 2.3 CPS Framework v6.1 From Isaksen, Dorval, & Treffinger (2000) as cited in Treffinger & Isaksen (2005, p.348).

Towards the 21st century, research started to focus on social and cultural aspects of creativity. For instance Csikszentmihalyi (2014) proposed a systemic view of creativity. In his framework, creativity emerges from the dynamic interaction of three elements. Domain, Person, and Field. Domain can be explained as the system of socially learned symbols, rules, and conventions that shape human thought and production, such as art, science, and religion. Person is the individual who acquires and transforms knowledge within a domain through motivation and originality. Field can be the social institutions and gatekeepers who evaluate ideas and determine which innovations are accepted into the domain (Csikszentmihalyi, 2014).

Following all these efforts to accurately define creativity, Runco and Jaeger (2012) published the Standard Definition of Creativity (SDC). SDC claimed that, for a product to be considered as creative, it should remain both original and effective for a prolonged period of time. In Runco and Jaeger's view, originality alone is not enough, since an original idea may prove dysfunctional or meaningless later on.

Effectiveness, on the other hand, covers the appropriateness, functionality, and utilization of an idea (Runco & Jaeger, 2012).

This shift from trait-based to contextual and systemic thinking laid the conceptual groundwork for contemporary understandings of creativity in design, HCI, and computational systems where creativity is seen as an ecosystem of human and environmental interaction rather than an isolated mental event.

In the design context, creativity is viewed as a plan for intervention (product, service, or system) that aims to transform an undesirable situation into a desired reality, particularly a process where a subject activates their ability to produce new and useful ideas, solutions, or products (Chakrabarti, 2009). To draw attention to the relationship between creativity and design Goldschmidt (1999) states: "Design has always been closely associated with creativity because new artifacts are often expected to be innovative and original—two hallmarks of creative products. Therefore, designers are expected to be creative persons who exercise creative processes" (p.526).

In design disciplines, creativity is not only the act of solving a problem but also the act of redefining it (Cross, 2011). Therefore, design literature considers creativity not as a random "creative spark" but as a gradual process of problem framing and problem transformation (Cross, 1984). In this context, classical models of creativity are also directly linked to the design process. For example, Guilford's divergent and convergent thinking are clearly evident in contemporary models of the design process. Similarly, Creative Problem Solving (CPS) (Osborn, 1963; Parnes, 1977), which includes problem definition, idea generation, solution selection, and implementation is similar to the structure of the design process.

With the rise of computational systems, creativity has been increasingly examined as a socio-technical phenomenon, marking a paradigm shift. Digital creativity emerges through interactions among humans, tools, and data (Boden, 2016), casting the concept of originality into somewhat of a grey area. Raising the question: “can

computers be creative?" and now more recently "can AI be creative?" Boden categorizes creativity in 3 main categories shown in Table 2.1.

Table 2.1 Types of Creativity Digital (Adapted from Boden, 2016, p. 68-69)

Type	Definition
Combinational Creativity	It involves new, improbable combinations of familiar ideas. Examples include poetic imagery or analogies involving two new related ideas that share a structural similarity.
Exploratory Creativity	It involves generating new ideas through the exploration of structured conceptual spaces. The resulting structures may be novel and unexpected, but they conform to the rules of the relevant way of thinking.
Transformational Creativity	It involves transforming one or more dimensions of conceptual space, thereby generating new structures that were previously impossible. This can lead to astonishing new ideas, and seemingly impossible new concepts.

Boden (1998) notes that computer models of creativity contain examples of all three types. However, models focusing particularly on exploratory creativity have so far yielded more successful results. He also argues that concepts related to artificial intelligence offer an important framework for explaining human creativity (Boden, 2016).

While AI-generated outputs may satisfy originality and effectiveness criteria, Runco (2025) argues that AI lacks some aspects of human creativity like authenticity and intentional problem-finding. He suggests that its creative capacity is better understood as a form of artificial creativity rather than creativity in the human sense.

Similarly, in their study comparing artificial intelligence and human creativity, Cropley et al. (2023) emphasize the determining character of identifying the problem

and interpreting the meaning of the solution in creative thinking. As such they claim that "The greatest promise of AI for creative tasks lies not as a replacement for human creativity, but as a support to human divergent thinking." (p.7)

These discussions demonstrate that it is not meaningful to position artificial intelligence as a replacement for humans in the creative process, intead it can be positioned as a tool that supports human creativity. Especially considering that critical stages of the creative process such as problem definition still require human agency. Finally, it is important to examine how artificial intelligence should be positioned in design and creativity practices within the framework of the Creativity Support Tools (CST) literature. The next section is devoted to this topic.

2.2.2 Creativity Support Tools

The idea of supporting creativity in digital environments began to gain prominence in human-computer interaction (HCI) research in the mid-1990s.

In the 1990s, these themes included understanding and modeling creativity, computer-based (autonomous) creativity, computer-supported approaches to creative practice, and the cultural and artistic aspects of creativity and technology. By the 2000s, the focus shifted from modeling creative cognition to computational approaches that support human creativity (Candy & Hori, 2003).

Unlike traditional computer-aided design (CAD) tools, CST focus on the early, intuitive, and often tacit knowledge-based stages of the creative process (Shneiderman, 2007). CAD systems are more functional in rational processes where parameters are clearly defined and variables are optimized. For CST, on the other hand, research focuses on the limitations of traditional tools such as cognitive load and interface costs, effects that constrain creative thinking, and the inability to transfer expert designers' intuitive knowledge-based experiences can be shown as examples of these limitations (Frich et al., 2019; Resnick et al., 2005). Frich (2018, p.3) refers to the increasing research interest of CST's collaborative, digitalized, and

tool-based creative practices as the "third wave" of creativity research. Examples of CSTs discussed in the literature include digital sketching environments, concept mapping systems, collaborative ideation platforms, music composition software, and programmable media tools (Resnick et al., 2005). In addition, Frich (2018) discusses CSTs through broader categories such as digital sketching systems, idea management tools, collaborative creativity platforms, and algorithmic design tools (Frich et al., 2019).

Creativity Support Tools (CST) primary goal is to enable users of varying levels of expertise to be more creative, more frequently, and effectively (Shneiderman, 2002). Shneiderman describes CST research as a "grand challenge" for the HCI field. Shneiderman's Genex Framework presented in Figure 2.4, considers creativity through four cyclical phases (Collect–Relate–Create–Donate) and emphasizes continuous feedback between the learning, sharing, and production phases of the creative process (Shneiderman, 1999, 2000, 2002).

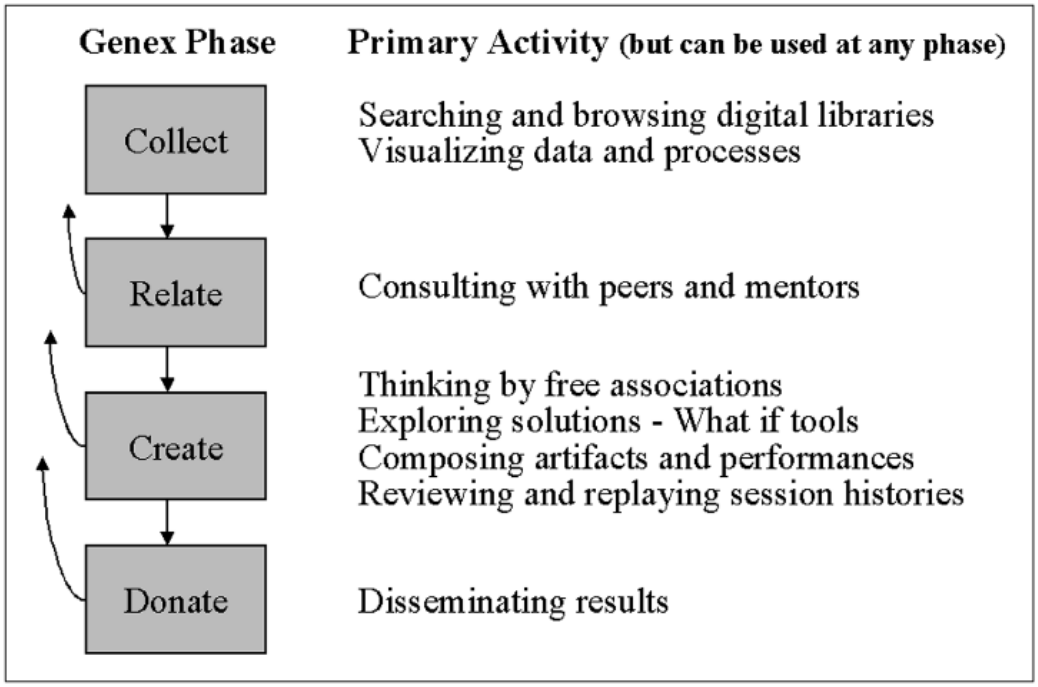


Figure 2.4 Genex Framework (Shneiderman, 2000, p.123).

Based on this framework, Shneiderman defines a list of eight activities for user interface and HCI research on creativity support tools. These activities such as

visualization, free association, reviewing history, and consulting with peers (Figure 2.5), suggest that CST should support the entire process, not just the moment of production. Therefore, Genex and the eight activities together place the idea of integration (the seamless flow of data, interface, and interfunctionality) at the center of CST design (Shneiderman, 2000, 2002).

(1) **Searching** and browsing digital libraries, the Web, and other resources
(2) **Visualizing** data and processes to understand and discover relationships
(3) **Consulting** with peers and mentors for intellectual and emotional support
(4) **Thinking** by free associations to make new combinations of ideas
(5) **Exploring** solutions—What-if tools and simulation models
(6) **Composing** artifacts and performances step-by-step
(7) **Reviewing** and replaying session histories to support reflection
(8) **Disseminating** results to gain recognition and add to the searchable resources

Figure 2.5 Eight tasks to support creativity (Shneiderman, 2002, p.118).

Later, the "Design Principles for Tools to Support Creative Thinking" were developed in the NSF Creativity Support Tools Workshop in 2006. These principles suggest that the CSTs should be designed as both accessible and expertise-enabling systems that support long-term learning through concepts such as "low-threshold-high ceiling-wide walls", exploratory search, collaboration, and rich history-keeping. Such approaches also provide important foundations for the design of today's AI-enhanced creativity support tools (Shneiderman et al., 2006).

The twelve principles listed as:

1. Support exploration.
2. Low threshold, high ceiling, and wide walls.
3. Support many paths and many styles.
4. Support collaboration.
5. Support open interchange.
6. Make it as simple as possible—and maybe even simpler.
7. Choose black boxes carefully.

8. Invent things that you would want to use yourself.

9. Balance user suggestions with observation and participatory processes.

10. Iterate, iterate—then iterate again.

11. Design for designers.

12. Evaluate your tools. (p.70)

Following the NSF Creativity Support Tools Workshop, researchers have increasingly emphasized the need for detailed evaluation, such as rigorous, longitudinal, and context-sensitive evaluation methods. This shift reflects a broader concern within the field, summarized by Marc Vass's significant question at the Creativity and Cognition conference: "What is the best measurement for the support of creativity?" This question highlights that CST research must address both how creativity is supported via these tools and how that support is meaningfully measured (Candy & Hori, 2003).

Shneiderman et al. (2006) note that although early generations of creative and domain-specific software have profoundly transformed both industry and individual creative practices, most general-purpose creativity tools still depend on anecdotal evidence rather than systematic evaluation. However, evaluating CST effectiveness is challenging, not because of their interdisciplinary nature but because it is difficult to measure creativity itself (Carroll & Latulipe, 2009; Shneiderman, 2007; Remy et al., 2020).

To address this challenge, Caroll et al. (2009) proposed the Creativity Support Index (CSI). As a standardized framework, CSI captures both the user's subjective experience and the tool's contribution to the creative process (Cherry & Latulipe, 2014; Cox et al., 2025). First introduced in 2009, the CSI's aim was to translate the conceptual foundations of creativity support into a measurable structure. The Beta version of CSI presented six factors which are "Exploration, Collaboration, Engagement, Effort/Reward Tradeoff, Tool Transparency, and Expressiveness" (Caroll et al., 2009). Those factors were derived from creativity theories and

empirical studies. In later revisions, these factors were refined as Exploration, Expressiveness, Enjoyment, Immersion, Collaboration, and Results Worth Effort presented in Figure 2.6 (Caroll et al., 2009; Caroll & Latulipe, 2009; Cherry & Latulipe, 2014).

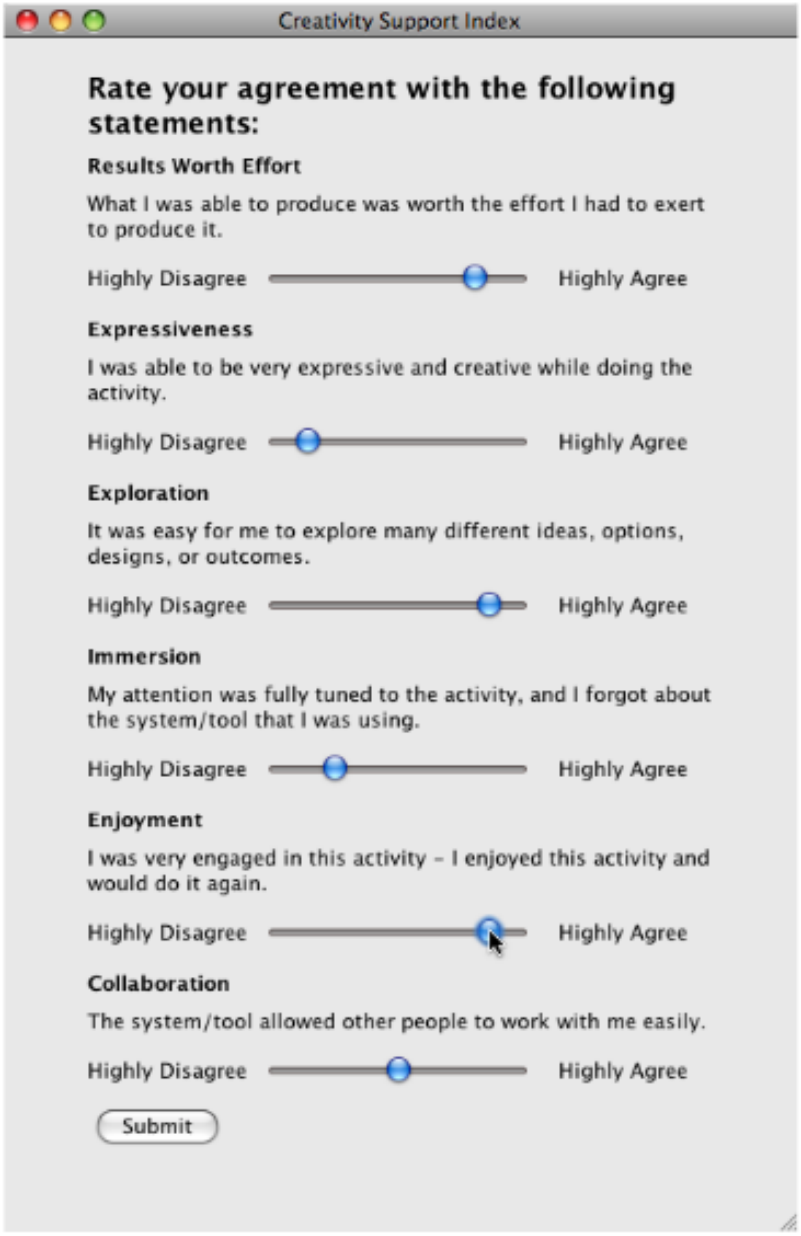


Figure 2.6 Factor ratings page for the CSI (Caroll et al., 2009, p.135).

Recent studies emphasize the need for new, validated, and holistic evaluation metrics for creativity support tools, especially as generative AI becomes more prevalent. For example, Remy et al. (2020) note that many studies in CST research assess creativity without explicitly defining it, and only a small number rely on creative performance measures. They also emphasize that classical usability principles often contradict the nature of creative processes such as discovery and trial-and-error, identifying the tension between usability and creativity as one of the main methodological challenges of the field. For these reasons, they suggest that instead of a single standard method in CST evaluations, a multidimensional method that can be adapted to different tool types, user profiles, and contexts should be adopted (Remy et al. 2020).

The studies that are examined here are significant to understand the framework regarding what should be considered when designing creativity support tools and how these tools should be evaluated. The next section, on the other hand, offers a groundwork for how AI-based technologies are positioned as creative support tools and how they operate within design processes. The tools that are in the scope of this thesis will be examined in detail in the following sections.

2.2.3 AI-Enhanced Creativity Support

While traditional Creativity Support Tools (CSTs) aim to enhance creative performance through features such as exploration, visualization, and reflection (Shneiderman, 2000; Cherry & Latulipe, 2014), the integration of AI expands these capabilities by introducing generative mechanisms into the process. To better understand this integration, it is crucial to examine a spectrum that encompasses approaches such as human-AI collaboration, human-AI co-creation, and human-AI co-design. While these terms are sometimes used interchangeably, to better describe how these terms come into play in the creation of AI-enhanced CSTs, it is important to understand the nuances between these expressions.

Human-AI collaboration often offers a partnership based on task sharing, directed towards defined goals; humans and systems have roles structured to complement each other's strengths, and success is evaluated through productivity, efficiency, and output quality (Holter & El-Assady, 2024), and can be regarded as the main framework that encapsulates Human-AI Co-Creation and Human-AI Co-Design.

Recently, generative AI has expanded the capabilities of CSTs and introduced the concept of Human-AI Co-Creativity (Wingström et al., 2024). In this context, humans and AI are viewed as partners working together on a shared creative product. Classic Creativity Support Tools (CSTs) have been limited to generating suggestions and variations; they have not produced "creative" outputs without user input (Shneiderman, 2007; Resnick et al., 2005). However, in recent years, the rise of generative AI models have transformed Creativity Support Tools from a mere "suggesting" agent to a "producing" agent (Wingström et al., 2024). In co-creation approaches, the process is more fluid and unpredictable; human and AI contribute simultaneously and interactively to creative production, agency distribution is negotiated within the process, and value is sought in the resulting innovation and diversity (Rezwana & Ford, 2023; Rezwana & Maher, 2025).

In Co-Design applications, on the other hand, participant- and user-based cycles are more prominent. In such applications, compared to human-AI co-creativity where AI contributes as a generative agent AI mostly takes on a supportive role that facilitates, suggests, and evaluates, and the individual is responsible for direction and decision (Shi et al., 2023; Zhou et al., 2024; Luo, 2025).

The common point of all these approaches is that the human-AI interaction is shaped through mechanisms such as turn-taking, transparency, feedback, and role-fit. Moreover, paradigms in the area differ from each other in accordance with the agency distribution within the interaction. Table 2.2 shows a synthesis of current research showing nuances of those collaboration dimentions. Drawing from literature, Table 2.2 highlghts the nuances in focus of the presented concepts instead of having definitive boundaries Human AI collaboration, co-design and co-creation

are positioned here as overlapping approaches representing different intensities and agency distributions of human-AI interaction.

Table 2.2 Dimensions of Human-AI Collaborations (Synthesized from Luo, 2025; Rezwana & Ford, 2023; Shi et al., 2023; Wingström et al., 2024; Zhou et al., 2024)

	Core Focus & Process	**Agency Dynamic**	**How Success is Measured**
Human-AI Collaboration	Working together towards shared goals, often with defined goals and tasks.	Structured Roles. Human and AI augment each other's strengths.	Productivity, efficiency, and the quality of the final output.
Human-AI Co-Creation	Producing artifacts through an emergent, unpredictable process.	Fluid & negotiated. Agency is Distributed between human and AI.	Novelty, creativity, diversity of output and mutual learning.
Human-AI Co-Design	Engaging in a participatory, user-centered design process with iterative cycles.	Human-led. AI acts as a facilitator or assistant to designers.	User experience, inclusivity and effectiveness of the design process.

AI-powered creativity tools stand out for their potential to expand users' creative possibilities, especially in the early stages of ideation. Generative systems, ranging from text to visual or language models, help generate a wide variety of ideas in a short time, broadening the search space, reducing cognitive load, and allowing users to generate more alternatives (Chandrasekera et al., 2025; Zhou et al., 2024; Tholander et al., 2023). Various classifications of AI-powered creative tools exist in the literature. One of these, Hwang (2022), categorizes the roles played by tools in the creative process into four categories.

Table 2.3 Hwang's (2022) Categorization of AI-Powered Creative Tools

	Definition	**Example**
Editors	They enable users to make tedious edits easily. These edits include erasing the background, object debugging and enhancing the image.	Adobe Photoshop's "Generative Fill"
Transformers	They transform the content from one form to another, reshaping it.	Text to Video / Image to Video Tools Such as Kling or Runway
Blenders	They combine more than one input while producing hybrid outputs. They are usually based on GAN models.	DeepArt.io (blending a visual with a selected art style)
Generators	They produce novel content based on directions, keywords, and limitations provided by the user.	Midjourney (producing new images from textual inputs).

A significant portion of existing generative tools is geared towards expediting the execution-focused stages of the design process. While functions like background removal, content transformation, style blending, and keyword-based image generation simplify the implementation steps at the end of the process, they offer limited support for the early and most critical stages of creative practice: problem definition, discovery, and conceptual development. Hwang's findings indicate that most of these tools lack mechanisms to facilitate teamwork and lack features such as transparency and explainability (2022).

Research shows that AI tools often help individuals, especially those with less creative experience, generate more creative and enjoyable outputs (Doshi & Hauser, 2024). However, when many people use similar AI tools, the resulting works tend to

become more similar, leading to a loss of diversity and uniqueness at the group or societal level (Doshi & Hauser, 2024; Zhou & Lee, 2024). Today, "AI Slop" is a popular term used to describe such works. It can be considered as a byproduct of such tools that skip early creative stages and focus on instant, polished outputs. Moreover, issues around authorship, intentionality, and the authenticity of creative work are becoming increasingly more important as AI-generated outputs become indistinguishable from human-made ones. However, the most effective creative outcomes often arise when humans direct and critique AI outputs, maintaining a balance between automation and human judgment (Anantrasirichai & Bull, 2020).

Similar concerns are also true for the design context. Some studies report increased fixation and less variety when designers depend too heavily on AI suggestions. For example a recent study investigating how GenAI outputs affect Design Fixation and Divergent Thinking by Wadinambiarachchi et al. (2024) suggest that "the effectiveness of co-ideation with AI rests on participants' chosen approach to prompt creation and on the strategies used by participants to generate ideas in response to the AI's suggestions." (p.1) Their findings indicate that while using GenAI, idea fluency decreases since participants spend more time interacting with the tool than generating ideas. As the designer puts more effort into interaction, shifting design direction becomes harder, which might cause design fixation.

Ironically, the extent of "creative support" GenAI tools offer depends on how "creative" one can get when using these tools. In reference to their discovery strategies and their interaction style with AI. In other words, AI's creative capacity scales with the user's interaction quality. This dynamic highlights that human agency remains central in AI-supported creativity, and it becomes especially important in structured processes such as UX/UI design.

While the previous sections addressed creativity, creativity support tools, and emerging forms of AI-supported creativity, the focus of this thesis is the design of AI-assisted tools specifically for UX/UI practitioners. Therefore, to understand

design principles for such tools, it is necessary to outline the UX/UI design process and the current research on the use of such tools in UX/UI design practice.

2.3 UX/UI Design

While explaining the evaluation of UX design field Quaresma et al. (2022), outlines that studies in human-computer interaction (HCI) conducted since the early 1980s, along with the proliferation of personal computers and the influence of cognitive psychology, paved the way for the emergence of what Shneiderman (1980) called "software psychology" and is now known as "usability." They also emphasize that the discussion of elements beyond usability criteria began in the late 1990s and early 2000s, giving rise to the concept of "user experience (UX)," coined by Donald Norman in the early 1990s, and defining a holistic interaction experience not limited to digital products. The authors state that while the concept of UX has broader applications today, it is still largely associated with the design of digital products.

The term "user experience" is still associated with many different meanings in the literature, and there is no unified and common theory for this concept within the design community (Forlizzi & Battarbee, 2004). However, within the context of digital product design, User Experience Design is defined as an interdisciplinary field that focuses on designing the overall experience and the impression left on the user by all interactions between a user and a product, system, or service (IxDF, 2016a).

User Interface Design, on the other hand, focuses on the visual and functional design of the interface through which a product or system interacts directly with the user such as the design of all visual/interactive elements that the user sees while navigating a mobile application, such as the layout of the screens, the design of buttons and menus, the selection of typography and color palette, icons, animations, and forms (IxDF, 2016b).

While user experience (UX) and user interface (UI) design have different definitions, they are, in practice, inseparable parts of a whole. The UX and UI design are both fields shaped by common goals and principles. Usability and interface design are often referred to as sub-elements of the user experience concept (IxDF, 2016a). Many roles and processes now blend both skill sets, especially in job market expectations and digital product development (Paneru et al. 2024). Titles such as UX Designer, UI Designer, UX/UI Designer, Product Designer, UX Engineer, UX Developer, Interactive UX Designer, Information Architect, or UX Architect represent different aspects of an area that can be signified under the umbrella term of "UX/UI design".

2.3.1 UX/UI Design Process and Frameworks

Modern UX practice is based mainly on the design thinking process, where problem framing, reasoning, and sensemaking play a central role (Dorst & Cross, 2001). When working with uncertain situations, designers redefine the problem, transform insights, and develop the solution space alongside the problem domain, forming the foundation of current UX methods. Over the years several frameworks have emerged. They are commonly used in contemporary UX/UI design processes today.

One of the most widely used structures in digital product design is the Stanford d.school's design thinking model (Figure 2.10) which consists of the Empathize, Define, Ideate, Prototype, and Test stages. The model considers understanding user needs, redefining the problem, generating creative ideas, and rapid prototyping and testing cycles as a holistic process. In the Empathize phase, user needs are sought to be understood and internalized. These insights are analyzed in the Define phase to create user-focused problem definitions. The Ideate phase generates ideas for alternative solution methods. The Prototype and Test phases allow these ideas to be quickly fleshed out and evaluated with users. The process is non-linear; feedback obtained during the Test phase guides the designer to redefine the problem or generate ideas.

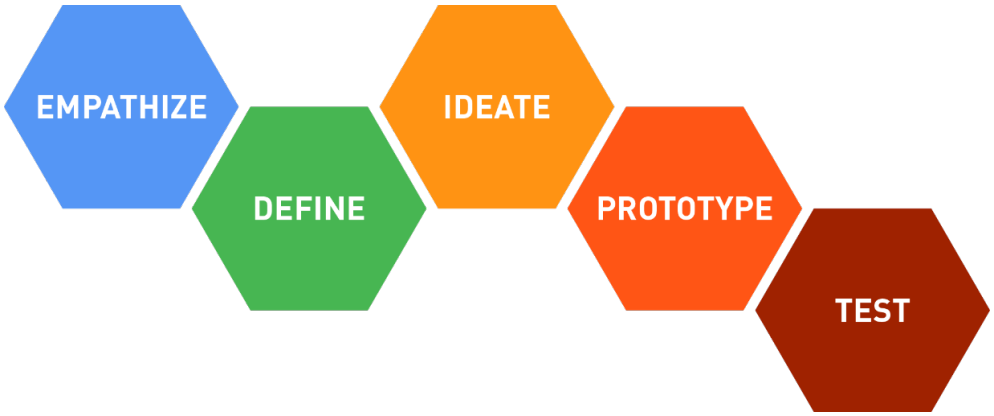


Figure 2.7 Design Thinking Model (d.school, 2010).

The Double Diamond model (Figure 2.11), developed by the UK Design Council, describes the design process through the alternating divergent (discover–develop) and convergent (define–deliver) thinking stages (Design Council, 2005). The Discover phase focuses on the underlying dynamics that form the design problem. The Define phase synthesizes the insights gathered during the discovery process to create a clear problem framework. In the Develop phase, different solution alternatives are developed for the defined problem. The Deliver phase is based on testing, comparing, and refining these solution proposals. The model's visual presentation of discovery, variation generation, and refinement cycles has made the double diamond model a widely used reference in contemporary UX practices.

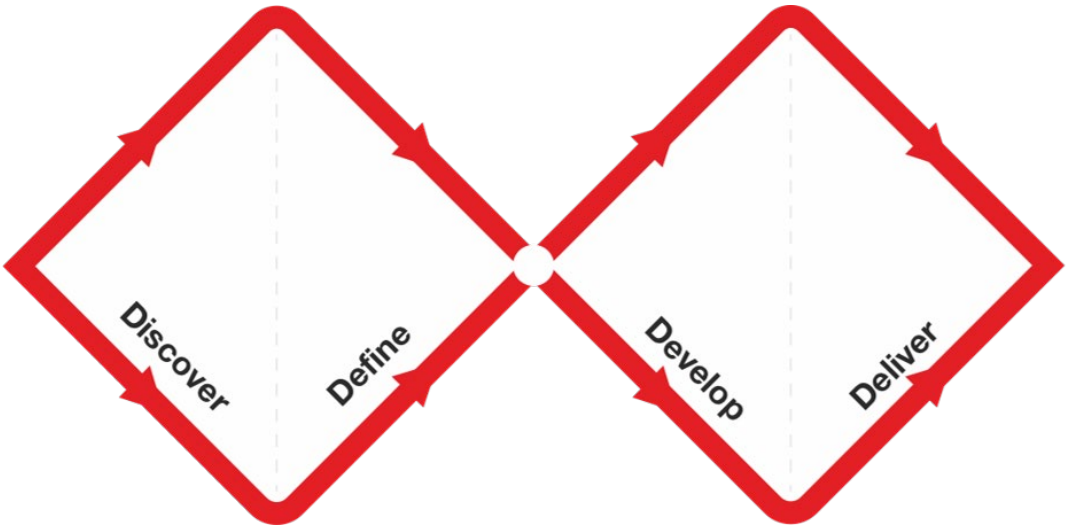


Figure 2.8 Double Diamond Model (Design Council, 2005).

While these frameworks use different terminology, they all share certain common characteristics. According to IxDF(2016a), all these design thinking models can be described with the following characteristics: the process begins with empathy; reframes the problem; initially uses divergent thinking styles in idea generation; then applies convergent thinking methods to select the best ideas; creates and tests prototypes; and returns to the iteration cycle based on test results.

2.3.2 AI in UX/UI Design

Today, AI is being researched for its potential to transform various aspects of the UX/UI design process, these aspects include an AI tool's ability to enhance efficiency, automate tasks, generate novel ideas, and personalize user experiences. According to Lee et al., AI agents can potentially assist designers by providing inspiration, defining design problems with constraints, and offering grounded metaphors (2024).

In current research, the positioning of AI's capacity in UX/UI processes is addressed from two main perspectives. AI can be viewed as a design material and as a design support.

In the first perspective, AI becomes the subject of the design itself. It functions as a material that determines the behaviors, properties, and user interaction patterns of the resulting product. Studies emphasize that this approach differs from traditional design materials due to AI's unique characteristics, such as data dependency and unpredictability (Dove et al., 2017; Holmquist, 2017; Yang et al., 2020). Artificial intelligence properties embedded in the product, such as adaptive interfaces or real-time personalization, require designers to understand these technical features. Therefore, designers need to develop an understanding of AI's capabilities and limitations. They need to be able to assess what value AI can generate for users or where it poses risks and be able to discern between what AI can and can't do. (Liao et al., 2023; Yang et al., 2020; Yıldırım et al., 2023).

Yang et al.'s (2020) model (Figure 2.12), visually illustrates the challenges designers face during the discovery, definition, development, and delivery phases when AI is integrated into a product as a design material.

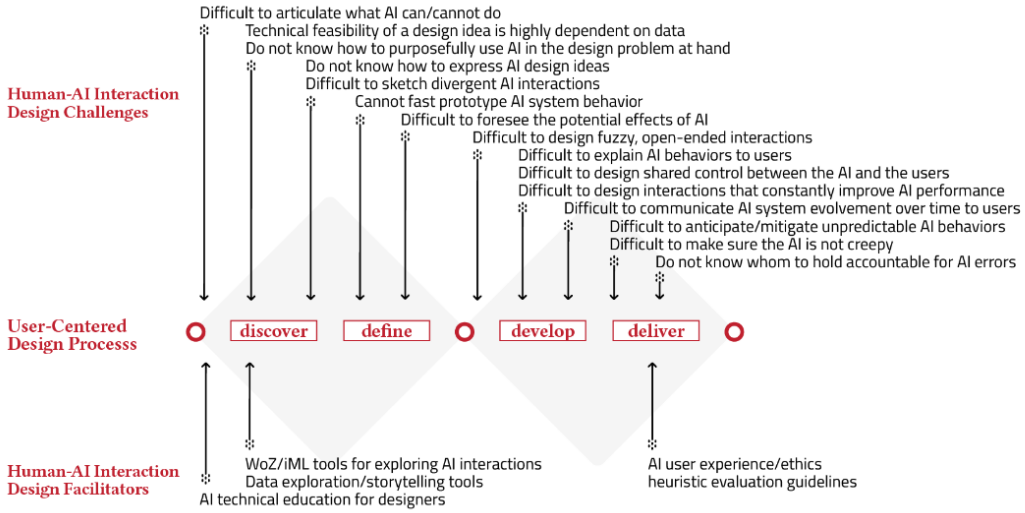


Figure 2.9 Yang et al.'s (2020, p.2) model showing the challenges designers face.

On the other hand, AI can serve as design support, assisting designers during ideation, exploration, prototyping, and refinement. Here, AI does not define the interface's behavior for end users; instead, it augments the designer's workflow by generating alternatives, reducing repetitive tasks, accelerating iteration, and enabling

richer creative exploration. In this capacity, AI acts as a creativity support mechanism - one that must preserve user agency, allow steering and control, and integrate smoothly into established UX/UI processes. Generative design tools empowered by the advancements in AI are increasingly being used in industry and research applications to augment the design process (Saadi & Yang, 2023a, 2003b).

Various studies show the potential of AI tools to ease the workload of designers and speed up the process, especially in terms of efficiency and productivity: It has been observed that AI tools accelerate innovation methods by providing analysis, idea generation and methodological support in UX/UI design processes, especially in the discovery and ideation phases of LLMs (Bilgram & Laarmann, 2023; Zhou et al., 2024; Zhu et al., 2024). LLM tools like ChatGPT are increasingly used as collaborative partners in brainstorming sessions. Designers leverage them to explore a wide range of design alternatives, generate initial concepts, and overcome the "blank page problem," thereby stimulating creativity (Lee et al., 2025; Luo, 2025).

Studies emphasize the role of generative imagery and flow-based systems for visual inspiration and conceptual exploration; generative imagery systems broaden designers' perspectives through semantic diversity (Cai et al., 2023; Verheijden & Funk, 2023), while tools like Flowy have shown that AI can analyze multi-screen flows to provide decision support focused on user journeys (Lu et al., 2022). GenUI(Chen et al.,2025) and similar studies demonstrate that high-fidelity interface generation from text can provide a “good first draft,” but still requires significant human effort to bring it to a professional standard in the “final step” (Chen et al., 2025; Wei et al., 2025).

Generative AI facilitates the rapid conversion of low-fidelity inputs, like hand-drawn sketches, into medium or high-fidelity digital mockups. It can also automatically generate graphic interfaces, advertising posters, and other visual assets, significantly speeding up the prototyping workflow (Lee et al., 2025; Stige et al., 2024; Luo, 2025).

Current research converges on a key finding: Even though LLM tools widely used by designers in initial stages (Zhou et al., 2024), the vast majority of current AI-enhanced tools specifically for design support are concentrated in the later phases of the design process, which are focused on generating, prototyping, and evaluating solutions (Lee et al., 2025). Stige et al. (2024), found the majority of tools centered on producing (35%) and developing (31%) solutions. Lee et al. (2025) report that 70% of AI-enhanced design support tools target the 'Develop' and 'Deliver' phases of the Double Diamond framework. Additionally Luo (2025), identifies the 'Test' phase as 'the most frequent research focus'.

The integration of artificial intelligence (AI) into UX/UI design is rapidly transforming creative workflows, offering new opportunities for ideation, prototyping, and user-centered innovation. AI integration can occur at various stages of the design process, from early-stage ideation and problem definition to design evaluation and prototyping.

Designers are cautious about privacy and confidentiality issues when using generative tools for learning, storytelling, and visualization and this caution leads them to maintain closer control over AI-generated outputs. (Uusitalo et al., 2024; Zhu et al., 2024). Concepts such as variation management, mechanisms for co-creation, and the visibility of uncertainty and imperfection that come with generative systems point to new design challenges and the need for design principles specific to GenAI (Weisz et al., 2024). Taken together, these studies reveal that the integration of AI into design processes is a multifaceted and not yet institutionalized field.

There is increasing interest in understanding how designers can effectively collaborate with AI systems. The increasing use of AI in design has prompted researchers to investigate various aspects of human-AI collaboration in this field (Lu et al., 2024).

In parallel, studies focused on agentic systems and orchestration show that designers are increasingly managing multiple GenAI tools at ‘project-level’ and ‘artifact-

level' orchestration layers; they expect semi-autonomous agents to take over repetitive tasks, yet want to maintain high agency in creative decisions (Palani & Ramos, 2024; Wadinambiarachchi et al., 2025; You et al., 2025). In UX/UI design context, a designer using different AI agents in different stages of a design project, such as summarizing user research with one tool while using another tool to generate alternative design strategies, and a third tool for assisting with repetitive tasks can be considered as an example of 'project-level' orchestration. In contrast, 'artifact-level' can be considered as requesting a specific design output, such as generating variations of a wireframe, or generating a single icon to use in UI design.

Managing multiple tools while triying to catch-up with new updates and discovering new strategies to adapt these tools in the design process requires designers to acquire new skills and also redefines their role in the design process. In addition to developing new skills, designers also need to be able to understand how these AI systems work since this knowledge directly affects how AI outputs are interpreted and applied in design decisions. For example Knearem et al. (2023) note that the training of AI systems might lead to bias, which raises ethical questions about inclusivity and accessibility. Current research also uncovers the potential risks of disassociating AI-created design outputs from real user needs. Though faster, AI programs can never fully substitute for the depth of human knowledge and the subtlety of understanding that needs to be absorbed in designing for empathy and users (Popescu & Schut, 2023). This misalignment leads to more work to recreate outputs, which defeats the point of efficiency in AI tools.

The core tension identified by Lu et al. (2022) is that current AI models often produce outputs that are too generic and narrowly focused on graphical elements. Practitioners, however, require support for more nuanced, context-specific "design thinking" activities. Recent studies have proposed the concept of "human-centered AI" (Lu et al., 2024; Shneiderman, 2020; Xu, 2024). An important part of the concept of "people-centered AI" is to emphasize the optimization of human-machine interaction and experience design of these intelligent systems.

The integration of AI into UX/UI processes is creating a complex interplay that is transforming design practices. Therefore, it is important to identify the principles that should inform the design of AI-powered UX/UI tools. The next section will explore these principles through the lens of creativity support tools (CST), human-AI interaction, and UX practices.

2.3.3 Principles for AI-Enhanced Design Support Tools

Research highlights several main design dimensions and considerations for developing AI-assisted tools that effectively support designers' creativity and design processes (Table 2.4). Studies emphasize that AI should augment rather than replace human creativity, with tools designed to facilitate inspiration, streamline repetitive tasks, and enhance divergent thinking while preserving the unique value of human insight and empathy (Khan et al., 2025; Stige et al., 2024; Wei et al.,2025). However, challenges remain in usability, explainability, and aligning AI outputs with designers' needs and values (Chaudhry, 2024).

Table 2.4 Principles for AI-Enhanced Design Support Tool

Design Dimension	Key Findings	Sources
Support for Divergent Thinking (Creativity Augmentation)	Tools should empower creative thinking by presenting wider range of ideas and visual options to the designer.	(Cai et al., 2023; Chaudhry, 2024; Lee et al., 2025; Palani & Ramos, 2024; Shen et al., 2025)
Human Agency and Control (Designer-Led Collaboration)	Control should remain with the designer. AI should act as an assistant, partner, or facilitator. The designer should be able to choose the level of control and set the direction at each stage.	(Luo, 2025; Shi et al., 2023; Weisz et al., 2024; Wadinambiarachchi et al., 2025; You et al., 2025)

Design Dimension	Key Findings	Sources
Interaction Modality and Input Flexibility	The system should capture design intent more accurately by supporting multiple inputs, such as sketches, descriptions, mockups, and user flows, not just text.	(Palani & Ramos, 2024; You et al., 2025; Wadinambiarachchi et al., 2025)
Efficiency and Cognitive Load Management	AI should reduce mental overhead by automating repetitive and technical tasks, freeing the designer to focus on concept development and interpretation.	(Bertão & Joo, 2021; Palani & Ramos, 2024; Wadinambiarachchi et al.,2025; You et al., 2025)
Workflow Integration and Coherence	AI should seamlessly integrate into existing design systems, support iterative and fragmented production, and make the evolution of the design process and past steps visible.	(Chen et al., 2025; Shen et al., 2025; Zhou et al.,2024)
Personalization and Adaptation to Designer's Style	Tools should generate personalized recommendations by learning designers' style, preferred components, and work routines.	(De Peuter et al., 2023; McCormack et al., 2020; Wadinambiarachchi et al., 2025)
Clear Scope and Limitations	Designers should understand the extent to which AI cannot replicate human capabilities such as creative intuition, emotional connection, and cultural context; tools should facilitate exploration of model boundaries.	(Liao et al., 2020; Lu et al., 2024; Palani & Ramos, 2024; Wallach et al., 2020)

Design Dimension	Key Findings	Sources
Transparency and Explainability (XAI)	The system should clearly provide justification for its recommendations; capabilities, limitations, and biases should be clearly understandable. The designer should be able to rely on these explanations when making decisions about things like UI flows and information architecture.	(Chaudhry, 2024; Liao et al., 2023; Lu et al., 2022)
Ethicality and Responsible AI (RAI)	AI should be designed according to the principles of fairness, inclusiveness, and transparency; it should protect data privacy, mitigate biases, and clarify the IP/ethical responsibilities of productions.	(Chaudhry,2024; Germanakos et al., 2025; Zhu et al., 2024)

These dimensions from the literature also align with the principles of the Genex Framework (Shneiderman, 2000), two fundamental frameworks in the Creativity Support literature. Genex's focus is on idea diversity and creative exploration (Create/Explore), user agency and control (Relate), multiple interaction modes and input flexibility (Collect), reduced cognitive load and flow maintenance (Create), workflow integration and information traceability (Relate–Donate), and ethical accountability and contribution visibility (Donate). Similarly, the NSF (2006) workshop's recommendations, such as user control, low interaction barriers, support for multimodal expression, maintaining flow, collaboration and co-creation, explainability, and ethical design, align with design dimensions presented in Table 2.4.

2.3.4 Commonly Used AI-Supported Tools in UX/UI Practice

This section aims to understand the current landscape of AI tools and create a contextual foundation for the co-design workshop conducted in later stages of the study by reviewing these tools.

Generative AI-based UX/UI tools are generally positioned with the promise of accelerating the design process and providing users with highly accurate outputs in a short time. For example, the Figma Make product page states that users can express their ideas directly in text and quickly transform these ideas into working prototypes (Figma Make, 2025). Similarly, Google Stitch, promoted by Google Labs, stands out with phrases like ideas into UI, claiming to transform design ideas from natural language or visual inputs into user interface designs in minutes (Google Stitch, 2025). These descriptions exemplify how these tools are positioned in the UX/UI process with a focus on speed and production. However, this focus on speed and lack of emphasis on the process can be associated with the "fixation" effect, which can lead to the narrowing of the alternative solution space without sufficient exploration (Wadinambiarachchi et al., 2024). Additionally, in the literature, creative thinking requires generating multiple alternatives, exploring different possibilities, and returning to previous stages if necessary (Shneiderman, 2007), which some of these tools offer in varying degrees.

Text-to-app tools like Bolt and Lovable offer a production model where AI largely handles the technical burden in the design and development process (Shkutnik, 2025). These tools aim to have the user contribute more at the idea level and for the system to make detailed implementation decisions. While this approach accelerates the prototyping process, it can also create some risks for the user agency. This model appears problem-free when the output largely meets expectations. However, it is stated that in cases where the output is partially inadequate, the correction and intervention options offered to the user remain limited (Li et al., 2024, 2025; Rezwana & Maher, 2023).

The study “AI Prototyping in Real Design Contexts,” conducted by the Nielsen Norman Group, examines the use of generative AI tools in UX/UI design, particularly in the prototyping phase. The study notes that the quality of output provided by AI tools largely depends on the detail of the prompts. AI-powered prototyping tools can rapidly generate interfaces by responding to natural language prompts; however, this automated production process alone does not guarantee detailed and contextual design decisions that align with design requirements (Wang & Brown, 2025). These findings parallel academic criticisms that the rapid output goal observed in commercially available tools makes it difficult to produce original, contextual, and finely tuned solutions without the designer's judgment and process control.

The overview in Table 2.5 focuses on which stage of the design process the tools are involved in and the type of support they offer to the designer. Table covering, *UI and flow generation*, *Prompt-Based Textual Assistants* and *Code/Prototype-Focused Tools* includes developments and features available up to November 2025 and is limited to tools that were explicitly mentioned by the interview participants of this thesis research (See further details in Section 3.2) as part of their UX/UI design practice.

Table 2.5 Overview of Generative AI Tools in UX/UI Design

Category	Tool Name	Key Features	References
UI and Flow Generation Tools	**Visily**	Converting screenshots to editable wireframes, converting hand-drawn sketches to digital wireframes, quick prototyping, text prompt to design.	(Cheung, 2023; Visily, 2025)
	Motiff	AI-powered layout generation based on best-practice heuristics, pre-built design systems, and code-ready export.	(Fard, 2025; Motif, 2025)
	Uizard	Autodesigner generates multi-screen UI flows from text prompts; supports importing existing images or sketches; real-time collaboration; AI Assistant chat for design adjustments; Theme Generator, easy export (images or React/Tailwind code).	(Uizard,2025)
Prompt-Based Textual Assistants	**ChatGPT**	Generating design ideas and concepts; drafting UX copy (e.g., interface text), suggesting research questions; summarization (e.g., transcripts), role-playing as a user for UX pitfalls.	(ChatGPT, n.d.; Serednya, 2024)

Category	Tool Name	Key Features	References
	Claude	High-context retention (can process and remember long documents), summarizing lengthy research reports, analyzing long-form user feedback and multi-page requirements (PRDs).	(*Claude*, 2023)
Code/Prototype-Focused	**Bolt (Bolt.new)**	Generates code, design, and deployment; sets up backend logic (databases, authentication), built-in IDE for code editing; integrates with GitHub/Expo, **Bolt Cloud** for hosting and deployment.	(*Bolt*, n.d.)
	Cursor	AI code autocompletion, error detection and fixes, natural language commands for code generation/modification, understands the context of the entire codebase, code explanation and refactoring.	(Cursor, 2025; Kramer, N. 2025)
	Lovable	Generates interfaces from natural language, ingests context from existing project documentation, visual editor for refinement, Theme/image generation, Export code.	(Lovable, 2025)

Category	Tool Name	Key Features	References
	UX Pilot	AI-powered UI generation, suggestions for visual hierarchy/alignment, automated user research insights (analyzes raw user data for themes), generates design system components/style guides.	(UXPilot, 2025)
	Figma Make	Generates prototypes directly in Figma, applies existing design system styling, iterative refinement via prompts, connects to real data sources.	(Fard, 2025; Figma, 2025)

To conclude, Many AI-powered tools used in the landscape for UX/UI design present the speed of deployment as a key success metric. These tools position themselves with a production-oriented discourse aiming to deliver a working product to the user as quickly as possible. However, current assessments indicate that the impact of such AI tools on creative, reflective, and exploratory practices in the UX/UI design process has not yet been sufficiently addressed in the academic literature (Luo, 2025; Stige, 2024). This situation shows that how speed and output-oriented approaches relate to the more cognitive and reflective dimensions of the design process remains an open area of research.

CHAPTER 3

METHODOLOGY

This study aims to understand how generative AI tools impact UX/UI designers' creative processes and the extent to which designers adopt these tools into their workflows. It seeks to identify the key considerations of a generative AI-enhanced UX/UI tool that focuses on designer needs. To better understand these needs, a two-stage research project was conducted. This section will first describe the overview of the study, then detail how the participant sample is selected and the steps involved in the research, including semi-structured interviews and a co-design workshop. Then, the methods used to analyze the data will be explained. The presearch and analysis methods have been reviewed and approved by Applied Ethics Research Center of the Middle East Technical University with protocol number 0478-ODTÜİAEK-2025 (Appendix A).

3.1 Research Overview

This study is built upon a qualitative approach and conducted via a two-phased user research. Qualitative research aims to examine the individuals' experiences, perceptions, and meaning-attribution styles in a thorough manner rather than a quantitative evaluation of available data and generalizations. This approach is considered an effective method to understand complex, context-sensitive and not so completely defined phenomena (Patton, 2002).

This research is planned in two phases, an overview of the research methodology can be seen in Figure 3.1. In the first phase of the research, the current use of AI-support tools in design processes, the opportunities they present, and the limitations they have are examined through semi-structured interviews carried out with UX/UI

designers. The data gathered via these interviews are evaluated with thematic analysis.

In the second phase of the research, a co-design workshop is realised along the findings and principles derived from the first phase. In the workshop process, the participants discuss, criticize, and restructure design scenarios. Following a thematic analysis of the findings obtained in the workshop, affinity mapping is used to support the thematic analysis of the workshop and connect the workshop findings to the findings from the interviews, leading to insights for the design of designer-centered AI-enhanced UX/UI tools.

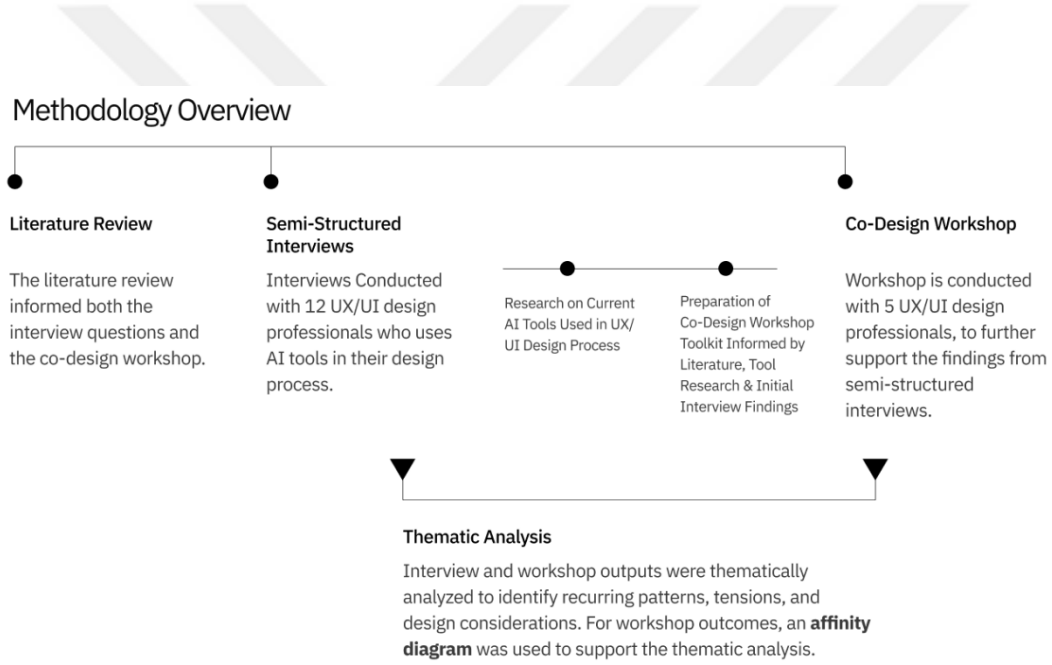


Figure 3.1 Methodology overview of the study

3.2 Sampling of the Study and Recruitment Process

The research sample for this study consisted of professional designers actively working in the UX/UI field who have used generative AI-based tools for UX/UI design in at least one project. Participants were expected to be experienced in UX/UI

design and processes. Professional experience and practical knowledge of generative AI tools were determined as the primary selection criteria.

The sampling process was planned at two levels. Participants for the pilot studies were selected through convenience sampling; which is the selection of participants based on accessibility and convenience to the researcher (Saumure & Given, 2008). In the pilot study, since the researcher was part of the target group, this sampling method was used to recruit participants from the professionals accessible within the researcher's own environment. Because the primary purpose of the pilot phase was to test the research tools (e.g., interview questions, protocol) and improve methodological processes, quick access and practicality were prioritized over representativeness. Working with participants accessible from the researcher's personal/professional network both saved time and enabled early methodological adjustments. Maintaining the criterion of "having used generative AI in at least one UX/UI design project" ensured that pilot participants were relevant to the context.

This study employs a purposive sampling method as it is the most suitable approach. In qualitative research, the sampling process depends on a different logic than quantitative approaches aiming for a statistical generalization. On the contrary, the main aim of qualitative research is to obtain a thorough and contextual insight on the subject matter. In that regard, rather than the sampling size, the emphasis is on the relationship between the participants and the research questions where it enables the gathering of a large amount of information (Patton, 2002).

According to Patton (2002), the strength of purposive sampling originates from intentional selection of information-rich cases that have the most potential to learn from the main themes of research questions. This approach is regarded as an intentional preference that serves the purpose of the study.

In the scope of this study, the primary goal was to collect in-depth qualitative data on generative AI experiences in a specific area of expertise (UX/UI), it was critical that participants meet certain criteria. The criterion of "having used a generative AI-based tool for UX/UI design in at least one project" guaranteed that the data obtained

was directly relevant to the context and that participants shared practical experience on the topic.

To reach potential participants, the research announcement was shared on the department's and researcher's social media accounts. A Google Forms link was included in the announcement to facilitate access and more effectively organize interview scheduling (Appendix B). This form is then used to collect basic information and contact details from volunteer participants. Additionally, UX/UI designers actively working in the industry and with access to individuals who might meet the research sample criteria were asked to share the announcement with their professional networks. As a result of this announcement process, a total of 16 responses were received to the shared form; all participants who provided their contact information were individually emailed to finalize interview dates. Semi-structured interviews, each lasting 45-50 minutes, were conducted with 12 participants who responded to the emails and confirmed their interview dates. Among the 14 participants (see Table 3.1), several identified their professional role as product designer. However, all participants had direct experience working on UX/UI design projects and actively used generative AI tools within these processes. Given the overlapping and fluid nature of professional role definitions in the field, this study adopts UX/UI designer as an umbrella term to refer to participants engaged in the design of digital products and interfaces. Following the interviews, participants were informed about the next phase of the study, the co-design workshop, and three participants who agreed to participate were contacted again to schedule the workshop dates.

A snowball sampling method was also utilized in this process. Interview participants were asked to recommend other professionals who might have similar qualifications, and they were asked to share the research announcement and participation link with them. This aimed to expand the sample by reaching individuals with similar qualifications through the professionals participating in the interviews, thus achieving a more balanced distribution. Thanks to this strategy, two additional

participants were contacted to be included in the workshop phase as displayed in Table 3.1.

Table 3.1 Overview of Participants, their Professional Backgrounds and Stages Involved.

Participant	**Professional Role**	**Experience (Years)**	**Participation Stage**
P1	UX/UI Designer	2	Interview, Workshop
P2	UX/UI Designer	3	Intervew
P3	UX/UI Team Lead	6	Interview
P4	Product Designer	7	Interview
P5	UX/UI Designer	3	Interview, Workshop
P6	UX Researcher	7	Interview
P7	UX/UI Designer	5	Interview
P8	UX/UI Designer	8	Interview
P9	UX/UI Designer	4	Interview
P10	Senior Product Manager	11	Interview
P11	Product Designer	3	Interview, Workshsop
P12	UX Designer	2	Interview
P13	UI Designer	5	Workshop
P14	UX Researcher	4	Workshop

3.3 Semi-Structured Interviews

One of the primary data collection methods used in academic research is semi-structured interviews. Semi-structured interviews are qualitative data collection methods that rely on a pre-prepared set of questions but can proceed flexibly based on participant responses (Patton, 2002). In social sciences and design research, this method is commonly used for understanding cases that are particularly dependent on experience, context, and that are open to interpretation. According to Kvale and Brinkmann (2009), semi-structured interviews put forward how the participants attribute meaning to their experiences. Such interviews also enable the researcher to lead the interview processes in accordance with the study's subject matter. In similar fashion, Creswell (2013) defines semi-structured interviews as perfect fit for thorough inspection of participant perceptions, especially in exploratory qualitative studies.

In the context of this study interviews helped to understand the current practices and perceptions of professional UX/UI designers regarding the integration of generative AI in their design processes, as well as the challenges they face in this process. These findings provided insights based on the designers' professional experiences.

3.3.1 Pilot Study

A pilot study was conducted prior to these interviews to test the effectiveness of the interview protocol and assess the understandability of the questions While a predetermined question guide was available for the interviews (Appendix C) these questions were not posed in a strict order during the interviews. Instead, the question set served as a guide defining the overall framework of the interview and the areas to be covered. Based on the findings of the pilot interview, this approach was found to be more suitable in terms of both the flow of the interview and the comfort of the participant.

In addition to testing the interview content, the pilot study was used to examine the technical aspects of the data collection process. Different options for audio recording and transcription were tested. Consequently, conducting the interviews via Microsoft Teams was finalized as the primary method for reliable audio recording and automatic transcription. This decision also facilitated the scheduling and management of interviews, as all stages of the process could be handled within a single platform.

3.3.2 The Conduct of the Interviews

The interviews proceeded in a way that encouraged participants to elaborate on their experiences with AI-powered tools through their own workflows and practices. Depending on the interview flow, some participants were asked four to six main questions; however, it was observed that other questions from the question set were naturally referred to during the participants' narratives. In these cases, the participant was encouraged to elaborate on the topic. Although the questions were not phrased in exactly the same way in every interview, each of the following subjects were addressed in all interviews:

1. AI tools used in the UX/UI design process and their purposes
2. The role of AI in different stages of the design process
3. The advantages and challenges created by AI-powered tools
4. Experiences regarding design agency, control, and trust issues
5. Perceived impacts of AI on the creative process
6. Expectations and criticisms regarding an AI tool specific to an ideal UX/UI design

During the interviews, explanatory and in-depth follow-up questions (e.g., “Could you elaborate on this situation?”, “What would be necessary for this to work better?”) were asked to encourage participants to elaborate on specific experiences. This flexible structure allowed participants to prioritize their own experiences while

ensuring that the themes identified in the research were addressed in each interview. All interviews for this study were conducted between 29 October 2025 – 16 November 2025.

In addition to testing the interview content the pilot study was used to examine the technical aspects of the data collection process. Different options for audio recording and transcription were tested. Consequently, conducting the interviews via Microsoft Teams was finalized as the primary method for reliable audio recording and automatic transcription. This decision also facilitated the scheduling and management of interviews, as all stages of the process could be handled within a single platform.

3.3.3 Thematic Analysis

Thematic Analysis is a qualitative analysis method widely used in social sciences. It aims to systematically uncover patterns of meaning (themes) within qualitative datasets in line with the research question (Braun & Clarke, 2022). It is based on processes of familiarization with the data, coding, and theme development; and it is theoretically flexible and encompasses diverse approaches.

In this study, thematic analysis is used to analyse the data collected from semi-structured interviews. Interviews were conducted via the Microsoft Teams platform. The application's features for recording interviews and generating automatic transcriptions were utilized. Participants were informed again at the beginning of each interview that they would be recorded. After the interviews were completed, the recordings were reviewed and the automatically generated transcripts were corrected by the researcher through multiple rounds of listening.

Later, the transcripts were transferred to MAXQDA software and coded using thematic analysis methods. During the coding process, meaningful and recurring data segments in relation to the research questions were systematically identified. Coding was primarily performed at the semantic level. Visual mapping techniques

were used to develop themes and examine their relationships as creating thematic maps allows for the independent consideration of temporary themes as a general analytical practice, and also enables the systematic exploration of possible relationships between these temporary themes (Braun & Clarke, 2022). The original versions of quotations from participants used in the findings section can be viewed in Appendix E. Finally, codes that were related in terms of content and meaning were clustered, reviewed, and grouped under four overarching themes to represent common patterns, which are (1) Designers' Workflow Integration of Generative AI Tools, (2) Transformation of Designers' Process, (3) Designers' Perceptions of AI Tools' Capacity, (4) Designers' Expectations from AI Tools (see Table 4.1). The detailed schema of the themes will be discussed in the Findings chapter of this thesis.

3.4 Co-Design Workshop

Overall this research aims to answer the role of generative AI tools in UX/UI design processes and to understand the key design considerations that will guide development of new tools to be utilized in these processes. However, as mentioned in Chapter 1, the field of generative AI-powered UX design is still in an early and rapidly evolving stage. Therefore, insights derived from designers' experiences are a critical source of information. To be able to collect these insights, a co-design workshop was organized as the second part of this research. The workshop is designed based on the findings from semi-structured interviews to make designers' needs visible and to better understand their expectations from AI-powered tools. Co-design is a design research approach that positions participants as actively contributing to shaping design concepts, interaction rules, and decision structures throughout the design process. (Sanders & Stappers, 2008, 2012). For this study Co-design is a suitable method because it enables exploration of interaction and design considerations while allowing participants to directly intervene in design concepts.

For the workshop, a co-design toolkit was prepared to structure the process and support the active involvement of participants. In co-design and participatory design

research, a toolkit refers to a structured set of tools consisting of various artifacts, guiding questions, templates, and facilitating materials used to support collaborative thinking and designing during the workshop process (Sanders & Stappers, 2014). Such toolkits do not aim to provide participants with ready-made solutions but they enable participants to express their own experiences, expectations, and ideas. As part of the toolkit low-fidelity wireframes used in the workshop as speculative design artifacts designed to trigger the designers' thinking and discussion processes. In total the workshop toolkit consisted of three main components: (1) thematic cards derived from interview findings, (2) a low-fidelity wireframe of a Gen-AI assisted design tool proposal consisting of 4 individual screens which are designed to support the exploration of themes derived from the literature and the thematic analysis, and (3) activity introduction cards together with annotation materials. Overview of all three workshop activities shown in Figure 3.2. The complete toolkit and its English translation can be viewed in detail in Appendix D. The workshop was held on December 28, 2025. Workshop was conducted in Turkish and lasted around 180 minutes. Five UX/UI designers with different experience levels participated to workhop, three of whom also taken part in the Interviews.

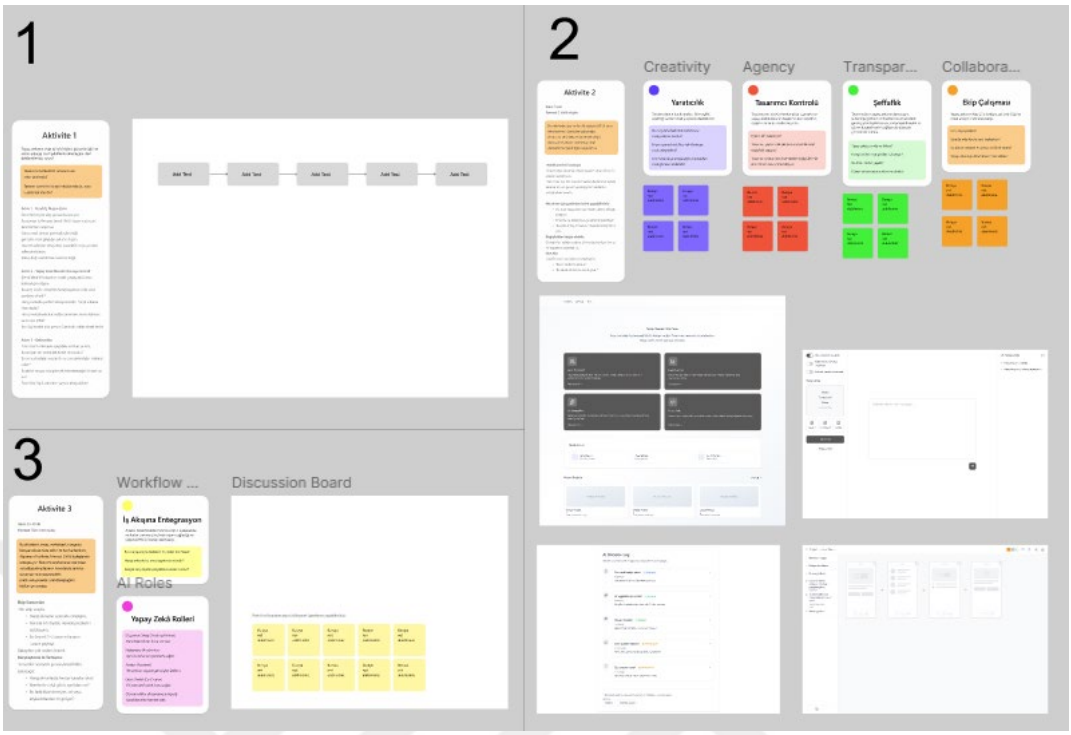


Figure 3.2 Collage of three workshop stages in Figma.

The workshop was planned to be conducted in the Figma environment, and components were prepared in advance for participants to interact with the prototype. Figma was used as a collaborative design tool to allow participants to work simultaneously on the prototype, and Zoom was used to conduct the online session, facilitating interaction between the participants. It also enabled recording of the session. Participants who volunteered were employed to record screen recordings from different groups.

The workshop flow was structured as follows:

Opening and Warm-Up: The purpose of the research, the structure of the session, and the process were reintroduced to the participants followed by introduction of the toolkit (Appendix D). At the start of the workshop Participants were encouraged to reflect on their own professional experiences rather than evaluate a finished product.

Activity 1: Participants were individually asked to roughly map and visualize their current UX/UI design processes. Using these visuals, participants discussed where

an AI Tool specifically designed for UX/UI design support could contribute or create limitations. They were prompted to consider how such a tool could be used within their current workflows, what role they would expect AI to play. Figure 3.3 shows empty state of the Activity 1, while Figure 3.4 shows a completed version of the same activity from P1.

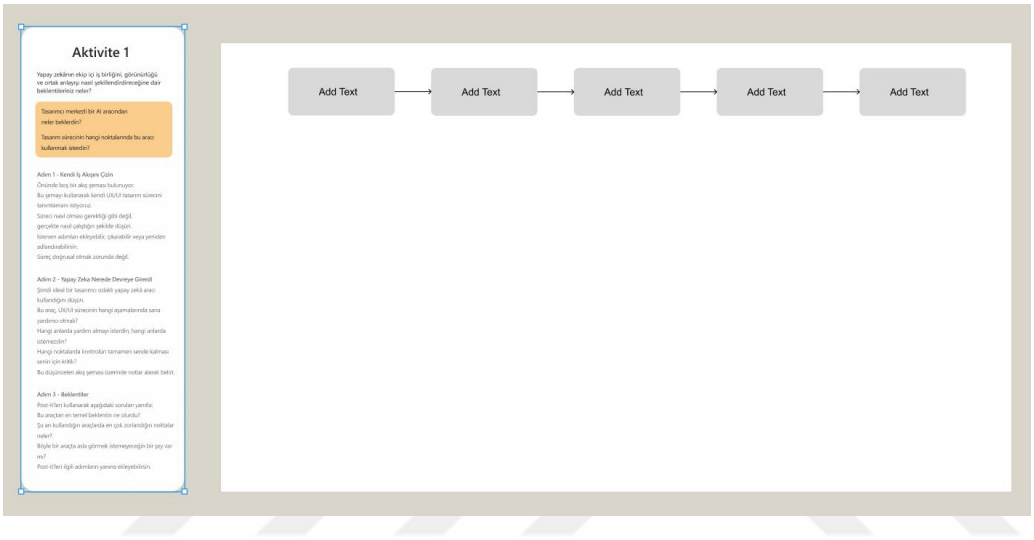


Figure 3.3 Activity introduction card (Appendix D) and empty state of Activity 1.

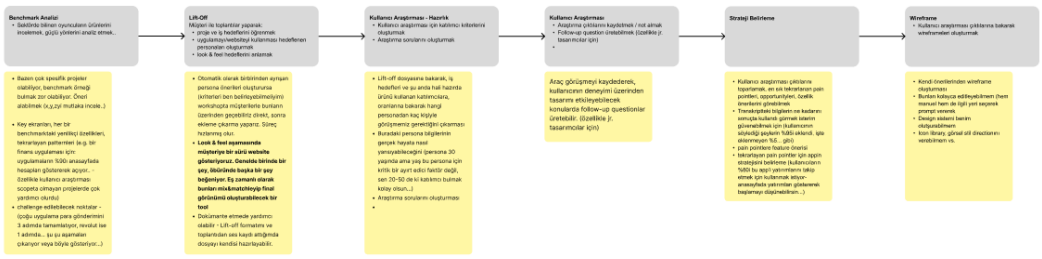


Figure 3.4 P1's completed Activity 1 Board close-up.

Activity 2: The second activity of the workshop was designed based on the preliminary thematic analysis of the interviews, with the aim of encouraging participants to generate concrete design solutions in response to the themes that had emerged. For this stage of the workshop, participants were divided into two groups. Group 1 (P5, P13, P14) and Group 2 (P1, P11) then introduced to low-fidelity

wireframes representing a speculative AI-supported UX/UI design tool. Building on their expectations from Activity 1, groups were asked to propose design changes and interventions to the wireframes. These interventions focused on issues of creativity support, designer agency, transparency and collaboration. Participants were encouraged to annotate the wireframes and explain the rationale behind their decisions. Wireframes for the toolkit Figure 3.5, Figure 3.6, Figure 3.7 and Figure 3.8, followed by completed Activity 2 board from Group 2 (Figure 3.9).

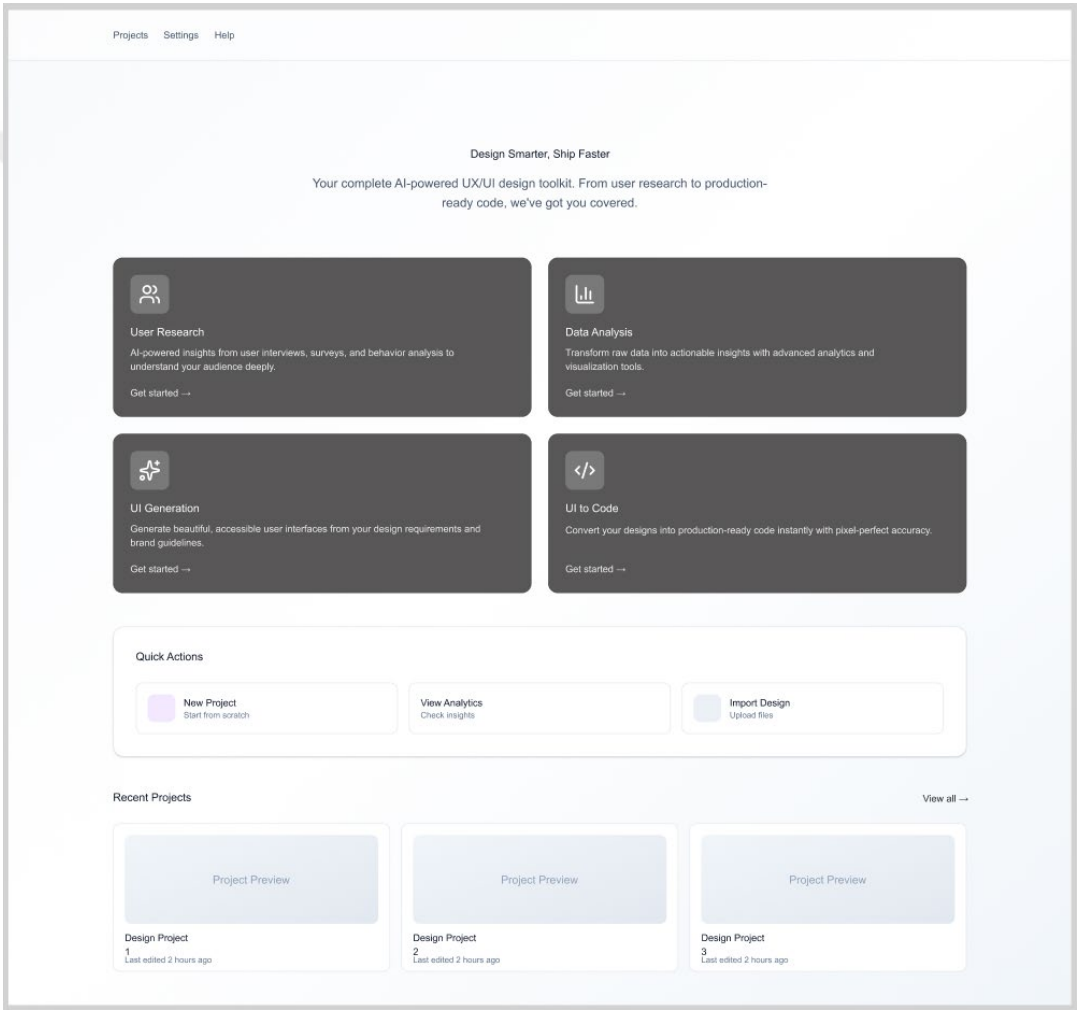


Figure 3.5 Wireframe 1.

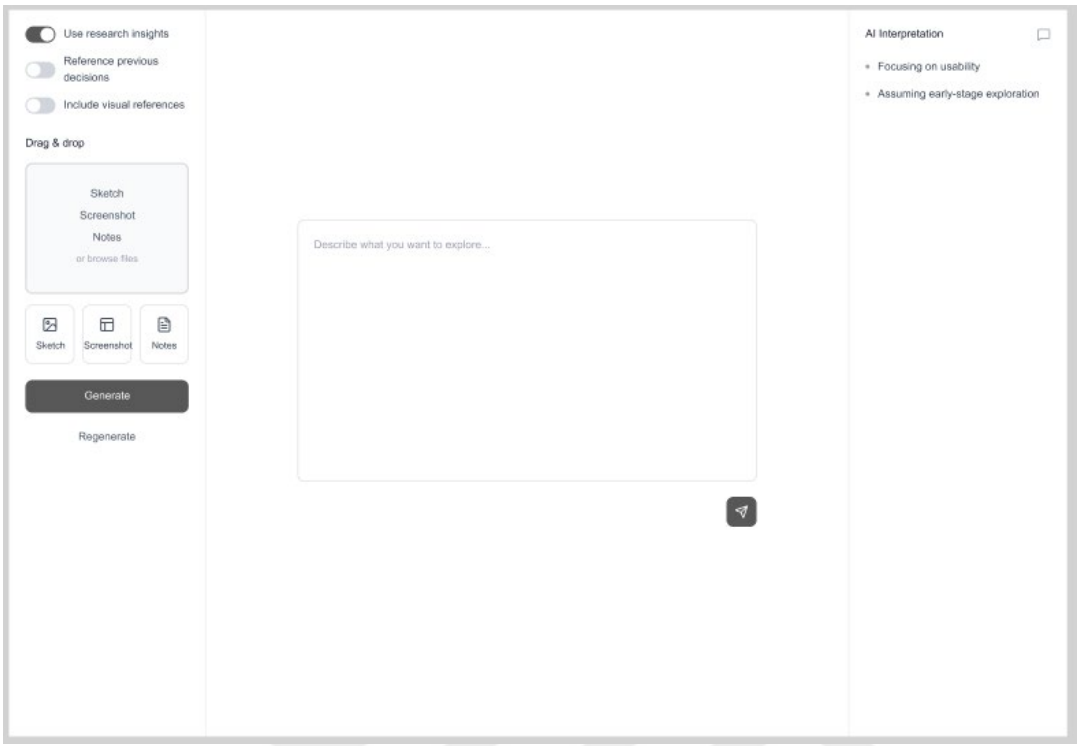


Figure 3.6 Wireframe 2.

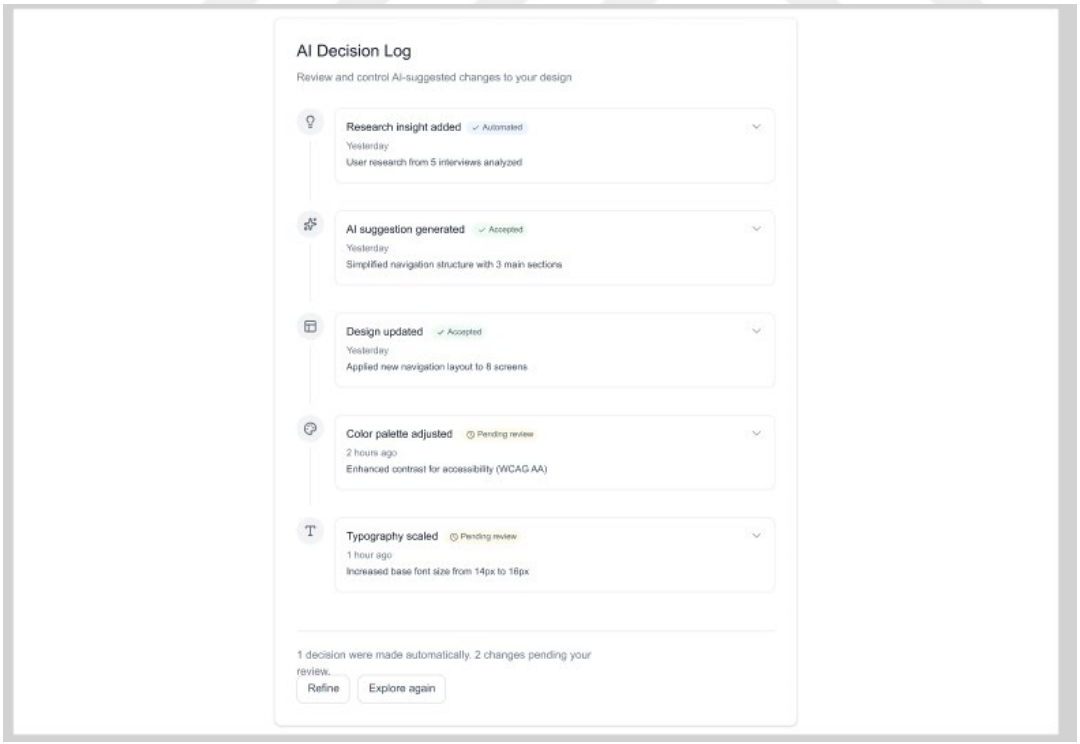


Figure 3.7 Wireframe 3.

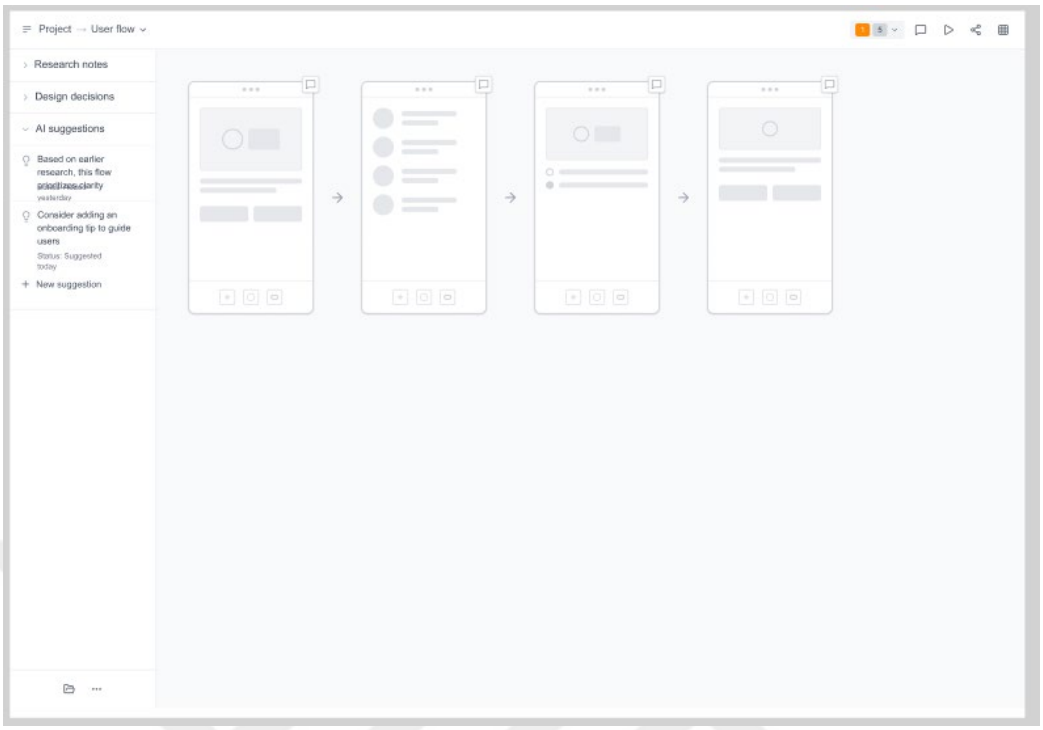


Figure 3.8 Wireframe 4.

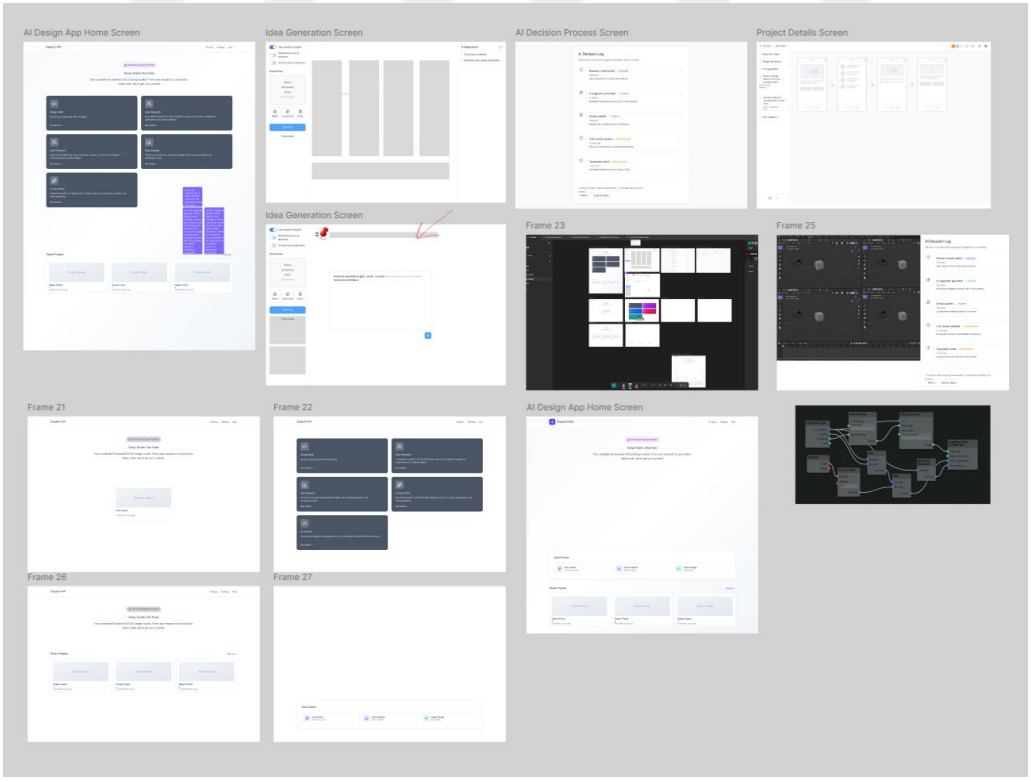


Figure 3.9 Overview of Group 2's completed Activity 2 Board.

More details regarding the toolkit and English translations of the information cards can be seen in Appendix D.

Activity 3: In the final activity, all participants gathered for a group discussion. Each participant briefly presented their proposed changes. The discussion focused on comparing the roles might AI take and examining how the proposed designs could realistically integrate into existing UX/UI workflows. The session concluded with a brief reminder regarding consent for the use of workshop materials (e.g., sketches, notes, and quotations) for research purposes. Participants were thanked for their contributions.

3.5 Affinity Diagram

The outputs of the co-design workshop process were analyzed using the affinity diagram method to support the overall thematic analysis and to examine the emerging patterns regarding designer experiences in a more holistic way. Affinity diagram is a synthesis technique widely used, especially in complex and multi-source datasets, that allows qualitative data to be organized into meaningful groups (Beyer & Holtzblatt, 1998). In design research, affinity mapping is considered an effective tool in collectively interpreting contextually sensitive insights such as user experiences, needs, and tension points (Martin, 2012).

In this study, an affinity diagram was used to examine how themes obtained from semi-structured interviews were re-emerged or reproduced during the workshop. The analysis was performed using the same tool used in the workshop (Figma). Firstly, the workshop outcomes were copied into a separate file. Then notes participants took during the workshop are color coded according to initial themes emerged from analysis of the semi-structured interviews. Following that, transcription of the screen and audio recording of the workshop was completed. Additional vocal comments participants made during the workshop session were noted while simultaneously listening to the audio recording and the screen capture

from the session. The vocal comments participants made then were color coded and added to analysis board (Figure 3.5).

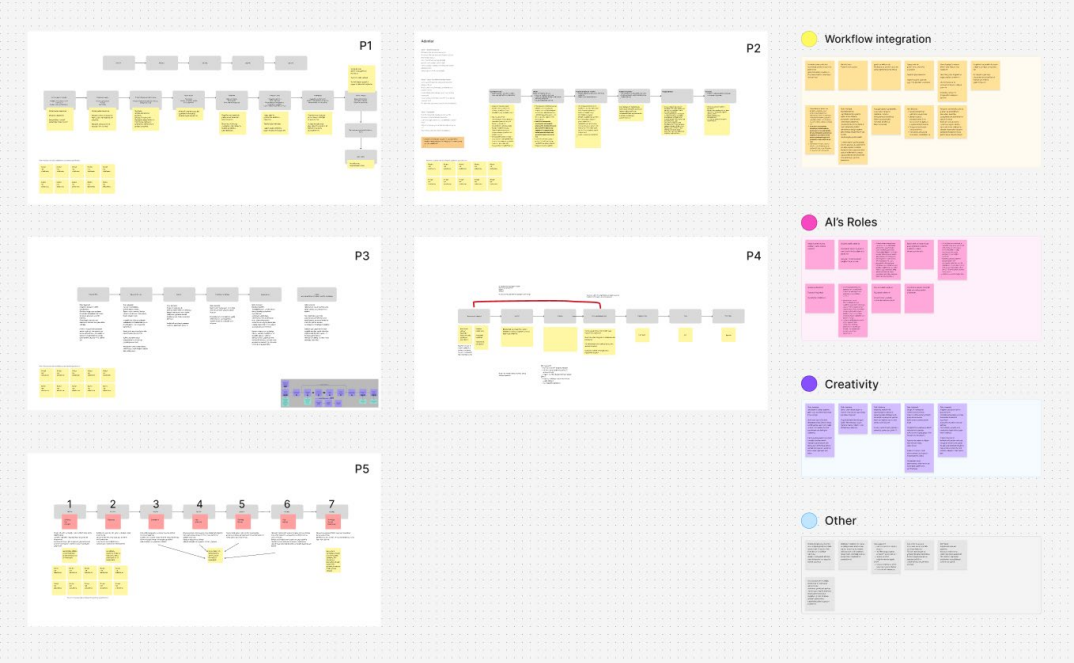


Figure 3.10 Affinity Mapping for Activity 1 of the Co-Design Workshop.

Finally, the grouped data were reviewed to examine how the themes from the interviews were reflected through the workshop outcomes. Therefore, data from the co-design workshop were integrated into the existing thematic structure, providing contextual depth and concrete examples of designers' expectations.

CHAPTER 4

FINDINGS

This section presents the findings resulting from a thematic analysis of a dataset obtained from 12 semi-structured interviews with UX/UI designers and a co-design workshop conducted with 5 participants. The interviews focused on understanding how participants use AI-powered tools in their current UI design processes, the roles they attribute to these tools, the strategies they follow, and their perception of these tools. The co-design workshop was shaped by findings of the interviews and aimed to understand how designers' expectations are expressed in the context of design considerations.

The thematic analysis resulted in the grouping of 4 main dimensions: (1) how designers integrate AI tools into their workflows, (2) perceptions of the capabilities of AI tools, (3) transformation in design processes and roles, and (4) expectations regarding AI-powered design tools. These themes demonstrate that designers' relationship with AI exhibits a structure that varies depending on the context, task, and stage of the process, rather than a singular or fixed use. The findings are structured through sub-themes under each theme. While the first three themes mainly reveal existing usage practices and experiences, the fourth theme covers designers' expectations for AI-assisted design tools and how these expectations were expressed during the workshop process.

The themes and sub-themes emerging from the research are presented in Table 4.1.

Table 4.1 Code Tree of the Study

Theme 1:	**Designers' workflow integration of AI tools**
	Research Support
	Data Analysis
	Idea Generation
	UI & Visual Asset Generation
	Prototyping
Theme 2:	**Transformation of designer's process**
	Efficiency
	Improving Communication
	Expanding Skillset
Theme 3:	**Designer's perceptions of AI tools capacity**
	Strengths
	Improving Constantly
	Lovering Barries
	Reducing Cognitive Load & Uncertainty
	Limitations & risks
	Diminishing Returns
	Ecosystem Overload
	Fixation
	Roles
	Assistant
	Co-worker
	Tool

Table 4.1 (Cont'd)

Theme 4:	**Designer's expectations from AI tools**
	Expectations Based on AI Models Capacity
	Context Awareness & Better Reasoning
	Creativity
	Expectations Based on AI Tools Design & Features
	Designer Agency & Control
	Explainability & Reliability
	Workflow integration

The semi-structured interviews conducted in this study were carried out in Turkish. The participant quotations included in the findings section were translated into English by the researcher to ensure consistency in the analysis and presentation process. During the translation process, care was taken to preserve the semantic integrity and contextual content of the participant statements. The original Turkish versions of the quotations are presented under Appendix E.

4.1 Designers' Workflow Integration of Generative AI Tools

This theme reveals how UX/UI designers integrate AI-powered tools into their design workflows. Findings show that AI tools are included selectively in specific stages and for specific purposes, rather than as an end-to-end solution in the design process. Instead of continuously using AI at every point in the process, designers tend to use it when needed. Designers shape their usage according to the nature of the task and the stage of the process. It has been observed that AI integration is frequently used in tasks such as research support, data analysis, ideation support, UI and asset generation and Prototyping stages of the UX/UI design process.

However, it is observed that designers do not prefer to leave the final design decisions to AI. The subtopics presented within this theme demonstrate how designers position AI tools in their UX/UI design process.

4.1.1 Research Support

The research phase refers to the early stage of the design process, focusing on understanding the problem domain, identifying user needs, and collecting data to inform design decisions. Research-oriented use stands out as the area where AI tools were first incorporated into the design process. Findings show that designers use AI specifically for preparing and structuring the research process. For example, P6 states that they received support from AI for methodological guidance before starting the research process, they mentioned asking ChatGPT *"Which research-oriented method do you recommend, what are the advantages and disadvantages of this one, etc*.?" (P6.1)

Creating user interview questions is another research step where AI use is preferred. Participants state that they use AI tools to review question sets, identify potential gaps, and expand the scope of the research:

"We start with user interviews at the very beginning of a project. We start with preparing questions for the user interview, that is, this first stage, and then after conducting the user interviews, I also use tools for transcripts." (P5.1)

Another area of AI use observed in the research phase was persona creation. Participants stated that they used AI to simulate specific user profiles and test prepared research questions before sharing them with real users:

"Or, for example, I create a specific profile in ChatGPT, saying, 'You are in this persona, if I give you this question, what would you think or how would you feel?' I was doing a test there before directly testing with users." (P2.1)

P2's statement demonstrates the use of AI in both persona creation and identifying potential gaps in the research process. On the other hand, it was observed that the uses for persona creation and user simulation went beyond ready-made AI tools for some participants, progressing through customized solutions. One participant, while discussing their corporate experience and working with the same fixed personas, described the AI integration in this process as follows:

"We have 3 personas, so we taught them (to AI)*, by the way, we created a custom GPT… and transformed them into the persona we created. They speak exactly like that. For example, one of them is named Mehmet."* (P9.1)

This usage pattern shows that AI is positioned not only as a ready-made support tool in the research process, but also as a structure shaped according to the research framework defined by the designer.

4.1.2 Data Analysis

Data analysis describes the process of structuring, classifying, and interpreting qualitative and quantitative data obtained during the research process. The findings demonstrate how AI tools are used in the data analysis phase. AI intervenes in this phase to summarize the obtained data, extract themes, and make complex information sets more manageable:

"At that point, it can classify the UX data within itself, analyze the data, and then interpret and compare this data with current existing sources…" (P1.1)

Participant statements show that AI plays an effective role, especially in the process of identifying pain points and user expectations. AI contributes to the creation of structures similar to customer journey maps based on user data, and allows analysis outputs to be visualized and discussed much faster.
One participant stated that AI can make experiential problems and expectations spread across different steps of the user journey visible within a holistic structure: *"It did this very well, or like language learners, different pain points and*

expectations at different steps, etc. It extracted many things in the form of a customer journey map." (P8.1) And another participant emphasized the value of similar analysis outputs in terms of time saving; especially when dealing with large and complex datasets, AI significantly speeds up manual analysis processes: *"...like extracting problematic pain points from large Excel files in seconds."* (P11.1)

4.1.3 Idea Generation

Ideation refers to the creative stage where possible solutions to the problem area are generated, ideas are diversified, and different design alternatives are explored. The findings show that AI tools are primarily used for diversification and expansion purposes in the idea generation process. Participants define AI not as a system that completely takes over idea generation, but as a support mechanism that multiplies existing ideas, offers alternatives, and opens up thinking in different directions. For example, P10 expressed this situation as, *"It's brainstorming with me now. It can even talk about the topic. These advanced features are really saving my life now."* (P10.1).

The use of AI comes into play especially when designers feel stuck at a certain point or when the process is not progressing. This effect is clearly observed in P6's statement; *"Apparently, as I said before, I don't like being faced with that blank white page. I'm not saying this in a UX sense, by the way, I'm saying it in a UI sense."* (P6.2).

In this context, AI helps the designer question their own thought framework and evaluate different possibilities by offering new perspectives. However, participants stated that ideas from AI were not directly adopted but rather treated as variations added to existing ideas. This finding is supported by the parallel statements of P3 and P7:

> *"So there's a very interesting toolbox, and you're imagining something in your head, like, 'If there was a graph like this, I could explain it really well,'*

or 'If there was a style like this, I could come up with something like this,' or you're brainstorming with AI, for example, briefly. I ask What could it be like? I have this idea in my head; I want to explain it. What kind of things would you suggest? And from that brainstorming it immediately suggests, for example, 5 things, 3 of which are garbage. I understand that they are garbage, like, this is really garbage.' But one of them, for example, seems really interesting. I take that interesting thing and improve it myself." (P3.1)

Similarly, P7 described its process as follows:

"Here, my friend (referring to AI), this is what the user needs, here are my components. And I get alternative designs from them (AI tools). From these alternative designs, I take the best one, like feature B from design A, or feature D, from design C. I mix them in this way until I reach a final conclusion." (P7.1)

These findings demonstrate a clear distinction between divergent support and creative ownership in the idea generation process. While AI is considered a tool that expands the idea space, the selection, combination, and determination of the final direction of ideas remain the designer's responsibility.

4.1.4 UI and Visual Asset Generation

UI generation encompasses the stage where design ideas are transformed into tangible visual outputs and interface components are produced. The sub-themes in this section involve creating elements such as individual screen designs, visual assets, and interface text. The findings show that AI tools are used extensively in the UI design process, particularly in the visual asset production and editing stages. Participants stated that they use AI for the rapid production of visual content, the transformation of existing visuals, and the faster preparation of interface components. This usage focuses on reducing manual processes in UI production and achieving faster output. One participant noted that AI can be used effectively,

especially in the context of UX writing and interface texts, but this text output is edited according to the designer's knowledge of the product language: *“For example, in UX writing, the things written by ChatGPT are very good, and since I already know the product language, I can edit it accordingly.”* (P12.1)
In the context of visual production, it is emphasized that AI plays a significant role in art asset production and visual editing processes. P11 stated that the area where AI currently contributes the most is visual asset production, saying, *"But I can say that what is particularly useful to us right now is visual asset production."* (P11.2) Similarly, P5 stated that they use AI for” image generation” and “visual editing”, and that modifying existing visuals is particularly beneficial in the UI process. The visual outputs generated by AI are mostly edited and finalized by the participants rather than being used directly. P2's statement, *"If the output satisfies me, I'll take it and use it, or I'll just go over it a little more in Photoshop..."* (P2.2), supports the idea that the output is used if it is deemed sufficient, but often additional edits are made. These findings, specifically shared regarding UI screen and visual asset production, also parallel the participants' strategies for using AI in the idea generation phase.

4.1.5 Prototyping

Prototyping refers to the stage where interactive or static representations of the generated interfaces are created, making the design's functionality testable. This stage makes it possible to share the design with users and stakeholders and receive feedback. The findings show that while AI is a tool that supports idea generation in the early stages, it is also used in visualizing interfaces and wireframes, creating rapid prototypes, and directly converting design decisions into testable outputs.

In the prototyping phase, the speed factor has been observed as one of the biggest factors increasing the use of AI. This can be seen in P5's statement: "*So it allows me to quickly get it into a presentable format and quickly interact with the user, or the customer."* adding, *"This also makes it easier to get feedback and move it back to the*

design." (P5.2) The same situation is clearly observed in another statement, *"I need to prepare things very quickly, otherwise the process takes too long. I need to quickly prepare a flowchart and discuss things like, 'Is this how you want it? Should it be this here or that there?' (referring to stakeholder communication). I use it (AI) especially there."* (P12.2). The emphasis on speed in these statements is also discussed separately under the section 4.2.1 Efficiency.

The findings show that the use of AI in this process goes a step further, with designers also utilizing AI in the development phase of the UX/UI process:

> *"Beyond prototypes, sometimes you need to change the product itself immediately, or some things are very complex, requiring engineering and expertise, but as a designer, you pay attention to different things, or you might say, 'Why are these buttons like this, why is this thing like that?' Normally, in a large company, you would have to talk to the engineers and convince them that solving this is important. In my current role, for example, I can do it directly with AI-powered code editors like Cursor or Claude without needing to do that much. I can do it myself. That's a huge thing, a very different way of working."* (P4.1)

The ways in which the use of AI changes design processes and the skills it provides to designers are discussed under Section *4.2. Transformation of Designers' Process.*

Furthermore, the findings show that AI integration does not always arise as a voluntary or curiosity-driven choice. Contextual constraints such as time pressure, vague job descriptions, missing references, and projects with limited domain knowledge play a decisive role in designers turning to AI tools:

> *"But if I have very limited time, and it's difficult for me, and I need to produce something quickly, I can still use one of these AI wireframing tools or ask ChatGPT what this screen will look like. I can use it to quickly understand what I'm doing."* (P12.3).

In this context, the use of AI emerges as a practical strategy for dealing with uncertainties encountered in the design process.

Participants consider these AI-generated outputs as drafts or starting points in most processes. The visual or textual suggestions offered by AI serve as a reference for the designer to shape their own decisions; however, final design decisions are made manually. *"I usually use it in UX research, but it's dangerous; it can lie. It can hallucinate. So, I don't use what I get from there as an as-is."* (P7.2).

The use of AI in UI generation and rapid prototyping reflects trends identified in literature (Chen et al., 2025; Takaffoli et al., 2024). In this study similar to the literature findings, participants emphasized speed, visual fidelity, and improved stakeholder communication as key benefits of AI-assisted prototyping.

However, this study also reveals the blurring of boundaries between design and development. The participants reported using AI-powered code editors to directly modify product behavior. While agentic futures have been discussed in prior studies (Wadinambiarachchi et al., 2025), this research provides empirical evidence that such role shifts are already occurring in practice, reshaping designers' workflows.

The Agency theme, which explores designers' control over the design decisions during the use of AI in the UX/UI design process, is presented in detail in Section 4.4.2 Expectations Based on AI Tools' Design & Features

4.2 Transformation of Designers' Process

This theme describes changes in designers' processes and roles. The findings show that this transformation builds upon and expands existing practices. Designers state that they have gained new responsibilities and competencies with AI integration. Under this theme, the expanding skill sets of designers, their perceptions of speed and efficiency in the work process, and changes in their professional roles have been observed.

4.2.1 Efficiency

The findings show that AI tools have created a significant transformation in designers' work processes, particularly in terms of speed and efficiency. Participants state that thanks to AI, tasks that previously required multiple people or longer time periods can now be completed by a single designer in a shorter time. One participant states that a fast process that previously required two or three people can now be managed by a single designer. This acceleration affects the output's production time and the overall flow of the process. Participants emphasize that AI-powered tools provide significant time savings in various stages, from idea generation and visualization to connecting flows and creating alternatives. The ability to automatically establish fundamental connections (for wireframes and prototypes), even in complex flows, reduces the need for manual intervention and speeds up the process: *"I still have to manually make the transitions between those flows, but the fact that it can connect even those ten things saves an incredible amount of time."* (P5.3)

However, participants also point out that speed is not always seen as an advantage. The need to validate and evaluate AI outputs necessitates the designer's active involvement in the process. Participants emphasize that while the speed offered by AI is valuable, speed doesn't always go hand in hand with reliability and quality: *"I don't put my signature on any AI output… of course, it saves time, you can do it faster, but speed isn't always our friend."* (P8.2).

Some participants state that the use of AI makes it possible to complete tasks that could take weeks in days or even hours. This time saving allows designers to produce faster and to create more space to evaluate and discuss the resulting outputs. In this context, speed is defined as an increase in the pace of production, the increased frequency of decision-making, and feedback cycles at different stages of the design process:

> *"With AI prototyping, you can convey very specific concepts very well to the other party, whether they are a developer, a product manager, or a stakeholder. For example, you might be giving a presentation to a CTO or CEO. Instead of showing them a Figma screen or spending hours creating a Figma prototype, you can now create prototypes that truly feel and look like the real product in a very short time."* (P3.2)

Participants frequently mentioned that these tools shaped the process in terms of communication within the team and with users. For example: *"The goal there is to solve the problem faster, to solve it without errors, to learn faster, and usually to get the job done faster. The faster you get the worker done, the more time you have to discuss."* (P7.3). This theme is detailed in following section.

The emphasis on speed and efficiency aligns strongly with prior literature, which frames AI as a productivity-enhancing technology (Bertão & Joo, 2021; Takaffoli et al., 2024). Participants confirmed that AI compresses production cycles and accelerates feedback loops, particularly in prototyping and visualization.

4.2.2 Improving Communication

The findings show that AI-powered tools are transforming designers' communication practices in two ways. First, designers are able to communicate more effectively with different stakeholders by acquiring new skills or expanding existing ones. While a detailed description of the nature of these skills is addressed in the next theme, this theme examines the dimensions of this communication. Second, communication is observed to be more intense and frequent in terms of time due to the acceleration of production and feedback cycles.

For example, P3 mentioned that among product teams, not only UX/UI designers but members of the other departments as well can use AI tools to create UI prototypes, stating, *"I think the most useful aspect of these AI tools for me at this stage is communication. They have greatly enhanced communication. Everyone can now*

express their thoughts much better, or at least try to." (P3.3), and this helps enormously with team communication. Similarly, P8 states that this transformation strengthens the designer's communication with different stakeholders: *"I think I can communicate better with programmers."* (P8.3). When these two statements are read together, it becomes clear that the impact of AI on communication is both related to "understanding" the ideas of different team members and "designers expressing themselves better". Thus, P12 states: "*Showing a prototype is always advantageous because it's more difficult to explain the flow verbally."* (P12.4). These findings reveal that AI integration affects design production and communication.

4.2.3 Expanding Skillsets

The findings show that the use of AI-powered tools expands designers' skill sets through new competencies. Participants state that they have had to develop new types of skills with the use of AI. Across the interviews, designers repeatedly describe AI as lowering the barrier to engaging with code. While participants do not position themselves as becoming full-fledged developers, they emphasize gaining functional coding literacy: *"You can try out some things without going to a programmer."* (P9.2), *"I can now touch everything from the backend to the database; I didn't know how to code before, but now I understand what's possible."* (P7.4). This shift allows designers to move from conceptual design to developed product, expanding their role within product development processes.

Another prominent skill expansion relates to AI literacy, particularly understanding how different models and tools behave, how prompts should be structured, and how outputs should be evaluated. Key skills include prompt creation and improvement, the ability to use multiple AI tools together for different purposes and recognizing the limitations of the tools. Participants state that different tools do not respond similarly to the same inputs, and effective use requires knowing how each tool responds to different levels of detail. This reveals that working with AI involves a

learning process that develops through trial and error. Participants also emphasize that writing prompts is a practice that develops over time rather than a fixed technique:

> *“I see it as a new skill set, a kind of profession, but of course, you shouldn't stick to it. Because prompt engineering isn't just about writing, or expressing yourself, or conveying what you have in mind in a better way, in a way that the computer can understand. Once you grasp that point, I think there's nothing beyond that."* (P2.3)

The repeated editing, improvement, and strategic structuring of prompts directly affect the quality of the output from AI. This is evident in P12's statement: *"Being able to write really good prompts is something that improves with practice*." (P12.5) It is also evident that designers are aware of this skillset expansion and actively improving themselves and developing new strategies: “*It's like I'm really training myself while training it [AI]. What did I write the right prompt for? What kind of prompt templates do I have? Maybe I could create a prompt list archive of things I use frequently."* (P6.3)

Instead of using just one tool, the designers stated that they orchestrate the process by engaging different AI tools at different stages. This shows that the use of AI has become a practice requiring coordination between tools rather than a singular competency:

> *“It’s also necessary to know which tool responds to how and with what prompts. Because we also noticed something while experimenting. While some tools produce excellent results even with a very simple prompt, others require very detailed ones. How should each tool be used? That requires a certain level of knowledge.”* (P12.6)

Furthermore, the findings show that designers have gained the capacity to develop tools tailored to both their own and customer needs. Participants state that they can develop additional small-scale software solutions for their customers, with AI-

supported approaches, especially for problems that seem difficult or excessively costly to solve within existing products:

> *"So, we are now making products with AI tools, for example. There are internal tools or external tools, for instance, there is a very specific problem, let's say a customer has a problem in a project. It will be very difficult for us to solve it within the main product, or it will be a very problematic thing, but you can design a mini software for that use, a very small software, and a designer can now do this."* (P3.4)

This expansion of skills is not limited to these products. Some participants state that they have developed tools that play an active role in design processes by training and customizing AI. For example, modeling personas representing different user profiles through AI and interacting with these personas is described as a new approach to *"testing design decisions"* (P9.3). Such tools allow designers to handle hypothetical user scenarios in a more dynamic and interactive way. Similarly, participants reported that the use cases of AI-powered tools developed within the team have diversified:

> *"One person developed a tool for this persona, where you can both generate a persona and talk to it when you add the generated persona; another developed a Figma plugin that, when you give them the screen, is quite like a usability test, dealing with accessibility and everything else. Those who are interested and enthusiastic to try it can do great things with it."* (P12.7)

These findings reveal that AI is becoming an infrastructure that enables the creation of tools that they can integrate into their own processes.

4.3 Designers' Perceptions of AI Tools' Capacity

This theme explores how designers interpret artificial intelligence tools, focusing on their cognitive and emotional evaluations of AI Tools' capacity. The findings show

that designers perceive AI as a tool that exhibits variable performance depending on the context, task, and their own level of expertise.

4.3.1 Perceived Strengths

The findings show that designers primarily perceive AI tools as strong in aspects grouped under the sub-themes of Lowering Barriers, Improving Constantly, and Reducing Cognitive Load. Participants state that AI tools can provide support quickly and flexibly in a variety of design tasks. This support the process more manageable, especially in contexts where time pressure is high or quick decisions are required.

Lowering Barriers

Participants stated that many tasks that otherwise required extensive technical knowledge, experience, or other expertise have become achievable with AI support. This allows designers to access information from different disciplines more easily, without being limited to their own areas of expertise.

Participant statements reveal that AI tools serve a supportive function, especially in accessing non-field-specific information, translating between technical languages, and understanding complex processes. For example, designers with limited coding knowledge stated that they were able to create prototypes, understand existing codebases, or more directly translate design decisions into the product through AI. For example, P4 expressed this situation as, *"I don't know much about coding but these tools actually democratize that situation."*(P4.2) In addition, P3 interpreted this as a regained control point stating: *“I honestly see this as a bit more about the designer taking back what was originally their responsibility, and the areas that the designer really needed to own are now becoming things that the designer can control more easily.”* (P3.5)

A particularly noteworthy finding is that AI tools reduce designers' dependence on others. Participants emphasize that processes that previously required high costs or

long turnaround times for validation, learning, or testing purposes can now be managed individually with AI support: *"If you want to validate something, if you want to understand something, you can do it yourself without paying hundreds of thousands of dollars. That's a good option."* (P8.4)

In this context, AI is positioned as a tool that expands access to new domains and enables the designer to take stronger ownership of their own field. Participants frequently associate this situation with expressions such as *"being able to do more," "expanding the area of control,"* and *"being able to implement design decisions more directly."*

Reducing Cognitive Load & Uncertainity

The findings show that AI-powered tools reduce the cognitive and decision-making burden for designers. Participants stated that the uncertainties encountered in the initial stages of their design process were reduced thanks to the outputs provided by the AI. P6 explains this situation as:

> *"Initially, when I don't know, or rather, when I'm still making decisions with a blank page in front of me, the design process is more difficult for me. Making the decision, after it generates something [referring to AI outputs], then adding those subtle finishing touches and detailing it, that's what I enjoy more."* (P6.4)

Participant narratives show that in some cases, AI indirectly supports the creative process, particularly through visualization and the opportunity to experiment with existing ideas in alternative ways. Yet, P7 distinguishes the impact of AI on productivity rather than creativity as follows: *"It positively affects my creative processes, but it increases my productivity more in my UX processes."* (P7.5)

Furthermore, participants state that being able to quickly conduct simple experiments thanks to AI both shortens decision-making time and reduces inter-team dependency:

> *"But one thing that happened was, as designers, we were able to experiment with simple things without needing developers, at least. It gave us a chance to develop our ideas quickly and take a look. Of course, this didn't completely replace our relationship with programmers. But perhaps our waiting times decreased."* (P12.8)

In this context, it has been observed that AI tools reduce uncertainty, facilitate decision-making, and make the process more fluid.

Improving Constantly

The findings show a strong perception among designers that AI tools have significantly improved and evolved over time. Participants stated that the consistency of outputs, ease of use, and the way they respond to prompts are more advanced compared to previous periods. This development has created a common opinion that AI tools have undergone a significant transformation in a short time.

Some participants noted that in their early experiences, AI tools relied on more limited datasets and mostly produced similar visual outputs. P1 expressed this situation as follows:*"When I first used it, it generated visuals very similar to the designs of certain designers […] from a very limited database."* (P1.2). However, the same participant emphasized that in the current situation, the responses of AI tools to prompts have become more "subjective" and their interpretation capacity has increased:*"But now, the AI's thinking ability has changed a bit; for example, its ability to interpret based on the prompts you give it has become more advanced."* (P1.3). Similarly, P2 notes that they observed the productivity potential of AI tools increasing over time, and that this development created a process that forced the designer to improve themselves: *"I had the chance to observe that the potential of AI is high. […] As AI improved itself, I also had to improve myself in order to achieve better results."* (P2.4)

Participant narratives also reveal that this development occurred in relatively short time frames: *"It wasn't so simple back then, and when I say back then I'm talking*

about ten months ago." (P8.5) However, an important finding is that this perceived improvement does not automatically translate into *trust*. Participants acknowledge that AI tools are improving; however, they specifically emphasize that this improvement does not mean delegating design decisions or leaving the process entirely to AI.

4.3.2 Perceived Limitations and Risks

Previous findings showed that designers perceived AI tools as powerful and supportive in terms of accessibility, speed, and reduced cognitive load. However, the findings reveal that perceptions of AI use are not one-sided; designers also attribute certain limitations and risks to these tools.

Participants indicated that if AI tools are mispositioned or used inappropriately, they can restrict creative thinking and create additional workload instead of supporting the design process. In addition, the reliability of the outputs was one of the most frequently recurring issues.

Fixation

Youmans and Arciszewski (2014) define design fixation as the tendency of designers to restrict their creative outcomes by relying too heavily on prior designs or on familiar knowledge structures associated with a given problem. Results from earlier studies point to a relationship between generative AI support and elevated design fixation, highlighting a potential unintended consequence of AI-assisted design (Wadinambiarachchi et al., 2024).

Consistent with these findings, the results of this study indicate that designers are aware of the risk of design fixation, particularly in relation to AI tools that predominantly generate outputs based on existing patterns and prior productions. *P1 expresses the impact of this situation on their own process as follows:*

> *"When I get to that part, that is, the design part, the things it offers me are already existing things, as I said, so it actually pushes me towards a certain point and restricts my consciousness towards things that already exist. At this point, it negatively affects my creative process."* (P1.4)

This perception aligns with concerns that the presence of AI outputs could push the designer's own original thought process into the background. P2 emphasizes that the presence of an output offered by AI does not automatically guarantee the designer's subjective contribution: *"There is an output, but when you ask whether you created the output with your own free will, with your own idea, that space remains empty."* (P2.5). He/she adds that skipping the research and problem definition stages and going directly to design leads to the formation of an early and fixed framework in the designer's mind: *"Someone who skips the design directly… now the things about the design that form in their mind are clouding their mind, I think they can't get out of that point."*

As observed in this statement, incorporating AI outputs early in the process risks forcing the designer into convergence before adequately exploring the problem area. P4 states that evaluating the outputs offered by AI contains both opportunities and risks; specifically pointing out that if these outputs are relied upon excessively, alternatives may be overlooked:

> *"So, being able to see whether a new design [in this case, they are mentioning an AI-generated UI screen] fits with the existing product, to what extent it fits, or to what extent it doesn't, is both a good thing and a bad thing. The good part is that it's really convincing, quite real, and works. The bad part is that if you believe in it too much, you miss out on other possibilities. You miss out on alternative futures. That's why, at the very beginning, you should at least think about how it should be, how it should be done, even if it's something very simple at first, like a quick exploration in Figma, that's why it's important to do it."* (P4.3).

Finally, P11 emphasizes that the risk of fixation may stem not entirely from the tool, but also from the designer's own approach: *“You might see something you didn't have in mind and like it, which can restrict you… but this actually depends on the designer's own vision.”* (P11.3) Indicating that AI's ability to produce powerful and persuasive outputs in the design process, when used without appropriate boundaries and awareness, can have a restrictive effect on creative thinking.

Trust Issues

The findings show that AI-powered tools are cautiously evaluated in terms of output reliability during the design process. Participants state that the content provided by AI is not used "as-is," especially in stages requiring research and knowledge production; the risk of producing erroneous, incomplete, or fabricated information (hallucinations) significantly limits trust in these tools. One participant expresses that it is not possible to blindly trust AI when requesting information as follows:

> *"If I ask ChatGPT to give me information content, I shouldn't blindly trust it, of course. Because they themselves write warnings like 'don't trust it'... the information it gives is often just guesswork, or the links and information it provides are cut and combined from different places."* (P7.6).

Similarly, another participant emphasizes that AI tools sometimes refer to non-existent sources, making the need for verification necessary*: "If you're not using deep search, it finds non-existent sources. So I have to go and confirm it."* (P10.2). These kinds of experiences reveal that the use of AI creates an additional validation step for designers. Participants state that AI outputs need to be supported by other tools, checked from different sources, or manually confirmed; this process creates additional work (see next section; Diminishing returns) requiring time and attention. This case shows that AI does not always provide increased efficiency and can make the process more complex depending on the context. Participants also emphasize that uncertainties regarding the usage practices and data collection policies of AI tools deepen the trust issue. One participant expressed their discomfort with the tendency of AI systems to use user input for training purposes by default as follows:

> *"The 'train with AI' button came selected when they [participant refers here to a UI design app they use] pushed the AI update. It's as if they're politely asking if we should train the next ones since we've already trained the ones before. I don't trust any of them in that regard. At the end of the day, I don't want to give them know-how."* (P7.8)

This statement shows that the issue of trust is not limited only to the accuracy of the output; it also includes ethical and strategic concerns related to the transfer of the knowledge, experience, and corporate expertise produced by the designer to AI systems. Multiple participants, therefore, stated that they prefer to run AI tools in a local environment rather than on online platforms. This approach reveals that trust issues arising from the use of AI are leading designers to develop alternative usage strategies.

Designers' lack of trust in AI aligns with widespread concerns about hallucinations and unreliable sources reported before (Uusitalo et al., 2024; Zhu et al., 2024). Similar to prior findings from literature, the participants emphasized verification and cross-checking as necessary steps in AI-facilitated workflows, particularly in research-intensive tasks.

The participants also framed explainability (see Explainability & Reliability under 4.4.2 Expectations Based on AI Tools' Design & Features) as a dimension contributing to the sense of trust. They did not expect perfect accuracy from AI tools; instead, they wanted visibility into how outputs were generated and why certain suggestions were made.

Diminishing Returns

The findings show that AI-powered tools do not increase productivity in every use case; in some cases, the benefit decreases and can even slow down the process. Participants state that the use of AI becomes a waste of time. Instead of producing added value, especially when the variety of outputs is limited or in situations that can be quickly resolved by the designer, it slows down the process.

P5 explains this situation through the example of getting generic results in UI generation:

> *"For example, I try it a few times. If the result it gives is completely different, or it looks the same as what it normally gives to banking [while prompted for retail screens], I think, 'Okay, instead of wasting time here, and it takes minutes to generate it anyway, I should have just looked at the benchmark and done it myself.'"* (P5.4)

Such situations sometimes create frustration in the designer: "*When that happens, why am I even using it?" "It makes you think, 'I'm wasting my money on this.'"* (P10.3)

The findings reveal that the use of AI is evaluated not only in terms of output quality but also in terms of factors such as waiting time, response time, and contextual appropriateness of the output.

Ecosystem Overload

Participants stated that the rapid expansion of the AI tool ecosystem has, over time, ceased to be supportive and instead created a cognitive and operational burden. The need to keep up with, learn, and integrate new tools into existing workflows is becoming unsustainable for some designers: *"I don't have the energy to go and use another AI tool right now. I don't have the energy to learn it."* (P8.6)

This narrative shows that the proliferation of AI tools doesn't always mean more possibilities; on the contrary, it forces designers to be selective. Similarly, P9 expressed the feeling of fragmentation created by the variety of tools on the market as follows:

> *"One says Lovable, one says Bolt, one says Figma Make… They all can do different things, and they all can't do other things. There's nothing single and sustainable, nothing you can say 'whenever I write this, I get the same result,' and that's very annoying. [...] I want to try the same prompt with all 4-5 tools in my inventory, and that's tiring me out"* (P9.4).

As seen in this statement, participants emphasize that while the fact that tools have different capabilities theoretically offers richness, in practice, it leads to a lack of consistency and repeatability.

One participant stated that although following these tools is challenging, it also creates an expectation for future developments: *"Following new ones is a bit tiring and impossible, but… it's also great to see how they evolve, how they change."* (P12.9)

4.3.3 Role Attribution to AI Tools

The findings show that designers understand AI tools not through a singular and fixed role, but through roles that vary depending on the context, the nature of the task, and their own expertise limits. When asked how they position AI tools in workflows, it reveals that AI is sometimes positioned as a simple tool, sometimes as an assistant or colleague. The role attribution identified in this study closely parallels findings from Khan et al. (2025) and Tholander & Jonsson (2023), who note that designers switch between viewing AI as a tool, collaborator, or conversational partner. Hovewer, it has been observed that the roles designers attribute to AI can be viewed through perceptions of trust and agency (see section 4.4.2 Expectations Based on AI Tools Design & Features). The findings show that perceptions and user experience characteristics of AI tools can also change depending on the role in which AI is positioned. While some examples define AI as a "tool" and others as an "assistant," the differences between these labels do not always correspond directly to practical usage patterns. Furthermore, when asked how they regard ai's role, different role definitions can sometimes be attributed to similar work and permissions.

Tool

For some participants, AI is not primarily an actor that directly shapes the design process, it is seen as a technical tool that facilitates the designer's production. In this

approach, AI serves to help the designer implement their decisions faster and effortlessly, rather than influencing design decisions. P1 explicitly states this situation as follows: *"So, I think it's more positive if it's not just for design purposes, but a tool that makes it easier for the designer to do this work."* (P1.5). In this positioning, AI intervenes in the parts of the design process that are defined as "menial," requiring time and physical effort; however, it does not assume a creative guidance role: *"I use it more in the menial part of the visualization process […] it's not a partner for me."* (P1.6)

Assistant

One of the most commonly attributed roles of AI is assistantship. In this role, AI is positioned as a support element that speeds up the process by taking over repetitive or operational tasks that the designer considers less important. P1 defines this approach as follows: *"For me, it's just a tool I use to get my less important tasks done faster in terms of physical effort and time."* (P1.7)

Similarly, P12 states that they see AI not only as a support in design production but also as an assistant in different business processes: *"If there is a workshop to be held, I use it to generate ideas for it, or if I am going to write something at different points in my business processes… I use it in every area."* (P12.10). In this context, the assistant role shows that AI is not in a decision-making position, but in a supportive position.

Co-worker

Some participants, especially as their interaction practices with AI develop, define this relationship through a kind of co-worker metaphor. In this role, AI is perceived as an actor that provides feedback, responds to the designer's directions, and can produce "better results" over time. P2 expresses this situation as follows: "*It's like we have something like a coworker… but a coworker who doesn't disobey your orders."* (P2.6) Although this analogy gives the impression that AI has a certain

autonomy, it clearly shows that control still remains with the designer. AI is positioned like a colleague who is criticized, guided, and corrected when it makes a mistake: *"Just as you warn a colleague when they do something wrong, I also give feedback to the AI."* (P2.7)

Finally, when AI is positioned in a "higher" representation (e.g., from tool to assistant), designers are more comfortable and flexible regarding agency roles. Particularly in areas where designers' professional definitions extend beyond their current skill areas, or where newly acquired or developing skills are still developing, delegating more responsibility to AI appears more acceptable. In instances such as the following, this phenomenon is more apparent, where designers step out of their domains and consider the AI usage from different angles.

> *"So you're already feeding it [AI] with what you're working on. I said, 'Look, I have an idea. Can I do this idea? Can we do it?' [He's referring to ChatGPT] It said, 'We can, here's the code.' After it gave me the code that day, I was in shock because, as a designer, on the software side, which is a discipline I don't know, let me summarize it like this: if you're a designer, the software outputs enchant you. If you're a programmer, the design outputs enchant you. [...] Probably, if programmers saw the code I wrote, they would say, 'What is this?' But at the end of the day, does it work? It works for me.* (P8.7)

4.4 Designers' Expectations from AI Tools

This theme reveals what UX/UI designers expect from AI-powered tools. The findings show that designers' expectations focus on the technical capabilities of AI, how the tools behave, how they integrate into the process, and the extent to which they allow the designer control.

4.4.1 Expectations Based on AI Model Capabilities

This sub-theme addresses the cognitive competencies that UX/UI designers expect from AI-powered tools, referring to the scope of the models used.

Creativity

When asked how artificial intelligence tools affect their creative processes, it was observed that participants gave answers regarding the capacity of artificial intelligence in addition to their own processes.

The aspects participants mentioned show parallels with Torrance's (1988) model of Creativity. As designers' expectations regarding AI tools' capacity echo the definitions (See Almeida, et al., 2008) of flexibility (number of ideas), fluency (different categories of ideas and alternative approaches), and elaboration (the tendency to expand, enrich, and deepen an idea with additional details) (For further details, see Section 2.2.1 Understanding Creativity). On the other hand, participants did not express an expectation of originality (unusual, new, or statistically rare ideas) from artificial intelligence tools.

In this context, *Fluency* emerges as AI's ability to generate a large number of alternatives in a short time, thus accelerating the design process. It was observed that participants' expectation of "creativity" was not so much that AI directly produces original designs, but rather that it externalizes the designer's idea, quickly produces variants, and obtains raw material to feed design decisions. One participant (P3) described AI as a *"toolbox",* stating that they receive numerous suggestions through a short brainstorming session while using AI and develop only a small portion of them.

On the other hand, *Flexibility* is described by participants as AI's ability to generate options in different directions and differentiate itself in the direction guided by the designer. However, participant narratives show that even if the existing tools often produce some options, they are not always translated into different design directions.

For example, the appearance of "*repeating layouts*" and "*repeating color palettes*" in template production (P2) reinforces the perception that flexibility remains superficial and that the AI output becomes uniform in its design language.

Similarly, P5 defines the production of similar UI screens across different domains (banking, etc., playful retail) as *"not yielding useful results"* and *"looking uniform"* (P5). This shows that designers essentially expect contextually differentiated alternatives rather than more options.

Regarding *Originality*, P1 states that AI outputs create problems when *"delivering a unique design",* and the lack of differentiation also triggers ethical debates. In this sense, through the interviews originality appears as a concern rather than an expectation.

Finally, *Elaboration* can be defined as the expectation that AI can maintain, improve upon, and scale the production of a solution initiated by the designer:

> *"Let's say you're going to design icons. Let's say you've designed 2-3 of them, you should be able to say something like this [To AI]: Okay, you do the rest of them now and let me see how it turns out."*(P4.4)

This narrative shows that AI is not expected to "create from scratch," but rather to continue and adapt based on a style defined by the designer. In this respect, the theme of elaboration is also closely related to the next topic: context awareness.

Context Awareness & Better Reasoning

Participants expressed strong expectations regarding the extent to which AI tools understand what is being said and accurately capture intent, regardless of the creative production of the tools.

P1 stated that the generative AI's *"interpretation"* did not align with the user's intended goal and that *"prompt communication could be better"* (P1). The same participant noted that with each new prompt, the tool's variant expanded and its *"deviation from its intended point"* increased (P1). This indicated that context

awareness should be maintained consistently throughout the iteration. P3 discussed this issue, referring to a podcast they listened to about the subject:

> *"They said, 'Why should I learn these things? Why can't AI learn to communicate well with me? For example, why can't AI learn to understand me better? Why should I learn to write better prompts for AI?' That's a very interesting perspective, I think, and it's very true. And I think AI will evolve in this way as well.* " (P3.6)

This view shows that the expectation of context awareness is based on remembering the context as well as the interaction, becoming increasingly easier.

The lack of context awareness is pointed out by some participants with a common metaphor:

> *"as I said, imagine you're constantly asking for a glass of water. And imagine you've defined that glass. Let's say it's a water glass, the simplest one. Yet sometimes, it goes and brings it in a coffee cup, for example. When you say, "I just want you to bring me a glass of water, a little water," and you repeat this 100 times, it'll fail at least 20 times."*(P8.8).

This metaphor clarifies that the problem area is the AI Model's inability to understand the user's limitations and scale or to correctly interpret the intention.

A similar example is seen in P9: *"We're going to create 10 boarding pages for a shopping app. I expect it to say: 'What kind of shopping app?' but it doesn't say that. It just does it instantly."* demonstrates the absence of context-building behavior. Similarly, P8 emphasizes this by sayig: *"I just wish there was one thing. I gave it something [prompt]. It's not answering like, 'Hey, you didn't give me the empty state of this,' or 'These states are missing, should we add them?'"*

P7, on the other hand, states that AI is weak in specific problems but stronger in "filtering" from large datasets, expressing that context awareness is experienced as a capacity that varies depending on the task type.

This expectation from P5:

> *"It gave me this, it gave me that [mentioning AI outputs]. Let's say it also comes up with a functional suggestion, and then it could prioritize those, like 'Because these are the most frequently encountered pain points. I created a persona like this...'"* (P5.5)

similarly indicates that the system should establish a prioritization logic and provide a reasoning to support the decision, rather than simply listing them. P11's statement: *"It extracts problematic points… but it doesn't have something that can tell what the reason is."*(P11.4) shows that it is not enough for the AI to simply produce findings; designers want to see causality/justification. At this point, this theme crossed with the theme of Explainability (see Expectations Based on AI Tools' Design & Features).

The Expectations Based on AI Model Capabilities, addressed in this theme, first emerged in the analysis of the Interview findings. However, in the workshop session, participants discussed these expectations in terms of possible solutions and product principles; thus, some expectations were transformed into applicable design insights from a tool design perspective. A systematic summary and interpretation of these insights from a design perspective is presented under the title Considerations for Tool Design.

4.4.2 Expectations Based on AI Tools' Design and Features

This sub-theme focuses on designers' expectations regarding how AI tools should be designed and how they should behave at the interaction level. Beyond model capabilities, participants emphasized the importance of interface features, workflow integration, and control mechanisms that shape the overall user experience of AI-supported design tools.

Explainability & Reliability

Explainability is the level at which artificial intelligence systems show which inputs and logic were used to generate their outputs (Xu,2025). In a UX context, explainability directly impacts user trust and experience by making system behavior more visible and open to questioning.

Participants do not position the AI output as an authority to be blindly trusted, especially when it comes to responses containing critical information: P2's statement that it "*often makes things up… cuts and combines links… from different places*" directly addresses the issue of accuracy. At this point, the expectation is not just "*a more accurate answer*"; it is whether how the answer is produced is visible and carries verifiable clues. A feature mentioned by P12, which provides a step-by-step explanation while generating the screen, such as "*I'm looking at these sites… I'm examining these examples*," acts as a response to this need. Even if the participant is not sure whether the system actually looked at those sources, they say that "*even seeing it… reassures*," indicating that the explainability indicator generates perceptual trust (P12). This shows that explainability functions in increasing the trustworthiness of an interface however, it also creates the need for verifiability, along with the suspicion that "it might be made up., echoing the prior findings indicating that provision of insight into why the AI made a suggestion can support a greater sense of control and trust (Liao et al. 2020).

Workflow Integration

Participants' expectations for workflow integration are shaped around process continuity by connecting the fragmented steps in the design process, rather than AI tools performing individual tasks. This expectation manifests itself at two levels: end-to-end workflow support for the design process and the ability to share information, outputs, and decisions collaboratively at the team level.

Participants emphasize that using multiple AI tools sequentially in practice creates fatigue and rework labor, contrary to the speed initially promised. Therefore, the

desire to continue the process "in a single tool" becomes evident: "*It would be much easier to do them... in a single tool"* (P5.6). P5 states that they have not seen any tools that offer a "holistic approach, starting from user interview analysis to the finished product.

In P11, a similar need is expressed through the capacity to both explain and solve problems after identifying them: the lack of a system that can not only say "this problem exists" but also “implement the solution” is emphasized (P11). The expectation here is the ability to connect the AI integration into the design process in a single flow: “*I mean, if only I had a Swiss Army knife so I could do all these things in one place, that's what I desire, but I can't*.” P9's "Swiss Army knife" metaphor summarizes this tension: although the ideal would be to do everything in one place, the impossibility of this in practice makes the tool ecosystem "disturbingly" fragmented (P9). P6's statement, "*we shouldn't be using so many tools*," also points to the same weariness. However, this desire for a "single platform" should not be interpreted as an absolute desire to "lock into a single ecosystem." While P2 states that they will use a single platform if it does the job, they also emphasize the importance of seeing alternatives and being able to receive support from different platforms at certain stages. Therefore, while participants want integration and continuity on the one hand, they are cautious about the risk of uniformity and dependency on the other.

Another expectation of workflow integration is shaped by how AI will be integrated into the collaborative production and decision-making processes of teams. The need for integration at the team level manifests itself as access to corporate knowledge. P4 emphasizes the value of being able to access the accumulated learnings of 10-year-old companies as a new designer and relates this to the documentation culture of organizations. This expectation is concretized by AI acting as a "corporate memory interface," providing examples from past projects: being able to say, *"this company actually did this 3 years ago, and this was the result"* (P4.5). Collaboration is about making scattered information within the organization accessible and enabling teams to make decisions with the same set of references. Similarly, P12

states that they began considering how different research and production activities (wireframe, UI, research, design system) related to AI tools within the team could be “combined,” and discussed how they could handle processes like the transition from brief to wireframe with AI (P12).

Agency

“At the highest level, the term agency refers to who is in control during the analysis process (i.e., decides how to proceed) and has the responsibility of decision-making.” (Holter & El-Hassady, 2024, p.11). The participants' emphasis on *"designer agency"* revolves around two critical expectations: control and ownership. These two dimensions, in parallel with the previously discussed theme of AI positioning/roles, show that *"what role the AI assumes"* directly determines the boundaries of agency. While AI is considered acceptable when positioned as an execution helper or analyst in most scenarios, it is seen as risky when it approaches a role that *"replaces the designer*" or takes over the decision.

The control dimension of agency stems from the need for participants to be able to direct the AI output, slow it down when necessary, and intervene in the output at low cost. P1 states that even with the most specific prompts, the tool, through its own interpretation, adds "too much detail," deviating from the designer's goal and requiring continuous correction/retrieval to achieve the desired result (P1). This shows that the need for control also requires mechanisms that more directly follow the designer's intention. Similarly, P10 emphasizes that control is intertwined with iteration costs, stating that providing explanations/prompts each time in variation generation creates *"incredible time loss"* (P10).

This need for control is directly linked to the expectation of new interaction modalities: rather than "abandoning the chat," participants want to complement chat-based interaction with UI layers that will enable quick and targeted intervention on the output. While P3 describes the chat interface as a powerful engineering solution, it notes that it does not offer a good experience in every use case.The same participant argues that the integration of classic GUI interactions such as buttons,

filters, drag-and-drop, and selection into AI products is "inevitable". This approach points to an expectation of an interaction architecture where the designer will convey their intentions more ergonomically and intervene in the output more quickly, rather than solving the control problem through prompts. In this context, P3 predicts that in the long run, the burden of "prompt engineering" will decrease and users will have tools to better explain things. Control thus becomes an agency component that encompasses not only model behavior but also interaction costs.

P3 also finds it problematic to give product requirements and tell AI *"make me a nice UX"*; it emphasizes that AI should only support the designer's idea in execution. Here, control is established by the designer accepting/rejecting the AI's suggestions through critical evaluation and redefining the direction. P3's statement *"you have to make the final decision"* clarifies this point: as long as the decision-making power remains with the designer, supporting processes (including AI) can be used.

In the agency's ownership dimension, participants do not directly replace the AI output with the final delivery; they emphasize that the designer must customize and creatively own the "final" version. P1 states that the *"directly provided data"* from the AI cannot be used in the final delivery; the output must be personalized and finalized, while seeing AI as more useful in the steps of the design process (P1). Similarly, P2 states that they only use the output if it satisfies them; they often go over it and change it.

The agency theme aligns directly with the findings regarding AI roles. P11 states that the role of AI changes depending on the work done; it can be positioned as an assistant in art asset production, an analyst (co-worker) in data analysis, etc., but even in these roles, it is the designer who makes the distinction. P11 also emphasizes that it can be an advantage for AI to suggest something that the designer did not have in mind, but the decision determining its value and continuation remains with the designer.

4.5 Design Considerations for AI-Supported UX/UI Tools

This section explains the design considerations derived from the co-design workshop. While the workshop findings **aligned with the interview-derived themes**, engaging with conceptual wireframes (Appendix D) enabled participants to articulate considerations, revealing how these themes manifest at the level of interaction, system behavior, and tool configuration.

Project-Based Flows

One group of suggestions provided by the workshop participants concentrated on the navigation of the AI-assisted tasks in UX/UI design workflows. They generally considered the presentation of the project phases in AI-supported tools within a linear structure as a usable and non-confusing approach. However, this linearity is not considered mandatory by participants. Participants emphasized the importance of being able to directly access different design phases whenever needed within a project:

> *"It would be better to get involved in the project and do it that way. Quick actions might not be necessary here." (Group 1)*

> *The transition between them [mentioning the stages of Ux/UI design process] doesn't have to be very linear… I can directly click on UI generation, for example. But I might see the user research, data analysis, and design brief tabs of the same project as small tabs next to it.* (Group 2)

This finding shows that designers did not reject linear process definitions; however, they demanded the freedom of non-linear navigation. For example, both groups preferred to have a project-based rather than workflow-based navigation.

Selective Inclusion of Insights

Participants viewed AI's automatic inclusion of all project data at every stage as a loss of control. Instead, they wanted to consciously select which insights affected which screen or design decision by stating that *"Something can happen, wouldn't*

you want to see it all together? ... Maybe I'll want to ignore it on the payment screen at Logout, I'll want to say don't take this." (Group 2) They also mentioned *"For example, we currently have 5 options, but here there are 7. You lock and close the priority ones and don't display the locked ones."* (Group 2)

These statements reveal that the design agency's ability to reject AI output and also determine which inputs are given to the AI is relevant.

Group 2 gave examples of pinning selections to the top of the screen or node-based interaction, an example they are starting to see in current AI tools:

> *What if something like this happened, you know, those tools that connect things, like Node-Based, for example, you say that the design brief should only affect UI generation. I'll connect user research from the design brief to UI generation. Those two will feed off each other, but it won't touch, say, data analysis at all."*

Figure 4.2 contains screenshots given by Group 2 during the workshop as an example of this interaction.

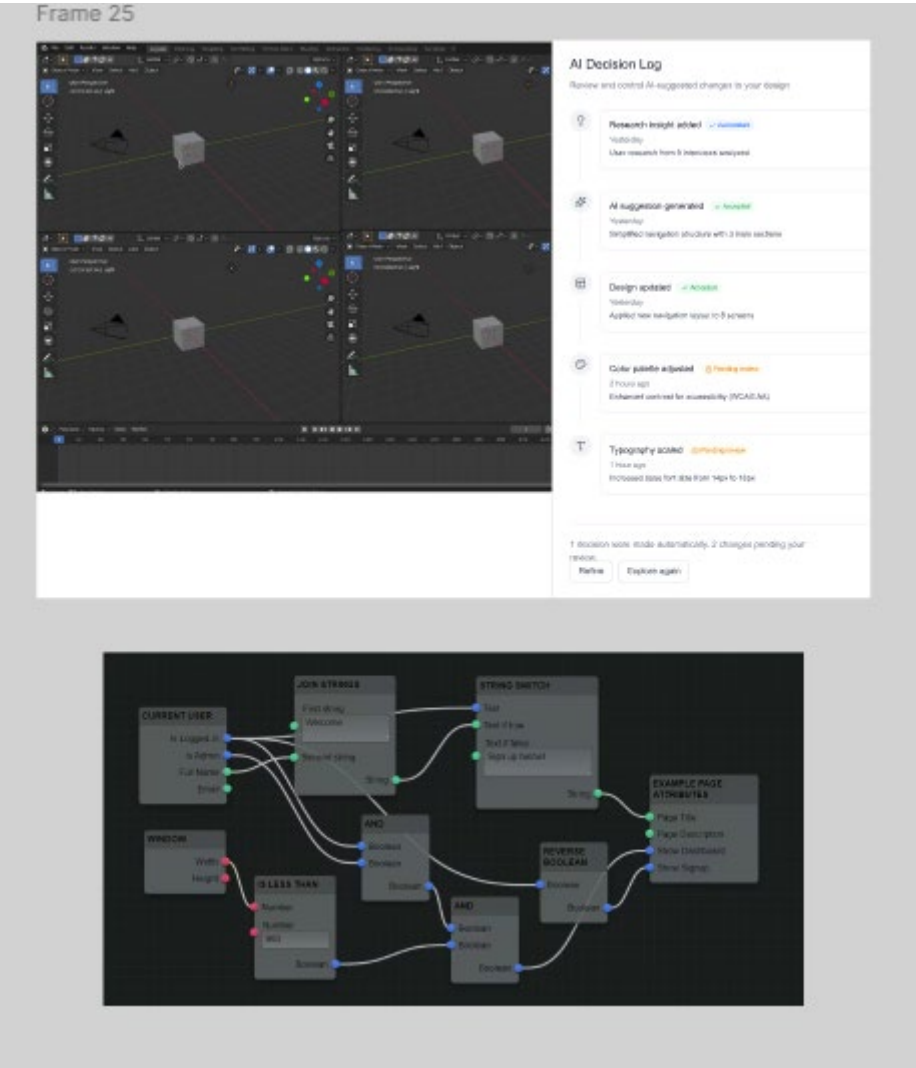


Figure 4.1 Showing Group 2's Interaction suggestions based on Inspiration from other creativity support tools.

Group 1 defined this through a screen they could use in the research & analysis phase, and where they could define the boundaries of the prompt with filters based on users, seen in Figure 4.3

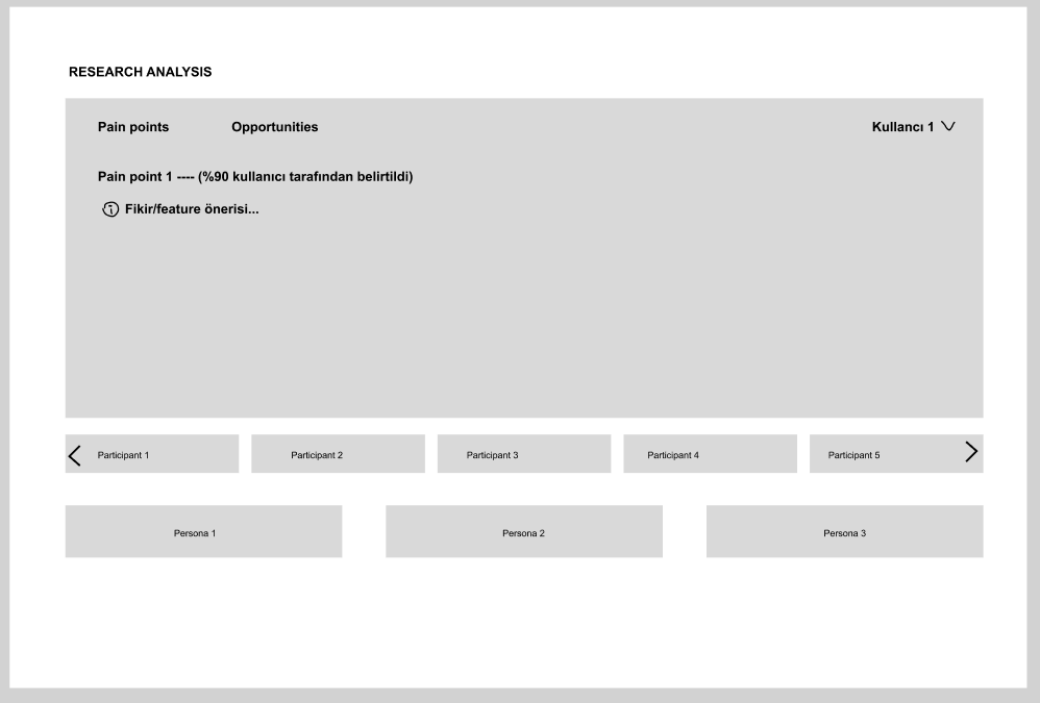


Figure 4.2 Group 1's filtering & display suggestion for research results.

Adjustable Guidance for Different Experience Levels

Participants stated that presenting AI-powered guidance in the same way at every experience level can be problematic:

> *It's important that the modes we see change. For example, someone might not want guidance during a user interview, as I mentioned earlier. They don't want it to take their attention, but a junior might prefer it. So, at each stage, it's for juniors, for people in different positions. The level of guidance might be overwhelming for one person, more knowledgeable, but it might be an opportunity for a junior*. (Group 1)

This situation indicates that AI guidance should be customizable to the user.

Learning Support Beyond Output Generation

Participants expected AI to play a role in supporting learning in the design process, rather than simply producing results: "*It should suggest questions during the interview. Follow-up questions could be included.", "It can help with terminology*

in UX writing sections in niche sectors." "Look and feel: emotion–design match… it can offer suggestions such as color palettes." (Group 1)

Non-Intrusive, Real-Time Feedback Mechanisms & Design Feedback

Participants stated that they wanted to avoid constantly distracting feedback; however, they found instant and contextual alerts useful.*"It could give instant notifications like a toaster… and gather the others in a fixed notification center."* (Group 1) This finding shows that AI feedback should be designed in a way that doesn't disrupt the flow.

In addition, AI is expected to step in as a warning and correction mechanism in certain situations and give guidance*: "For example, I entered 10 pixels. It says don't enter 10 pixels, it needs to be at least 12."* (Group 1)

History, Change Tracking, and Decision Traceability

One of the strongest shared expectations during the workshop was the need for changes to be traceable. *"Without history, you can evolve to a point where you can't understand what you've changed."* (Group 2) *"There needs to be something that allows you to understand what has changed."* (Group 1)

This stands out as a critical requirement, especially in systems where AI affects multiple stages. During the workshop, the ambiguity regarding the source of the suggestions offered by the AI emerged as a significant point of distrust. Participants wanted to clearly see *"why the AI offered such a suggestion." "Why is this here and not there? ... I would like to see if it linked this to a research output or a benchmark analysis."*

4.6 Discussion: Rethinking Creativity Support in AI-Assisted Design

This chapter discusses how the themes from interviews and co-design workshop outputs turn into design considerations for designer-centered AI-supported UX/UI tools.

Recent literature indicates that AI-powered design tools largely adopt technology-centric approaches and mostly focus on individual UI screens or narrowly defined problems revealing that these tools offer fragmented and task-oriented solutions (Lu et al., 2024). This points to a structural mismatch between professional design practices and the support offered by the tools.

The literature positions generative AI systems as creativity augmentation tools when they expand the solution space and promote variation (Cai et al., 2023; Chaudhry, 2024; Lee et al., 2025; Palani & Ramos, 2024; Shen et al., 2025). The interview findings align with these views. Participants describe AI as a "brainstorming partner" that produces many options quickly (e.g., P3's "toolbox" metaphor), but they prefer filtering and refining outputs instead of accepting them as is. This also supports the view that AI's perceived "creativity" is mostly related to fluency and elaboration, rather than originality.

In the literature and empirical findings, agency emerges as the core requirement for designers to accept and integrate AI tools to their design process (Luo, 2025; Shi et al., 2023; Weisz et al., 2024; Wadinambiarachchi et al., 2025; You et al., 2025). Parallel to existing literature, in interviews, designers categorized AI in various roles such as a tool, an assistant, or a co-worker. Yet, in this study it is observed that "role attribution" shifts according to tasks given to AI and the designer's expertise level in given tasks. This shows that the level of agency needed can shift depending on the situation while also affecting how AI's roles in the process are perceived. The proposed design suggestions from the workshop, such as pinning/locking insights, node-based linking for UI generation and filtered prompts by persona/user segments show how designers can gain this control and agency at the interface level by enabling or disabling AI inputs.

Findings of this study shows designers consider efficiency is a major perceived strength of AI tools, aligning with prior work framing AI as productivity-enhancing (Bertão & Joo, 2021; Palani & Ramos, 2024; Wadinambiarachchi et al., 2025; You et al., 2025). In addition, this study shows that efficiency is conditional and might

cause diminishing returns. When AI outputs are generic, slow, or contextually inappropriate, designers abandon AI tools. In relation, design suggestions from workshop participants, such as prioritizing project-based flows, and history/traceability features that reduce rework and can help designers stay oriented as speed increases while easing workflow integration. Which is also a theme commonly discussed in the literature (Chen et al., 2025; Shen et al., 2025; Zhou et al., 2024) and is strongly echoed in interviews.

Literature suggests that designers should understand what AI cannot replicate (Liao et al., 2020; Lu et al., 2024; Palani & Ramos, 2024; Wallach et al., 2020). The findings of this study show designers already internalize this view as participants stated they avoid *"putting their signature"* (P8) on AI outputs. It is observed in this study that designers expect *honest constraints* and interaction structures from AI tools, instead of perfect results. Workshop discussions reinforce this through the desire for contextual warnings, constraint checks (e.g., pixel-size guidance or color checking), and non-intrusive alerts.

The findings of this study shows that the Genex framework (Shneiderman, 2002) and The CSI (Carroll et al., 2009). The participants' use of artificial intelligence for purposes such as method determination, creating user interview questions, summarizing transcripts, and developing persona scenarios parallels Genex's Phase 1 activities, which is defined as searching and browsing digital libraries and visualizing data and processes (Schneiderman, 2002). At this stage, AI is positioned as a tool that structures and makes information accessible. During the workshop, the expectation for this "collection and analysis" support became more concrete; participants specifically stated that AI could be valuable in tasks such as finding competitors and generating UI/UX-focused benchmarks.

The Relate phase aligns with findings that designers view AI as a tool for organizing thought and facilitating communication. AI-powered prototypes create a common point of reference among stakeholders from different disciplines, offering a

functional equivalent to the consulting with peers and mentors role described in the literature.

Aditionally, The Create phase is embodied in idea generation, UI and visual asset production, and prototyping practices. Participants stated that they used AI, especially in moments of being “stuck,” to expand the idea field and generate alternatives. This usage aligns with creative support mechanisms such as free associations and exploring what-if solutions (Schneiderman, 2002). However, it was also emphasized that the risk of design fixation increases at this stage because AI produces outputs based on existing patterns. This situation aligns with discussions in the literature regarding the potential limitations of creative diversity in AI-powered systems (Wadinambiarachchi et al., 2024). In contrast, AI’s ability to handle tedious and repetitive tasks (e.g., auto layout, quickly moving components to the screen) was viewed positively. This distinction demonstrates that in the Create phase, designers clearly draw a line between “creative core decisions” and “operational production tasks.”

Finally, the Donate phase becomes visible through AI-powered outputs, enabling designers to produce prototypes faster and test these outputs with users and stakeholders at an earlier stage. This directly relates to the themes of efficiency and communication identified in the study. Workshop outcomes demonstrated that traceability is a critical requirement in this sharing and iteration process. Participants particularly considered the visibility of history, change tracking, and decision traces indispensable.

The findings also strongly intersect with the factors defined within the Creativity Support Index (Carroll et al., 2009, p.135), the "Results worth effort" and "exploration" dimensions are associated with AI's ability to accelerate processes and generate alternatives, while the "diminishing returns" findings indicate that AI use does not produce equal value in every context. While "expressiveness" and "exploration" align with AI's ability to foster diversity of ideas, "immersion" and "enjoyment" are sometimes weakened due to the fragmented nature of the tool

ecosystem and reliability issues. Workshop outputs highlighted the "immersion" and "enjoyment" dimensions, particularly through interaction design; participants indicated a preference for real-time feedback that doesn't disrupt the flow, rather than constantly distracting interventions. The "collaboration" factor is directly linked to AI-powered prototypes strengthening intra-team communication.

In conclusion, the findings of this study show that artificial intelligence is positioned as an infrastructure that supports, accelerates, and makes visible the relationships within the design process. The workshop outcomes further reinforced this positioning. This position strongly aligns with the process-oriented, iterative frameworks emphasized in the CST literature.

CHAPTER 5

CONCLUSION

This thesis aimed to examine how generative AI tools are integrated into UX/UI design processes and the effects of this integration on designers' practices. The findings of this study contribute a designer-centered perspective grounded in practitioners' experiences, perceptions, and expectations. To this end, a two-stage user research study was conducted. In the first stage, semi-structured interviews with UX/UI designers revealed how designers integrated generative AI tools into their existing workflows, the roles they assigned to these tools, and the opportunities and challenges they encountered. The co-design workshop conducted in the second stage built upon these findings, generating insights into the design principles that should guide the development of designer-focused AI-powered tools. The research findings indicate that UX/UI designers primarily use generative AI tools in stages such as research, idea generation, visual variation creation, and prototyping. The study shows that designers consciously maintain control over problem definition and final design decisions. While designers view AI tools as supportive systems that accelerate the process and expand the idea space, they also highlight significant risks such as a lack of explainability, homogenous outputs, and contextual inadequacy. The findings also reveal that designers guide AI generation in line with their own design goals and visions by developing strategies such as iterative prompt writing, selective output usage, and manual intervention.

Current research on the role of generative AI tools in UX/UI design mostly focuses on specific stages in the process. Unlike the existing literature, this thesis treats the UX/UI design process as a holistic workflow and examines how generative AI tools are positioned within this workflow through the experiences of designers. Therefore, the study focuses not so much on "what AI tools produce" at which

point in the process, but rather on how designers think, interact, and control these tools.

5.1 Revisiting Research Questions

RQ1: How do UX/UI designers integrate AI tools into their UI design processes?

-What are the distinct roles played by designers and the AI Tools they use?

-What are the challenges and opportunities encountered & perceived by UX/UI designers when incorporating AI tools into their design workflows?

-How do designers strategize and control the generation of ideas by AI tools to align with their design goals and vision?

Findings of this study aligns with prior research suggesting that current AI design tools tend to support isolated tasks rather than the broader UX process (Lu et al., 2024). Especially, designers' positioning of AI as a facilitator rather than a decision-maker resonates with studies on human-AI collaboration that emphasize structured role distribution and retained human oversight (Bertão & Joo, 2021; Chen et al., 2025). Participants emphasis on maintaining control over critical design decisions directly echoes findings by Khan et al. (2025), who report that AI can play a particularly supportive role in UX/UI design, from collecting and synthesizing research data to initiating the creative process to generating alternatives. However, it stressed that this should be implemented while maintaining the design agency's involvement, reflective thinking, and contextual control (Khan et al., 2025).

The findings reveal that AI integration exhibits an iterative and interactive structure. Instead of engaging with AI outputs only once, designers continuously guide the production process through prompt writing and manual editing. Consequently, UX/UI designers are integrating AI tools into the design process in a way that transforms their existing practices without giving up control; this integration process

provides speed and efficiency, as well as new negotiations regarding design agencies, creativity, and decision-making processes.

Research findings show that UX/UI designers generally position generative AI tools in accelerating, and supportive roles. While designers retain responsibility for critical stages such as problem definition, interpretation of user needs, contextual decisions, and final design decisions, they primarily use AI tools in areas such as research support, idea diversification, visual variation generation, and prototyping.

The findings indicate that when AI is positioned at a higher level of representation, designers demonstrate greater comfort and flexibility in negotiating agency roles. In particular, designers appear more willing to delegate responsibility to AI in areas that fall outside their established professional expertise or in domains where their skills are still emerging. This tendency becomes more visible in situations where designers temporarily step beyond their core practice, such as engaging with development tasks or unfamiliar problem spaces. In these contexts, AI is not perceived as a threat to creative control but rather as a supportive intermediary that enables designers to extend their capabilities.

This study shows that designers are increasingly using AI tools for code generation. This usage allows designers to overcome technical barriers and express their ideas more concretely, especially during prototyping and communication with developers.

The findings of this study demonstrate that generative AI tools not only support the existing skill sets of UX/UI designers but also expand the scope and definition of these skill sets. As designers begin to utilize AI tools, they are taking on a more hybrid and multidisciplinary role, not limited solely to visual and experiential design.

In addition, the study shows that AI competency has emerged as a distinct and critical area of expertise for UX/UI designers. AI competency is not limited to the ability to use specific tools; it encompasses the ability to understand the capabilities and limitations of AI systems, identify appropriate use cases, and critically evaluate the outputs produced.

Participants stated that generative AI tools offer significant opportunities, particularly in terms of saving time, increasing production speed, and expanding the idea space. Furthermore, it was observed that these tools support communication within the team and with stakeholders, and enable the production of more tangible outputs at an early stage. However, the findings also point to significant challenges. Designers are concerned about issues such as the production of similar and repetitive results, the absence of contextual awareness, and the reduced sense of control over the design.

RQ2: What are the main design considerations for AI-assisted design tools to support designers' creativity and UX/UI design processes in the development of digital products?

The synthesis of the literature revealed (see Table 2.4) design considerations for AI-supported creativity support tools as *Support for Divergent Thinking* (Cai et al., 2023; Chaudhry, 2024; Lee et al., 2025; Palani & Ramos, 2024; Shen et al., 2025) *Human Agency and Control*, (Luo, 2025; Shi et al., 2023; Weisz et al., 2024; Wadinambiarachchi et al., 2025; You et al., 2025*), Interaction Modality and Input Flexibility* (Palani & Ramos, 2024; You et al., 2025; Wadinambiarachchi et al., 2025) *, Efficiency and Cognitive Load Management* (Bertão & Joo, 2021; Palani & Ramos, 2024; Wadinambiarachchi et al., 2025; You et al., 2025.), *Workflow Integration and Coherence* (Chen et al., 2025; Shen et al., 2025; Zhou et al., 2024), *Personalization and Adaptation to Designer's Style* (De Peuter et al., 2023; McCormack et al., 2020; Wadinambiarachchi et al., 2025), *Clear Scope and Limitations* (Liao et al., 2020; Lu et al., 2024; Palani & Ramos, 2024; Wallach et al., 2020) *Transparency and Explainability* (Chaudhry, 2024; Liao et al., 2023; Lu et al., 2022*) Ethicality and Responsible AI* (Chaudhry, 2024; Germanakos et al., 2025; Zhu et al., 2024). In parallel with these considerations from literature, the findings of this study similarly highlights the importance of supporting divergent exploration, maintaining designer agency, ensuring transparency, and embedding AI tools coherently within existing workflows. The empirical data from this study further refines these considerations by grounding them in designers' situated

practices and articulate how they translate into concrete design expectations through the lens of Creativity Support Tools (CSTs) for designer-centred AI-enhanced tools.

Participants in this study explicitly articulated the need for override control and clear authorship boundaries. This reinforces Chaudhry's (2024) argument that AI tools are accepted only insofar as they empower designers rather than encroach on core creative decisions.

Similarly, expectations on explainability and transparency such as understanding what inputs AI uses, and how suggestions are generated align with discussions on explainability and trust in AI (Chen et al., 2025).

Importantly, workshop findings demonstrated that designers seek tools embedded within the broader UX/UI workflow context. This finding extends Lu et al. (2024), who critique technology-centric tools for focusing narrowly on UI artifacts. Participants instead envisioned context-aware systems that integrate research insights, user data, and project history suggesting a shift from UI artifacts to end-to-end workflow support.

Finally, the transformation of interview themes into explicit design considerations during the workshop closely reflects CST research. Effective creativity tools should support exploration, combination, reflection, and evaluation (Caroll et al., 2009; Shneiderman, 2000). The proposed design considerations in this study discuss these principles within the domain of generative AI for UX/UI design.

The study shows that designers emphasize the freedom to move freely between different stages within the project. Therefore, designers considered flexible navigation structures instead of rigid workflows in AI-enhanced tools.

Another important finding shows need for selective control over AI inputs and outputs. Designers prefer consciously to decide which insight will influence which design decision. This demonstrates that the designer's role includes determining what AI will be fed in addition to evaluating the output.

Workshop findings revealed that providing AI-enhanced guidance in the same way for all users and all situations can be problematic. The ability to adjust the level of guidance according to the designers' experience level, the task context, and the design stage is found to be an important expectation. In this context, AI-powered systems should supply personalized support rather than uniform guidance.

Further along these lines, designers expect AI to play a role in supporting learning and thinking. Functions such as offering suggestions, developing alternative perspectives, and providing support on domain-specific terminology are considered by designers in co-design workshop.

At the interaction level, designers prefer contextual and non-disruptive feedback mechanisms instead of continuous and distracting feedback. While it is considered valuable for AI to play a stimulating and guiding role, when necessary, these interventions are expected to be designed in a way that does not interrupt the flow of the design process.

Finally, one of the strongest expectations from the workshop was the traceability of design-change history and the justification of AI's decisions. Clearly demonstrating which inputs, analyses, or previous decisions are based on recommendations in AI-powered systems has emerged as a critical requirement for designer confidence and the sustainability of the relationship with the system.

5.2 Limitations of The Study

The field of generative artificial intelligence is developing extremely rapidly; new tools, features, and use cases are emerging every day. This rapid development may have limited both the scope of the tools considered in the research process and the level of knowledge and experience of the participants with these tools. Participants are not expected to be familiar with all the new AI tools or updates released during the research period. This inevitably led to participant opinions being limited to certain tools and personal experiences. Therefore, the findings are shaped by the

tools that designers actively experienced and adopted at that time, rather than providing an assessment encompassing the entire generative AI ecosystem. In addition, the limited number of participants in the collaborative design workshop may have affected the diversity and representativeness of the resulting design proposals. The rapid advancement of the field affected all phases of the study, from the literature review to the research design and implementation; both the resources used and the tools considered throughout the research process required continuous updating.

5.3 Implications for Further Studies

Future studies could extend the qualitative findings of this research by involving larger and more diverse samples, enabling comparative analyses across different organizational contexts. In particular, examining AI-assisted design practices in corporate environments, agency settings, and freelance contexts may reveal how team size, organizational structure, and production constraints shape designers' relationships with AI tools.

Additionally, future research should consider AI-assisted UX/UI design as a collaborative practice rather than an isolated designer activity. Investigating how UX/UI designers work alongside closely related roles such as product managers and frontend developers could provide a more comprehensive understanding of how AI tools mediate coordination, responsibility, and decision-making across multidisciplinary teams.

Longitudinal studies, in particular, might make significant contributions to understanding how designers' relationships with AI tools evolve over time. They might also shed light on whether agency perception and role assignments are permanent or temporary. The rapid development of generative and agent-based AI systems is causing designers' perceptions of trust, control, and responsibility towards these systems to change constantly in unforeseen ways. Studies addressing the time-

related dimension of this transformation can broaden the validity of the current findings depending on the context.

Furthermore, testing the design elements related to designer-centered AI-enhanced UX/UI tools, as defined in this thesis, through experimental studies constitutes another important research area. Future research could develop prototypes based on these design elements and comparatively examine their impact further.

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APPENDICES

A. Ethical Committee Approval

UYGULAMALI ETİK ARAŞTIRMA MERKEZİ
APPLIED ETHICS RESEARCH CENTER

ORTA DOĞU TEKNİK ÜNİVERSİTESİ
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Konu	: Değerlendirme Sonucu	10.10.2025
Gönderen	: ODTÜ İnsan Araştırmaları Etik Kurulu	
İlgi	: İnsan Araştırmaları Etik Başvurunuz	

Sayın Dr. Öğr. Üyesi Güzin Şen,
Sayın Yasemin Kardelen Akça,

"UX/UI Tasarım Sürecinde Üretken Yapay Zeka: Tasarımcı Odaklı Bir Araç İçin Kriterlerin Belirlenmesi" başlıklı araştırmanız ODTÜ İnsan Araştırmaları Etik Kurulu tarafından uygun görülerek 0478-ODTÜİAEK-2025 protokol numarası ile onaylanmıştır.

Bilgilerinize sunarım.

B. Online Participant Information Form



UX/UI TASARIM SÜRECİNDE ÜRETKEN YAPAY ZEKA:
TASARIMCI ODAKLI BİR ARAÇ İÇİN KRİTERLERİN BELİRLENMESİ

ARAŞTIRMAYA GÖNÜLLÜ KATILIM FORMU

Bu araştırma, ODTÜ Endüstriyel Tasarım Bölümü Yüksek Lisans öğrencisi Yasemin Kardelen Akça tarafından Dr. Öğr. Üyesi Güzin Şen danışmanlığındaki yüksek lisans tezi kapsamında yürütülmektedir. Bu form sizi araştırma koşulları hakkında bilgilendirmek ve katılmayı kabul etmeniz durumunda size daha kolay ulaşabilmek için hazırlanmıştır.

Çalışmanın Amacı Nedir?

Çalışma, sektör profesyonellerinin deneyim ve görüşlerinden elde edilen bulgular ışığında, üretken yapay zekâ araçlarının UX/UI tasarımcılarının yaratıcı süreçlerini nasıl etkilediğini ve UX/UI tasarımı özelinde olası bir yapay zekâ destekli tasarım aracının taşıyabileceği temel özellikler ve arayüz kriterlerini ortaya koymayı amaçlamaktadır.

Bize Nasıl Yardımcı Olmanızı İsteyeceğiz?

Araştırmaya katılmayı kabul ederseniz, sizden yaklaşık 30-40 dakika sürecek bir yarı yapılandırılmış görüşmeye katılmanız beklenmektedir. Bu görüşme sırasında tasarım pratiğinizde yapay zekâ araçlarını nasıl kullandığınız, bu araçlara dair algılarınız ve deneyimleriniz hakkında sorular sorulacaktır. Cevapların daha sonra araştırmacı tarafından analiz edilebilmesi adına görüşmede ses kaydı alınacaktır.

Sizden Topladığımız Bilgileri Nasıl Kullanacağız?

Araştırmaya katılımınız tamamen gönüllülük esasına dayanmaktadır. Görüşmede kimlik ya da kurum belirleyici bilgi toplanmayacaktır. Veriler anonimleştirilerek yalnızca araştırma amacıyla kullanılacak, bilimsel yayınlarda toplu ve kimliksiz şekilde raporlanacaktır. Katılımcılardan elde edilen bilgiler, gönüllü katılım formundaki bilgilerle eşleştirilmeyecek, kimlik bilgileriniz kesinlikle gizli tutulacaktır.

Katılımınızla ilgili bilmeniz gerekenler:

Bu araştırma günlük hayatta karşılaşılması muhtemel olağan risklerin ötesinde herhangi bir risk içermemektedir. Görüşme sırasında herhangi bir soruya yanıt vermek istemez veya görüşmeden ayrılmak isterseniz bunu dilediğiniz anda belirtebilir, görüşmeden çekilebilirsiniz. Katılımınız, kullanıcı deneyimi tasarımında yapay zekâ araçlarının etkilerini daha iyi anlamaya yönelik öngörüler elde edebilmek adına bizim için çok değerlidir.

Konu ile ilgili daha fazla bilgi almak isterseniz kardelen.akca@metu.edu.tr adresine e-posta göndererek bana ulaşabilirsiniz.

C. Semi-Structured Interview Questions

YARI YAPILANDIRILMIŞ MÜLAKAT SORULARI

UX/UI alanında profesyonel olarak çalışan tasarımcılarla yarı yapılandırılmış mülakatlar gerçekleştirilecektir. Bu aşamada, katılımcıların mevcut pratikleri, karşılaştıkları zorluklar ve yaratıcılık ile yapay zekâ entegrasyonu konusundaki algıları anlaşılmaya çalışılacaktır.

Bu görüşmeler kapsamında sorulması planlanan sorular aşağıdaki gibidir:

-Şu ana kadar hangi yapay zeka araçlarını ya da özelliklerini kullandınız? Hangi amaçlarla?

-Yakın zamanda YZ kullanarak üzerinde çalıştığınız bir tasarım projesini anlatır mısınız?

-Tasarım sürecinizin hangi aşamalarında yapay zeka tabanlı araçlar kullanıyorsunuz? Neden?

-Size en çok yardımcı olduğunu hatırladığınız bir yapay zeka aracı deneyiminizi anlatır mısınız?

-Yapay zeka destekli bir araç kullanırken sizi zorlayan ya da tereddüt ettiren bir durum oldu mu? Ne yaşandı?

-Hangi tür görevleri yapay zekaya bırakıyorsunuz? Hangi görevleri mutlaka kendiniz yapmayı tercih ediyorsunuz?

-Tasarım sürecinizde yapay zekânın yetersiz kaldığını düşündüğünüz bölümler var mı? Neler?

-Yapay zeka araçlarının yaratıcı sürecinizi etkilediğini düşünüyor musunuz? Nasıl?

-Bu araçlar iş akışınızda sizce neyi daha iyi yapabilseydi sizin için çok faydalı olurdu?

-Sizin için "iyi bir yapay zekâ desteği" ne anlama geliyor? Gerçek bir iş akışında bu nasıl görünürdü?

-Sizce ideal bir UX/UI tasarımına özel üretken yapay zeka aracında olması gereken özellikler nelerdir? Asla olmaması gerektiğini düşündüğünüz özellikler var mı?

-Yapay zekâ ve tasarım ilişkisine dair bakış açınız zaman içinde değişti mi? Nasıl değişti?

Görüşmenin akışına göre katılımcılara yöneltilmesi planlanan takip soruları aşağıdaki gibidir;

-Bu konuyu/örneği biraz daha açabilir misiniz?

-Sizce .... nın daha iyi olması için ne olmalıydı?

-Aklınıza gelen buna benzer başka bir örnek var mı?

D. Workshop Toolkit

Thematic Information Cards:



Translation of information cards from left to right:

Introduction

Welcome

This workshop is designed to explore how UX/UI designers would like to work with AI-supported design tools, what they expect from these tools, and how these tools can be integrated into their existing design workflows.

The aim here is not to test a product, evaluate a tool, or find the “right” solution.

Rather, we will discuss the role of AI, its limitations, and forms of interaction from the designer’s perspective.

What Will We Do?

Warm-up

We will briefly review the study summary and the main outline of the workshop together.

Activity 1

First, you will reflect on your expectations and the role you associate with an AI-supported UX/UI tool.

Activity 2

Then, based on these expectations, you will work on an example AI-supported wireframe and transform your ideas into more concrete design decisions.

Activity 3

In the final stage, we will revisit the expectations discussed at the beginning.

What Should I Pay Attention To?

Think based on your own experiences.

Share your doubts, contradictions, and uncertainties.

Saying “I would never want this here” is as valuable as saying “This should be like this.”

For this study:

There are no right or wrong answers.

Different perspectives are especially valuable.

This is not a design evaluation or performance measurement.

A small reminder:

Throughout this workshop, we focus not on what AI can do, but on what you would want AI to do as a designer.

Thematic Cards

Creativity

Supporting idea exploration, diversity, and different perspectives without narrowing the design space.

How could this tool help you explore more ideas?

How could it help you avoid getting stuck on early ideas?

Could it make alternatives visible that you normally wouldn't think of?

Designer Control

The designer's authority to initiate, control, modify, or reject AI outputs at any stage.

Who initiates the action?

How does the designer make changes to AI outputs?

How is the AI's influence shaped when modifications are made to its outputs?

Transparency

Ensuring that designers can understand, question, and trust AI behavior by making its processes sufficiently visible.

What does the AI currently know?

What data or inputs does it use?

Why was this suggestion generated?

What would increase or decrease trust?

Teamwork

How AI shapes collaboration, visibility, and shared understanding within a design team.

Who sees what?

How are decisions shared within the team?

Does this create inequality within the team?

How might AI affect team dynamics?

Workflow Integration

How well the tool fits into designers' existing UX/UI workflows and whether it creates friction or smooth transitions.

Does this tool support the workflow, divide it, or disrupt it? How?

In which situations would you prefer to turn this tool off?

Would you actually use this in a real project?

AI Roles

Thinking Partner

Encourages reflection but does not make decisions.

Accelerator

Speeds things up; helps complete the same work faster.

Assistant

Handles repetitive or secondary tasks.

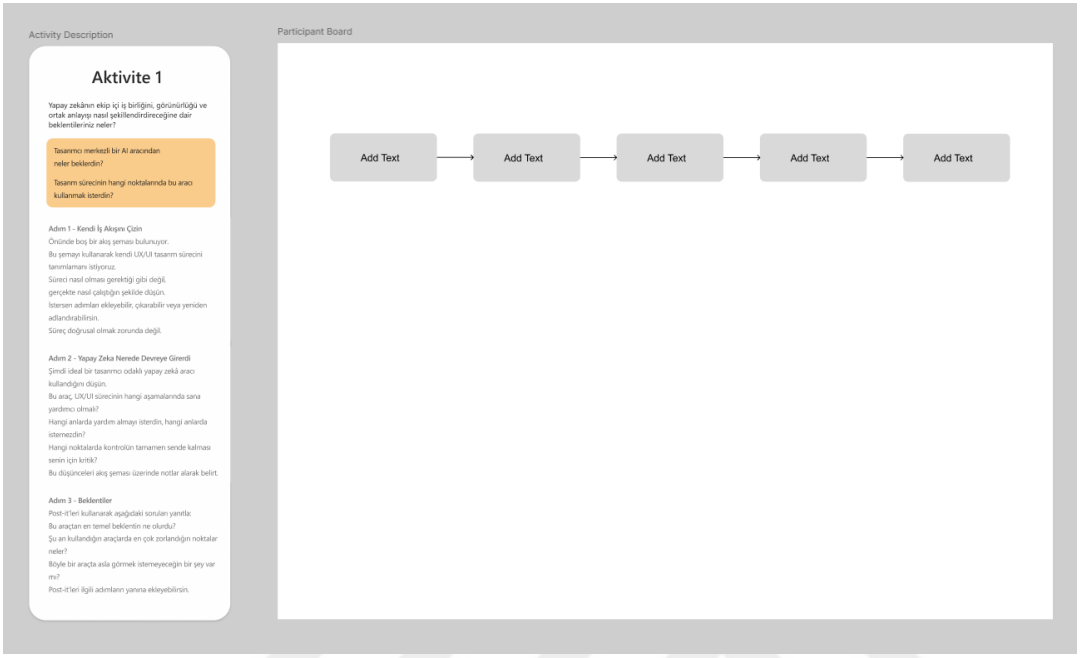
Co-Creator

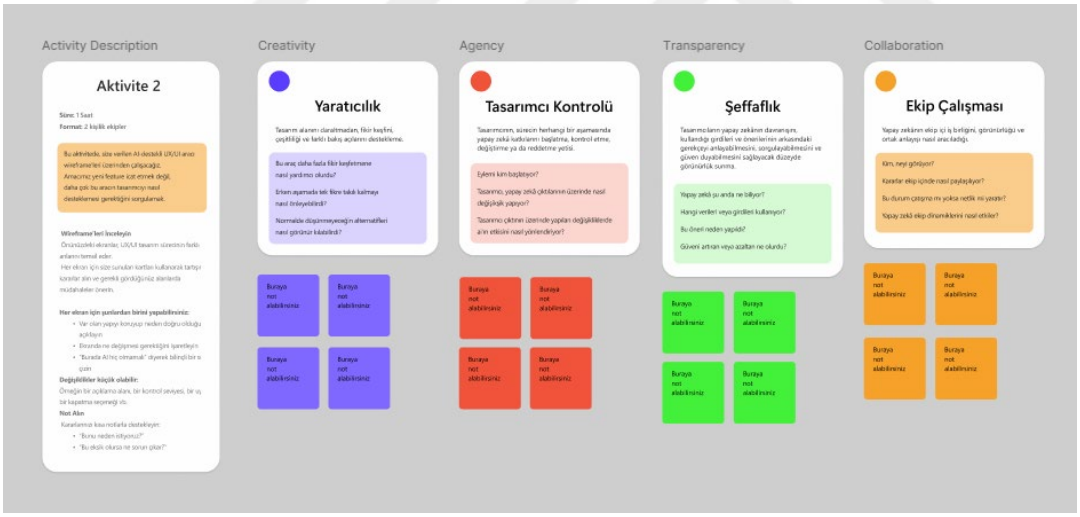
Actively contributes to idea generation.

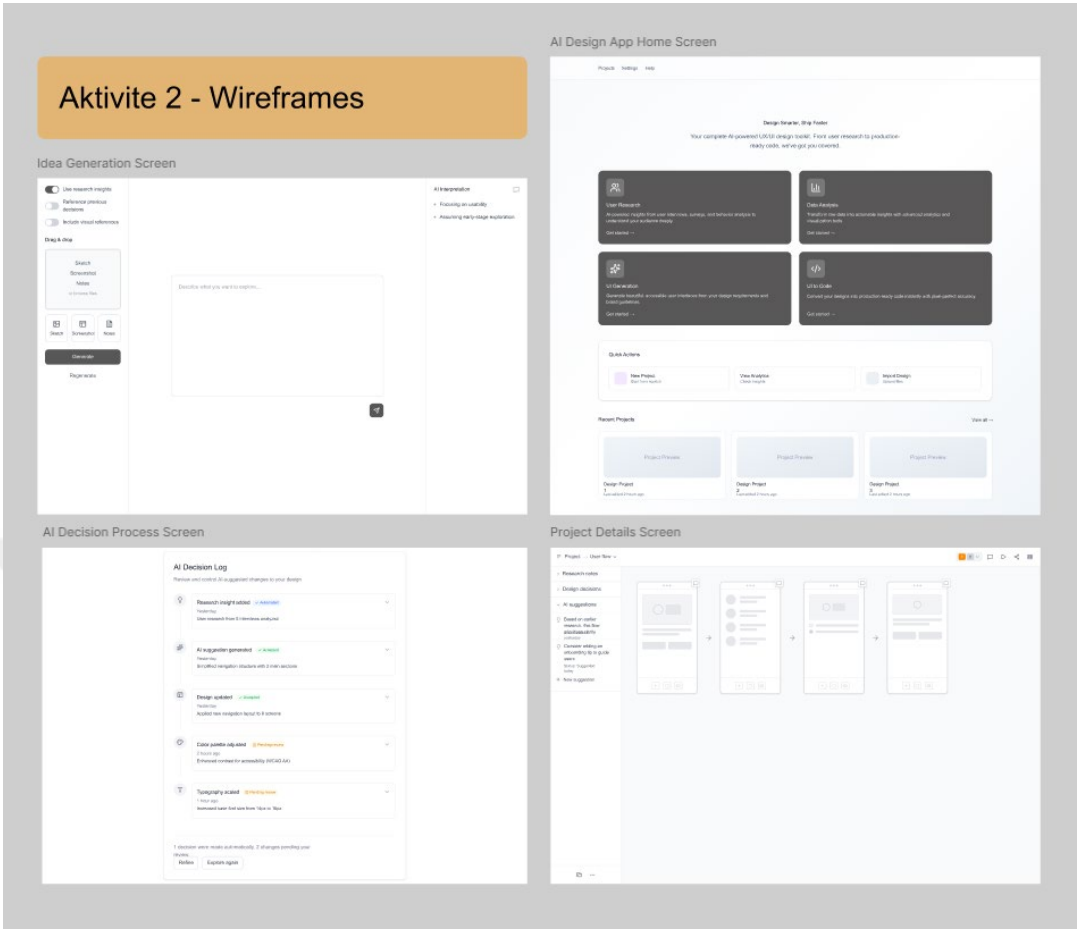
Autonomous Agent

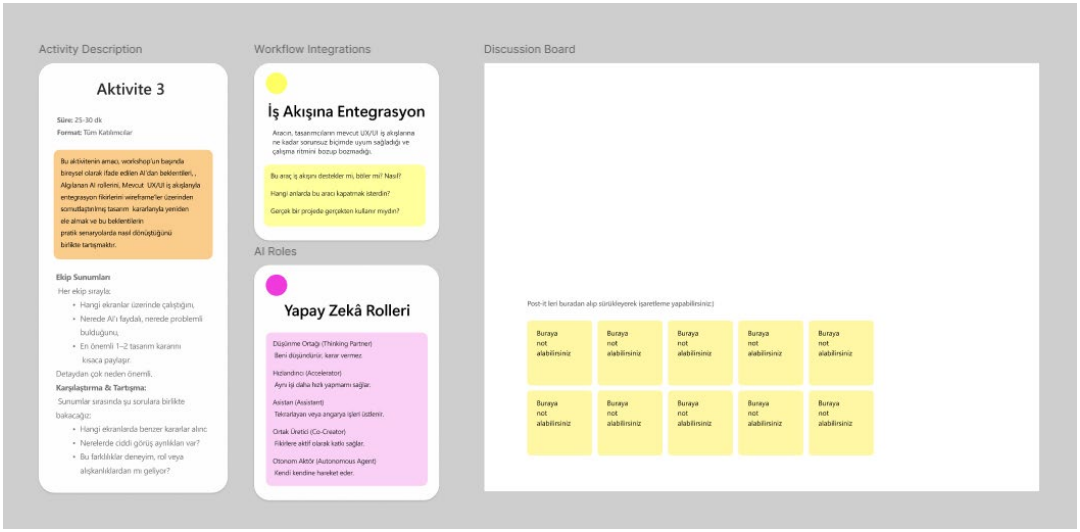
Acts independently.

Activities 1 to 3, with Explanations for each activity step and Thematic Information Cards






Aktivite 2 - Wireframes
Idea Generation Screen
AI Design App Home Screen
AI Decision Process Screen
Project Details Screen


Activity Description
Aktivite 3
Süre: 25-30 dk
Format: Tüm Katılımcılar
Ekip Sunumları
Her ekip sırayla:
Detaydan çok neden önemli.
Karşılaştırma & Tartışma:
Workflow Integrations
İş Akışına Entegrasyon
AI Roles
Yapay Zekâ Rolleri
Discussion Board

E. Original Quotations in Turkish

P1

“O noktada hem ux verilerini kendi içerisinde işte sınıflandırma olsun verileri analiz etme, onun üzerinden kendisi de bu verileri işte güncel var olan kaynaklardan yorumlama, karşılaştırma gibi şeyleri de yapabildiği için..” (P1.1)

“İlk kullandığımda, çok sınırlı bir veritabanından belirli tasarımcıların tasarımlarına çok benzer görseller üretiyordu […]” (P1.2).

“Ancak şimdi, yapay zekanın düşünme yeteneği biraz değişti; örneğin, ona verdiğiniz komutlara göre yorumlama yeteneği daha gelişmiş hale geldi.” (P1.3).

“Tasarım aşamasına geldiğimde, bana sunduğu şeyler zaten var olan şeyler, dediğim gibi, bu yüzden beni belirli bir noktaya doğru itiyor ve bilincimi zaten var olan şeylere doğru kısıtlıyor. Bu noktada, yaratıcı sürecimi olumsuz etkiliyor.” (P1.4)

“Bu nedenle, sadece tasarım amaçlı değil, tasarımcının bu işi yapmasını kolaylaştıran bir araç olması daha olumlu olur diye düşünüyorum.” (P1.5).

“Onu daha çok görselleştirme sürecinin önemsiz kısımlarında kullanıyorum […] benim için bir ortak değil.” (P1.6)

“Benim için, fiziksel çaba ve zaman açısından daha az önemli görevlerimi daha hızlı halletmek için kullandığım bir araçtan ibaret.” (P1.7)

P2

“ya da işte ChatGPT’ye belirli bir profil oluşturuyorum, diyorum ki sen işte bu profildesin sana böyle bir soru versem hani ne ne düşünürsün ya da nasıl hissedersin gibisinden hani direk kullanıcılara vermeden orada bir deneme yapıyordum.”(P2.1)

“Verdiği çıktı, beni tatmin ediyorsa onu alır kullanırım ya da işte photoshopta birazcık daha üstünden geçerim…” (P2.2)

“işte yeni bir skill set olarak da kendime edindiğim bir nasıl desem iş kolu gibi görüyorum ama tabii ki de ona bağlı kalmamak gerekiyor. Çünkü prompt engineering sadece işte yazıyı, hani ya da işte kendini ifade etme ya da kafandaki istediğin şeyi daha iyi bir şekilde daha hani bilgisayarın işte prompt Anlayacağı şekilde gerçekleştirmek yazmak gerekiyor. O noktayı zaten bir kere kavradıktan sonra oradan bence ötesi yok diye düşünüyorum bence.” (P2.3)

“Yapay zekanın […] potansiyelinin yüksek olduğunu gözlemleme şansım oldu. […] Yapay zeka kendini geliştirirken ben de daha iyi sonuçlar elde edebilmek için kendimi geliştirmem gerekiyordu.” (P2.4)

“Çıktı var ama çıktıyı kendi özgür iradenle, kendi fikrinle oluşturdun mu dediğin zaman orası boş kalıyor.” (P2.5).

“Sanki bir coworker tarzında bir şeyimiz var gibi… ama senin sözünden çıkmayan bir coworker gibi.” (P2.6)

“Bir iş arkadaşınız yanlış yaptığında nasıl uyarıyorsanız, yapay zekaya da feedback veriyorum.” (P2.7)

P3

“Yani çok ilginç bir tool box var ortada ve sen Kendin bir şekilde kafanda bir şey hayal ediyorsun diyorsun ki yani ya şöyle bir grafik olsa çok güzel anlatabilirim ya da şöyle bir tarz olsa şöyle bir şey çıkartabilirim veya bunu bir brainstorming yapıyorsun mesela AI’la kısaca. nasıl bir şey olabilir? Böyle bir kafamda şöyle bir şey var, bunu anlatmak istiyorum ne ne gibi şeyler önerirsin falan işte o brainstorming hemen mesela sana 5 tane şey öneriyor mesela 3 tanesi çöp yani onun çöp olduğunu anlıyorum ama mesela ya bu gerçekten çöp bir şey. Bir tanesini mesela gerçekten ilginç geliyor. O ilginç gelen şeyi alıyorum. Onu biraz daha kendimi geliştiriyorum.” (P3.1)

“AI prototyping ile çok Spesifik konuları çok güzel bir şekilde aktarabiliyorsun karşıdakine, bu işte bir developer olabilir ya da bir şey olabilir, işte product manager olabilir ya da stake holder olabilir. Atıyorum, cto veya ceo’ya sunum yapıyorsundur. Yani onun gidip figmdan ekranını göstermek ya da işte bir durağan ya da böyle figma saatlerce uğraşıp bir tane figma prototipi yapmak var, bir yandan da hani gerçekten ürün nasıl hissediliyor, nasıl oluyor yani neredeyse gerçek ürünmüş gibi gibi artık prototipler yapabiliyoruz çok kısa sürede.” (P3.2)

“hani bu AI toolların şu anki aşamada Bende en çok işe yaradığı kısmın şey olduğunu düşünüyorum: iletişim. iletişimi çok güçlendirdi. Yani çok herkes herkes kafasındakini çok daha güzel bir şekilde anlatabiliyor Artık. ya da anlatmaya çalışıyor diyeyim.” (P3.3)

“Yani ürünler yapıyoruz AI toollarla artık mesela. Ya internal tools ya da external tools dediğimiz konular var, atıyorum Mesela çok spesifik bir problem var, Bir işte müşterinin bir problemi var diyelim. Onu işte bizim asıl ürünün içerisinde çözmemiz çok zor olacak ya da işte çok sıkıntılı bir şey ama mini bir software tasarlayabiliyorsun mesela o kullanım için, çok küçük bir software, ya bir tasarımcı artık bunu yapabiliyor.” (P3.4)

“ Hani bu aslında biraz daha tasarımcının ilk alanındaki şeyleri geri alması gibi görüyorum ben açıkçası hani gerçekten tasarımcının own etmesi gereken alanların artık tasarımcının daha kolay kontrol edebileceği şeyler haline gelmesi gibi görüyorum. “ (P3.5)

“Orada şey diyordu ‘Neden bunları öğrenmeliyim? Yapay zeka neden benimle iyi iletişim kurmayı öğrenemiyor? Örneğin, yapay zeka neden beni daha iyi anlamayı öğrenemiyor? Neden yapay zeka için daha iyi komutlar yazmayı öğrenmeliyim?’ Bence bu çok ilginç bir bakış açısı ve çok doğru. Ve bence yapay zeka da bu şekilde gelişecek.” (P3.6)

P4

“Prototiplerin ötesinde bazen hani ürünün kendisini değiştirmek gerekiyor hemen ya da işte bazısı öyle şeyler oluyor ki bazı hani şeyler çok kompleks işte mühendislik gerektiren şeyler, ekspertiz gerektiren şeyler ama hani bir tasarımcı olarak da senin dikkat ettiğin şeyler farklı olabiliyor ya da işte ya işte şu, bu butonlar niye böyle bu şey niye böyle hani diyebildiğin şeyler oluyor. Normalde büyük bir şirkette bunu konuşarak işte söylemen gerekir mühendislere işte onları hani bunun çözülmesinin önemli bir şey olduğunu ikna etmen gerekir. Şu andaki mesela rolümde hemen öyle bir şey çok gerek duymadan direk işte Cursor ya da cloude gibi yapay zeka destekli işte code editörler editörlerle yapabiliyorum. Kendim yapabiliyorum. O çok büyük bir şey mesela çok farklı bir çalışma biçimi.” (P4.1)

“Ben böyle hani yani yapmak istiyorum ama işte hani kodlama da çok değil diyorum […] O durumu demokratize eden bir şey aslında işte bu tool'lar” (P4.2)

“Yani hala hazırda olan ürünün üstünde oturuyor mu, oturmuyor mu, nasıl ne derece oturuyor, ne derece oturmuyor onu görebilmek şey hani hem iyi bir şey, hem kötü bir şey mesela iyi kısmı; Hani gerçekten inandırıcı, yani bayağı gerçek ve çalışıyor. Hani kötü kısmı da o işte buna çok inanırsan hani başka şeyler olabilir mi, o şeyleri kaçırıyorsun. Böyle alternatif gelecekleri kaçırıyorsun yani hani işte onun için böyle ilk başta bir en azından düşünüp işte bu nasıl olmalı, nasıl şey yapmalı ondan önce başta belki bir işte çok basit de olsa işte figmada exploration, hani yapmak o yüzden önemli.” (P4.3).

“Diyelim ki bi ikon tasarlayacaksın. Diyelim ki 2-3 tanesini tasarladın, yapay zekaya şöyle bir şey diyebilmelisin: diğerlerini de sen yap… ben bi [sonuçlara] bakayım.” (P4.4)

“bu şirket bunu aslında 3 yıl önce yaptı ve böyle bir sonuç çıktı” (P4.5)

P5

“En başta bir kullanıcı ya bir projenin başında kullanıcı görüşmesiyle zaten bu adımla başlıyoruz. Kullanıcı görüşmesine soru hazırlamaktan yani bu ilk aşamadan başlayıp buralarda, sonrasında

kullanıcı görüşmelerini yaptıktan sonra, ranskript için de toollar kullanıyorum, transkripti çıkarmak için." (P5.1)

"Yani çok hızlı bir şekilde bunu sunulabilecek bir formata gelip ama benim tasarımı sunulabilecek bir formata getirip user'la, kullanıcıyla ya da işte Müşteriyle çabucak bir şekilde etkileşim haline gelmemi sağlıyor," "Bu da tekrardan feedback alıp tasarıma geçireceğim sürece kolaylık sağlamış oluyor." (P5.2)

"O flowlar arası geçişleri elle yapmam gerekiyor ama yine de o on tane şeyi bile bağlayabilmesi inanılmaz vakit kazandırıyor." (P5.3)

"Yani birkaç kez deniyorum mesela işte Eğer verdiği sonuç tamamen bambaşka yine işte normalde o bankacılığa verdiğiyle aynı göründüğünde Ya tamam hani burada vakit kaybedeceğime bir de oluşturması da dakikalar sürüyor Zaten. dakikalarca bekleyeceğime ben kendim benchmarka baksaydım da yapsaydım oluyorum." (P5.4)

"Bana şunu verdi, bana bunu verdi [yapay zeka çıktılarından bahsediyor]. Diyelim ki işlevsel bir öneri de sunuyor ve sonra bunları önceliklendirebilse, örneğin 'bunla, bunlar en sık karşılaşılan sorunlar olduğu için öyle bir kullanıcı profili oluşturdum...' diyebilse" (P5.5)

"Onları yapabilmek… tek bir tool'da… çok daha kolay olurdu" (P5.6).

P6

"Research ağırlıklı hangi yöntemi önerirsin, bunun buna avantajı ne dezavantajı ne gibi gibi.." (P6.1)

"Belli ki ben, az önce de söylediğim gibi, aslında o bomboş bembeyaz bir sayfayla karşı karşıya kalmayı sevmiyorum. Bunu UX anlamında söylemiyorum bu arada UI anlamında söylüyorum." (P6.2).

"Sanki böyle hakikaten eğitiyormuşum gibi kendimi de eğitiyorum. Doğru prompt ne yazdım, neye şey böyle şablon promptlarım olup kendime belki bir. Promp listesi arşivi sık kullandığım şey yapabilir miyim falan diye düşünmüştüm." (P6.3)

"Başlangıçta, bilmediğim zaman, ya da daha doğrusu, önümde boş bir sayfa varken karar verirken, tasarım süreci benim için daha zor oluyor. Bir şey ürettikten sonra [yapay zeka çıktılarına atıfta bulunarak] karar vermek, ardından o ince rötuşları eklemek ve detaylandırmak, ondan daha çok keyif alıyorum." (P6.4)

P7

“Al arkadaşım, kullanıcı ihtiyacı bu al arkadaşım komponentlerim bunlar buradan bana alternatif tasarımlar çıkar. Bu alternatif tasarımlar arasından da en iyisini ben tekrardan işte bir a tasarımından b tasarımını aldım ya da c tasarımından d tasarımını aldım. Bu şekilde o onları mixleyerek son bir final tarafa gittiğim Yerleri var ya aslında.” (P7.1)

“Genellikle de UX research'de kullanıyorum ama tehlikeli yani yalan söyleyebiliyor. Hayal görebiliyor. Yani oradan aldığımı as-is olarak kullanmıyorum.” (P7.2)

“İşte oradaki problemi çözmek daha hızlı çözdürmek, hatasız çözdürmek, daha hızlı öğrendirmek olduğu için ve genellikle benim ya da daha hızlı işi çıkartmak. Her ne kadar hızlı işçi çıkartırsan o kadar tartışacak, vaktiniz olur” (P7.3)

“Backend’inden database’ine kadar artık hepsine dokunabiliyorum, kod yazmayı bilmiyordum ama artık neyin mümkün olduğunu anlayabiliyorum.” (P7.4)

“Yaratıcı süreçlerimi pozitif yönde etkiliyor ama UX süreçlerimde daha çok verimliliğimi artırıyor.” (P7.5)

"ChatGPT'den bilgi istiyorsam, elbette ona körü körüne güvenmiyorum. Çünkü kendileri de 'güvenmeyin' gibi uyarılar yazıyorlar zaten... verdikleri bilgiler genellikle sadece tahminden ibaret veya sağladıkları bağlantılar ve bilgiler farklı yerlerden kes-yapıştır." (P7.6).

"Yapay zeka güncellemesini yayınladıklarında [katılımcı burada kullandığı bir kullanıcı arayüzü tasarım uygulamasından bahsediyor] 'yapay zeka ile eğit' düğmesi seçili geldi. Sanki kibarca, hani biz zaten şimdiye kadar eğittik bundan sonra ne yapalım der gibi. Bu konuda hiçbirine güvenmiyorum. Sonuçta onlara bilgi birikimimi vermek istemiyorum." (P7.7)

P8

“Bunları çok güzel yaptı veya işte dil öğrenenlerin farklı işte adımlardaki farklı. Painpoint'leri işte expectation'ları vesaire hani customer journeymap şeklinde bir çok şey çıkardı.” (P8.1)

“imzamı atmam Yani herhangi bir AI çıktısının üzerine … zamanını tabii ki de Şey yapıyor, yani daha hızlı bir şekilde yapabiliyorsun ama hız her zaman bizim dostumuz olamayabiliyor yani.” (P8.2).

“işte yazılımcılarla veya işte farklı departmanlarla daha iyi iletişim kurabileceğimi düşünüyorum.” (P8.3)

“Eğer bir şeyi doğrulamak istiyorsan, Anlamak istiyorsan gidip yüz binlerce euro dolar vermeden yapabiliyorsun Kendin. bu güzel bir seçenek hani.” P(8.4)

“O zamanlar bu kadar basit değildi, o zamanlar dediğim de on ay öncesinden bahsediyorum.” (P8.5)

“Şu an gidip başka bir AI toolu kullanacak mecalim kalmadı. Onu öğrenecek mecalim yok.” (P8.6)

“So you’re already feeding it [AI] with what you’re working on. I said, ‘Look, I have an idea. Can I do this idea? Can we do it?’ [He’s referring to ChatGPT] It said, ‘We can, here’s the code.’ After it gave me the code that day, I was in shock because, as a designer, on the software side, which is a discipline I don’t know, let me summarize it like this: if you’re a designer, the software outputs enchant you. If you’re a programmer, the design outputs enchant you. [...] Probably, if programmers saw the code I wrote, they would say, ‘What is this?’ But at the end of the day, does it work? It works for me. (P8.7)

“Yani zaten üzerinde çalıştığın şeyleri [yapay zekaya] veriyorsun. Dedim ki, ‘Bak, benim bir fikrim var. Bu fikri uygulayabilir miyim? Bunu yapabilir miyiz?’ [ChatGPT'ye atıfta bulunuyor] ‘Yapabiliriz, al sana kod’ dedi. O gün bana kodu verdikten sonra şok oldum çünkü bir tasarımcı olarak, bilmediğim bir disiplin olan yazılım tarafında, şöyle özetleyeyim: Eğer tasarımcıysanız, yazılım çıktıları sizi büyülüyor. Eğer programcıysanız, tasarım çıktıları sizi büyülüyor. [...] Muhtemelen, bi yazılımcı da benim yazdığım kodu görse, ‘Bu ne?’ derdi. Ama günün sonunda, işe yarıyor mu? Benim için işe yarıyor.” (P8.8)

P9

“3 tane personamız var, dolayısıyla hani biz bunları da bu arada öğrettik bir custom GPT yapıp… onları böyle o yarattığımız personaya büründürdük. Aynen o şekilde konuşuyor. Birinin ismi Mehmet mesela.” (P9.1)

“Yazılımcıya gitmeden bazı şeyleri deneyebiliyorsun.” (P9.2)

“Biri Lovable diyor, biri Bolt diyor, biri Figma Make diyor… Hepsinin yaptıkları farklı, yapamadıkları farklı. Böyle tek ve sürdürülebilir, ‘ne zaman şunu yazsam aynı sonucu alırım’ dediğiniz hiçbir şey yok ve bu çok rahatsız edici. Elimdeki envanterimdeki 4-5 tane araçla hepsinde aynı promptu denemek istiyorum… ve bu beni yoruyor.” (P9.3).

P10

“Artık benimle beyin fırtınası yapıyor. Konunun üzerine konuşabiliyor da. Bu gelişmiş özellikleri de şu an iyice hayatımı kurtarıyor yani.” (P10.1)

"Derin arama kullanmıyorsanız, var olmayan kaynaklar buluyor. Bu yüzden gidip doğrulamam gerekiyor." (P10.2).

"Böyle bir durumda, neden kullanıyorum ki?" ,"İnsana 'Paramı boşa harcıyorum' diye düşündürüyor." (P10.3)

P11

“Büyük büyük Excel dosyalarının içinden hani saniyeler içinde problematik painpointları çıkarma gibi.” (P11.1)

"Ama şunu söyleyebilirim ki, şu anda bizim için özellikle faydalı olan şey görsel asset üretimi." (P11.2)

"Aklınızda olmayan bir şeyi görüp beğenebilirsiniz, bu da sizi kısıtlayabilir... ama bu aslında tasarımcının kendi vizyonuna da bağlı." (P11.3)

"Sorunlu noktaları ortaya çıkarıyor... ama nedenini söyleyebilecek bir şeye sahip değil." (P11.4)

P12

“Hani ux writingde chatgptinin yazdığı şeyler çok güzel ve zaten ürünün dilini ben biliyorum. ona göre editletebiliyorum.” (P12.1)

“Çok hızlı şekilde bir şeyler hazırlamam gerekiyor ki aksi takdirde süreç çok uzuyor. Çok hızlı bir şekilde bir akış hazılrayıp Böyle mi istiyorsunuz? Burada bu mu olsun Şurada şu mu olsun gibi bir şey üstünden konuşmam gerekiyor, özellikle orada kullanıyorum.” (P12.2)

.“Ama çok kısıtlı bir sürem varsa o da benim için zor olduğu için ve hızlı bir şey çıkartmam gerektiği için yine bu AI wireframeing toollarından birini Kullanıp ya da chatgpt’ye sorup bu ekran nasıl bir şeye benzeyecek? Çok hızlı bir şekilde yani ben ne yapıyorumu anlamak için de kullanabiliyorum diyebilirim.” (P12.3)

“Prototip göstermek her zaman avantajlı çünkü sözel olarak anlatıp, akışı anlatmaya çalışmak daha zor.” (P12.4).

“Gerçekten iyi prompt yazabilmek yaptıkça gelişen bir şey.” (P12.5)

“Hangi tool, nasıl promptlara, nasıl cevap veriyor onu da bilmek gerekiyor. Çünkü biz denerken şeyi de fark ettik. Bazı toollara çok basit bir prompt versen de çok güzel sonuçlar çıkartırken bazılarına çok detaylı vermen gerekiyor. Hangi tool nasıl kullanılmalı? Onun içinde bir bilgi birikimi gerekiyor.” (P12.6)

“Bir kişi bu persona için bir araç geliştirdi; bu araçta hem bir persona oluşturabiliyorsunuz hem de oluşturulan personayı eklediğinizde onunla konuşabiliyorsunuz; bir diğeri ise Figma için bir eklenti geliştirdi; bu eklenti, onlara ekranı verdiğinizde, erişilebilirlik ve diğer her şeyle ilgilenen bir

kullanılabilirlik testi gibi çalışıyor. İlgilenen ve denemeye hevesli olanlar bununla harika şeyler yapabilirler.” (P12.7)

“Ancak olan bir şey de şuydu ki, tasarımcılar olarak, en azından geliştiricilere ihtiyaç duymadan basit şeylerle denemeler yapabildik. Bu bize fikirlerimizi hızla geliştirme ve inceleme şansı verdi. Elbette bu, programcılarla olan ilişkimizi tamamen ortadan kaldırmadı. Ama belki de bekleme sürelerimiz azaldı.” (P12.8)

“Yenileri takip etmek biraz yorucu ve imkânsız ama… nasıl geliştiğini, nasıl değiştiğini görmek de çok güzel.” (P12.9)

“Bir workshop yapılacaksa ona fikir üretirken ya da iş süreçlerimle farklı noktalarda bir şey yazacaksam… her alanda kullanıyorum.” (P12.10).