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Analyzing the integration of generative AI in the design process through the double-diamond framework

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Research Article

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Abstract

Artificial intelligence (AI) tools, with their capacity to produce countless outputs from minimal input, continue to challenge and reshape creative workflows. While these developments support designers in various stages of the design process, there is growing interest in how designers integrate AI tools into their design processes, and how they engage with these tools in the conduct of designerly practices. This article investigates this topic through two consecutive studies. The first study involved a survey conducted among professional designers to understand which AI tools they use, their frequency of use, purposes of use, and self-reported proficiencies. The second study involved think-aloud interview sessions with 10 professional designers, each completing a design task specifically developed for this research using AI tools of their choice. Data from both studies were analyzed using the double-diamond design model as a framework. The findings reveal that AI tool usage is already prevalent among professional designers, extending across the entire design process and involving the coordinated use of multiple tools. These tools are used for a wide range of functions requiring analytical and synthesizing abilities in the exploration of the problem and solution spaces; prior experience and competences significantly shape AI tool usage. The findings also reveal that designers engage with these AI tools, displaying distinctive negative, neutral, or positive attitudes toward them, through different communication styles and interaction types.

Introduction

Latest developments in artificial intelligence (AI) have raised concerns about whether AI will replace human creativity and, consequently, whether designers will continue to remain relevant for the development of environments, products, and services in the near future (Irbite and Strode, 2021). However, recent research exploring designer–AI interaction in generative tasks identifies AI as an agent that assists rather than replaces in the design process (Chiou et al., 2023; Kalving et al., 2024; Tang et al., 2024). This perspective has contributed to a reframed understanding of AI in design, shifting from a tool-based view (Sarkar, 2023) toward models of human-computer collaboration (Cabrera et al., 2023), human–AI cooperation (Li et al., 2022), and human-AI symbiosis (Mahmud et al., 2023). These models describe designer–AI interaction as a strategic partnership where parties bring forth their strengths in achieving common goals (Stylos, 2023), a synergy where they leverage their strengths for heightened efficiency (Zhang and Yin, 2024), and a symbiosis where parties develop each other into smarter agents over time (Jarrahi, 2018). Although the view prevails that AI and humans still need time and new methods to learn each other's languages (Tang et al., 2024), such perspectives ease earlier anxieties about AI replacing designers and also position AI as a self-directed, adaptive assistant contributing meaningfully to both the process and outcomes of design (Zeytin et al., 2024).

AI's contributions to the design process include taking over chores and speeding up steps (Altavilla and Blanco, 2020) such as gathering information and analyzing data, carrying out specific acts not typically part of designer skill sets such as programming (Alexander, 1984), identifying potential issues affecting the development cycle early on in the process (Tholander and Jonsson, 2023), generating alternatives through diversification and variation (Gmeiner et al., 2023; Liang, 2024), and decision making through filtering and selecting solutions (Chung and Choi, 2022). These capabilities point to a transformative effect on how design processes are conducted (Adeleye, 2024), the qualities the outputs will possess (Irbite and Strode, 2021), the skill sets future designers will need (Singh and Duo, 2023), and what the role of designers will become (Seidel et al., 2018) within AI-integrated design processes.

This article adopts a collaborative perspective on AI and addresses a gap in the literature around how professional designers integrate AI tools into their workflows across different stages of the design process, examined through research that adopts a theoretical framework based on the double-diamond design model (Design Council, 2025). This model represents the design

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process as two sequences of divergence and convergence: the first for problem exploration and framing, and the second for solution exploration and naming. Within this structure, divergent and convergent thinking are iterative and interdependent, supported by analytical reasoning and synthesizing abilities, capacities often considered fundamental to design thinking (Tovey, 2012; Goldschmidt, 2016).

The research combines a survey for gathering information on the types of AI tools that designers use in their professional practices, with think-aloud interview sessions for observing and interactively discussing the designers' engagement with AI tools. The responses collected from the survey identify AI usage for different designerly functions, while findings from the sessions reveal how designers interact with AI tools, complementing written statements with observed engagements and providing an integrated perspective on the topic. As a contribution, the research reveals how designers plan, manage, and make decisions with AI support beyond idea generation, as well as suggesting insights into the attitudes, communication styles, and interactions that designers display in the way they engage with AI.

The research is conducted among professional designers in Türkiye, preferred for their competence in designerly skills, expertise in domain-related knowledge, and experience in implementing AI tools in their professional practices with access to tools, methods, and know-how in product development sectors. While the research is contextually localized, the findings may still be of interest to a wider design community, given the parallel structures of design education in Türkiye with international higher education systems (see Er et al., 2003; Şatır, 2006; Hasdoğan, 2009; Irkdaş Doğu et al., 2015; Korkut et al., 2023), and the alignment of the conduct of professional design practices with that of international counterparts, as both are fundamentally based on the same core design development processes (see Özcan, 2009; Tezel, 2011; Hasdogan, 2012; Ünsal, 2018; Kaygan et al., 2020; Kesdi and Kaygan, 2025).

The article first reviews the literature on design process, design thinking, creativity, and AI in design, followed by a review of research carried out on the topic. The methodology section presents the research questions and outlines the methodology for data collection and analysis, followed by the presentation of the findings with discussions on how AI integration aligns with stages of the double-diamond design model. The article concludes by addressing the research questions and shares suggestions for further research.

Design process, design thinking and creativity

Design is related to a series of activities defining a process as well as its outcomes, conducted for product renewal, development, or innovation (McKay, 2012). The design process typically initiates with a brief outlining a design problem and proceeds through various stages to reach a possible solution (Collier, 2012). These stages incorporate activities such as planning, managing, researching, developing, testing, and production set-up that run conjointly or in parallel with design-related activities, allowing the analysis of the design situation and synthesis of all related information toward a final design output. Independent of context, designing involves multiple tasks to achieve its goals (Roozenburg and Eekels, 1995; Pahl and Beitz, 1996) and imposes cognitive, physical, and psychological loads on the designer (Hong et al., 2023). While design problems and goals frequently shift, how designers deal with ill-structured problems and the ambiguity associated with them remains unique (Cross, 2006; Lawson and Dorst, 2009). Designers' work is characterized by continuous processes of understanding, reasoning, imagining, ideation, decision-making, and elaboration (Lawson, 2005; Cross, 2011). These activities are central to what has been called designerly thinking, requiring a mindset that believes in growth and includes being empathetic, analytical, critical, experimental, collaborative, and creative. Designerly thinking is based on the parallel dichotomies of divergent-convergent, reflective-impulsive, and verbal-non-verbal thinking, using the language of drawings in reflecting visual thinking (Tovey, 2012).

Although the design process is mostly represented as a linear model, the interplay of the activities in the stages requires iterations that allow diverging for exploration and then converging for detailing and development, giving it a cyclic nature. The double-diamond model (Design Council, 2025) is often referred to in the design thinking literature as a useful representation of the design process, with two consecutive phases of divergence and convergence. The first diamond involves discovering and defining the problem, while the second involves developing and delivering the solution. In the *discover* phase, information on the problem area is collected and expanded (divergence), while in the following *define* phase, the design challenge is identified by narrowing down this information (convergence). In the *develop* phase, the solution space is widely explored through ideation (divergence), followed by the *deliver* phase, where the solution space is narrowed down toward a final solution through development and detailing (convergence).

Creativity is generally associated with the qualities of the final design outcome, defined through its novelty, originality, and value (Roy, 2004; Tovey, 2012), as well as its functionality (Gero and Maher, 1993). However, research shows that how problems are explored, defined, and addressed, as well as how solutions are explored and synthesized, also require creative engagement (Maher et al., 1996; Dorst and Cross, 2001; Lawson, 2005). Cross (1997, p. 427) explains creativity in design as the achievement of the "creative leap," a shift in the perspective on the problem space resulting in a new insight on the solution space bridging the two, and indicates that this is more concerned with the design process and requires deliberate effort. To begin with, designers need to transform poorly defined problems into well-defined ones, as design problems are typically ill-structured (Simon, 1973). Each design problem represents a new domain of inquiry, and designers act as researchers in framing the problem in their own understanding (Cross, 2006). Design problems are solution-dependent, which calls for the need to extend and explore the solution space, as exploring solutions is often the means for understanding the problem (Dorst and Cross, 2001; Cross, 2021). The problem and the solution co-evolve through iterations carried out in a series of divergence–convergence (Dorst and Cross, 2001; Goldschmidt, 2016), aligning the explorative nature of the design process with the double-diamond model. Experience (Lawson, 2005) and expertise (Simon, 1985; Lawson and Dorst, 2009) influence this process and its outcomes, as they contribute to generating, accumulating, and using knowledge, as well as acting upon it and making evaluations. This explorative nature of design is why it has been considered a class of problem solving, and has laid the foundation for considering AI in designing as a mode of search (Gero, 1994, 2007). This, in turn, led to the development of symbolic search computation, generating formulations of designing, also reformulating the search space. The developments have resulted in a dynamic and prescriptive growing body of design space that changes continuously with new knowledge and new requirements generated through designing activities and their outputs each time (Gero, 2007).

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Amabile's and Mueller (2008) componential theory of creativity emphasizes three within-individual components as influencers: *domain-related skills* (including expertise), *creativity-relevant processes* (cognitive and personality related for novel thinking), and *task motivation* (intrinsic motivation other than interest, enjoyment or a sense of challenge). The model suggests a fourth component that is outside the individual, the *environment*, and the social environment in particular, that supplies the individual with diverse stimulus mechanisms through different viewpoints, ideas, information, supervision, encouragement, and collaboration. This model suggests that creativity is shaped not only by individual capabilities but also by environmental and contextual factors, including tools and technologies. This opens up a conceptual space for AI integration in the creative process. According to Simon (1985) creative acts are the same as those required for intelligent acts, as both involve thinking in the form of reading, writing, assembling, storing, and comparing symbols in relational structures and branching the outcomes, making creativity computer-programmable for intelligent behavior. As such, AI systems now seem to have the ability to make connections across unexpected and multiple solution spaces for synthesis, bringing them closer to displaying the ability to make the *creative leap* in the design process (Sankar and Sen, 2025).

Artificial intelligence in design

Artificial intelligence, broadly defined, refers to systems capable of fulfilling human needs by processing information, identifying problems, and offering responses based on learned data (Buchanan, 2006). The quality and scope of the data pool is crucial to AI's functionality, since it shapes the generated output. AI systems are categorized by their cognitive capacities: Artificial Narrow Intelligence (ANI) handles specific tasks (e.g., chatbots); Artificial General Intelligence (AGI) performs a wide range of tasks and acts like human memory and reasoning; and Artificial Super Intelligence (ASI) is a hypothetical future form that exceeds human capabilities (Zohuri and Rahmani, 2023).

The way AI operates is defined by the algorithms. Rule-based systems follow predefined "if-then" rules and are effective for planned tasks such as the systems that take necessary actions when the conditions are met (Fry, 2018). On the contrary, machine learning (ML) automates decisions and optimizes their performance by being exposed to data (Stryker and Belcic, n.d.). ML has three main approaches: supervised, reinforcement, and unsupervised learning, each with distinct strategies for training on data. Deep learning, a subfield of ML, uses artificial neural networks that are modelled after human cognition. Furthermore, foundation models such as generative AI (GAI) and large language models (LLMs) make it possible for the autonomous generation of novel content. LLMs such as generative pretrained transformers (GPTs) are AI models that can generate human-like conversations, with the ability to assist with decision making, support creativity and prototype (Ege et al., 2025).

Computer-aided design software has long supported designers with tasks such as creating, modifying, and analyzing designs. Recently, generative AI has emerged not only as a facilitator, but also as a potential partner in ideation, offering new ways in creative processes. Acknowledging that design problems are often complex, open-ended and composed of independent components, the designer's task additionally includes setting priorities (Lawson, 2005). Generative AI is specifically valuable in this context for its capacity to automate repetitive tasks and produce unique and unexpected outcomes, enabling a shift from individual creativity to co-creative partnerships (Kalving et al., 2024).

Active ideation refers to collaboration between humans and computers, where AI contributes by generating ideas, suggesting alternatives, and challenging assumptions, while designers curate, filter, and refine them (Sankar and Sen, 2025). Designers' expertise and active engagement help overcome ideation problems such as fixation, mental blocks, and cognitive fatigue. Besides visual thinking, designers also utilize verbal thinking in ideation and construct linguistic queries for information retrieval. In this context, with the ability to be trained to align with human values, conversational AI supports natural language interactions, responding to verbal queries and generating meaningful content and prompts to ensure coherence of the conversations and outputs generated in response (Sankar and Sen, 2025).

Humans and AI collaborating as partners for creative products form creative systems. In creative systems, AI is a means of generating novel creative products with value, supporting human creativity, and collaborating with the user for a shared creative product combining the creative abilities of both parties (Davis et al., 2015). When humans and AI act as colleagues pursuing the same goal, the system is referred to as a co-creative system (Davis, 2013). In processes led by co-creative systems, interaction and adaptability are important, as sometimes the human will want to lead, and other times the human will want AI to lead while conducting independent search (Rezwana and Maher, 2023).

Rezwana and Maher's (2023) Co-Creative Framework for Interaction Design (COFI) describes interaction in co-creative systems occurring as *between human and AI collaborators*, and *with the shared creative product*. Interaction between collaborators is affected by *collaboration style* and *communication style* (Rezwana and Maher, 2023). Collaboration style incorporates participation style (parallel working, turn-taking), task distribution (same task, divided task), timing of initiative (pre-planned, spontaneous), and mimicry (mimicked response, improvisational response). Communication style may be human-to-AI intentional, human-to-AI consequential, or AI-to-human, through various modes such as text, visual, voice, gaze, facial expression, haptic, or direct manipulation, used individually or in combination. Interaction with the shared creative product is characterized by *creative processes* and the *creative product* (Rezwana and Maher, 2023). Creative processes are activities followed for generating, evaluating and defining. The creative product is affected by the contribution types made by both parties (bringing new elements, extending, transforming, or refining existing elements), and contribution similarity (degree of divergence or convergence of the contributions made).

Research in the field

Numerous studies investigate the role of AI tools in design processes. Khanolkar et al. (2023) state that most AI-based methods are applied during the *conceptual* and *preliminary* stages of design, a key reason for this being the availability of open datasets that provide the necessary design-related information for AI to work with. Tang et al. (2024) interviewed seven designers on their recollections of their design processes, based on the double-diamond design model, revealing that the *discover* and *develop* stages are those where AI tools are mostly used. These stages require divergent thinking through activities such as searching for inspiration and research. A common agreement seemed to be a lesser

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reliance on AI for the final delivery; designers indicated that they found it important to study, filter, and develop the final scheme for the design themselves (Tang et al., 2024). While studying collective intelligence (i.e., a group composed of a human and AI) through a 2 × 2 mixed factorial experiment design involving a generative AI tool, Cai et al. (2023) focused on the *inspiration* and *initial idea generation* stages, comparing image search and image generation for broad design space exploration. They projected the task distribution pattern within the design process among humans and computers as "human specifies, computer generates, human selects (p. 9)," redefining the role of AI in design to increase creative output and provide options for designers.

In their study, Zeytin et al. (2024) observed students during architectural design work and issued a survey investigating their design process; they identified that students integrated AI in their processes from beginning to end, selectively for particular tasks, or mainly initially for ideation. A balanced integration of AI tools proved to be significant in preventing over-reliance and not undermining the designer's interpretative capacity (Zeytin et al., 2024). Following the identification of AI tool usage trends within the design process from the literature, Chung and Choi (2022) carried out in-depth interviews with designers. Their findings emphasized that while designers made use of AI in the generation of ideas and creation of prototypes, there seemed to be a gap in the availability of tools that help designers plan and follow through their design processes, as well as assist them in decision-making.

Framing the engineering design process as composed of the five stages of *problem definition*, *conceptual design*, *preliminary design*, *detailed design*, and *design communication*, Khanolkar et al. (2023) investigated the literature for studies (n = 108) conducted on AI in design. They revealed that machine learning, deep learning, and NLP are widely used AI-based methods, with deep learning spreading across all five stages of the design process, machine learning across the first four stages, and deep learning across the first three stages. It was seen that AI-based systems were used in *problem definition* for customer review analysis, design requirements analysis, and user requirements analysis. AI was used in *conceptual design* for design data analysis, design ideation, concept generation, conceptual modeling, obtaining design alternatives, and evaluation. AI was used in *preliminary design* for design analysis, synthesis, and evaluation. AI was used in *detailed design* for design optimization. A smaller number of studies indicated using AI in *design communication* for obtaining aesthetic feedback on appearance and style.

Ege et al. (2025) compared the 48-hour prototype development process, for a given task, of six engineering design teams, five composed of humans, and one involving human-AI (LLM) collaboration. The findings revealed that the LLM displayed similar prototyping practices to humans and was capable of generating concepts and finalizing a functioning physical prototype. On the other hand, the LLM tended to add unnecessary complexity to the design proposals, mistook feedback as failure, consequently prematurely abandoning potential ideas, was unable to effectively communicate design intent, disrupted continuity by diverging from the project context, and displayed design fixation.

The qualities of AI-supported design are not determined solely by the technology's capabilities but also depend on the knowledge, skills, and experience levels of the designer. Gmeiner et al. (2023) report that experienced designers actively follow advancements in AI tools and incorporate them in ways that complement and enhance their existing practices; by contrast, those less familiar with AI may feel hesitant or dissatisfied with the results. In their study, Tang et al. (2024) found that designers with less experience use AI tools in less frequency, whereas designers with more experience developed working ways with AI that are more extended throughout the design process. Experience levels influenced various aspects of their practice, including design competencies (e.g., skill sets and strategic thinking), process conduct (e.g., stage planning and time management), integration of domain knowledge and expertise, as well as personal motivation and interests.

AI technologies are increasingly integrated into creative workflows as a medium, taking on diverse roles within the design process (Negrete-Yankelevich and Morales-Zaragoza, 2014; Albukhari, 2025). Although generative AI has introduced new tools into design practice such as configuration builders and image generators, it has not displaced the core role of the designer. Designers incorporate their values into the design process for planning, executing, and critical decision-making through judgment and are still responsible for making the *creative leap* in bridging the problem and solution spaces. In this picture, AI tools are best understood as augmentative forces enhancing the outcomes of the design process rather than replacing or limiting human creativity (Figoli et al., 2022). There is a further need to investigate the interaction between designers and AI tools at the interface of designerly practices that implement analytical and synthesizing abilities through iterations of divergence and convergence.

Methodology

This research was designed to investigate how professional designers use generative artificial intelligence (GAI) tools in their design processes, using the double-diamond design model as the framework in examining the functions for which these tools are used, and how these are distributed across the design process in the exploration of the problem and solution spaces. It was hoped to explore through verbal inquiry and observations why and how designers engage with these tools in conducting a design task from beginning to end. The research questions were:

- How do designers integrate generative AI (GAI) tools in their design processes?
- How do designers engage with these tools in their design processes?

The research consisted of two studies. The first study involved a survey distributed via Google Forms to product designers in Türkiye, aiming to gather data on the AI tools they use in their design processes, their purposes for using AI tools, frequency of use, and self-assessed proficiency levels. The second study involved online think-aloud interview sessions with professional designers over Google Meet, during the conduct of a short design task that required them to integrate and interact with AI tools throughout the process and explain their actions in a think-aloud format. Google Meet, free to use with various tools, was chosen as the online platform for its availability and familiarity to each computer user. Meeting virtually expanded the participant pool, allowing the possibility of meeting with remote designers and in accordance with their convenience. Due to its exploratory approach, the study did not focus on particular AI tools, design stages, or designerly functions, leaving the designers free in their selection of and interaction with tools.

Survey

Theoretical-construct sampling was used to reach a wide pool of professional designers across Türkiye, who were industrial design graduates of various universities and working in different product

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development sectors. The sampling pool was drawn from the email database of the department affiliated with both authors that included alumni from all universities in Türkiye with industrial design departments, as well as personal contacts accumulated over years of academic and professional networking. The participant list was limited to graduates from the years 2013 to 2024, ensuring that respondents had at least 1 year and no more than 10 years of professional experience.

The survey was conducted online via Google Forms. At the beginning of the form, participants were informed about the aim and scope of the survey, and that their responses were gathered for academic purposes only. Participants were asked for their consent before continuing. The survey included four short-answer questions on demographic information and professional background, and six questions addressing the integration of AI tools into their design processes. The questions were whether they incorporate AI tools into their design processes (yes/no); how often they use these tools (between 1 and 5 on a Likert scale); which tools they use (short-answer); in which stages of their design processes they use these tools (short-answer); which AI tools they use for idea generation and visualization in particular (short-answer); and how they evaluate their proficiency levels (between 1 and 5 on a Likert scale). Additionally, respondents were asked whether they would be willing to participate in further stages of the research. The survey was distributed on April 15, 2024 to 3,004 designers and closed on May 17, 2024. A total of 103 responses were received, with 15 indicating no usage of AI tools and 88 valid responses. The analyses, including calculations and coding, were mainly conducted by the first author, with regular consultations and cross-checking with the second author.

Demographic information, AI tools usage frequency and proficiency levels

Respondents were industrial design graduates of eight different universities across five cities. Four respondents had 10 years of professional experience, 22 had between 5 and 9 years, 50 had between 1 and 4 years, and 12 had up to 1 year. Eighteen respondents graduated between 2022 and 2024, 39 graduated between 2019 and 2021 with the highest response rates per year, 24 graduated between 2016 and 2018, and 7 graduated between 2013 and 2018 with the lowest response rates per year. Their fields of practice included graphic design, UI/UX design, game design, product design, interior design, and industrial design. AI tool usage frequency was rated on a Likert scale from 1 (very rarely) to 5 (almost always). The average usage frequency was calculated as the weighted mean of responses, yielding a mean usage score of 3.04 over 5, indicating a moderate frequency of use ($1 \times 11 + 2 \times 15 + 3 \times 29 + 4 \times 25 + 5 \times 8 = 268$, $268/(11 + 15 + 29 + 25 + 8) = 3.04$). Proficiency levels were also rated on a Likert scale from 1 (very weak) to 5 (very proficient). The average proficiency level was calculated as the weighted mean of responses, yielding a mean usage score of 3.29 over 5, indicating a medium level of proficiency ($1 \times 2 + 2 \times 13 + 3 \times 38 + 4 \times 27 + 5 \times 8 = 290$, $290/(2 + 13 + 38 + 27 + 8) = 3.29$).

AI tools used

Respondents were asked which AI tools they used in their professional design practices and in which stages of the design process they used these. A total of 39 different AI tools were compiled from the responses of 87 participants (one respondent did not specify tool names), with the number of AI tools used by the respondents ranging from 1 to 9. The weighted mean number of tools used was calculated as 3 ($1 \times 12 + 2 \times 20 + 3 \times 30 + 4 \times 12 + 5 \times 10 + 6 \times 2 + 9 \times 1 = 261$, $261/(12 + 20 + 30 + 12 + 10 + 2 + 1) = 3$), and the median was calculated as 3.

The most frequently mentioned tool was *ChatGPT* ($n = 68$), a generative AI chatbot, followed by *Midjourney* ($n = 36$), an image generation tool. Other than these, 4 tools were mentioned by 11–17 respondents (1 by 17, 2 by 15, 1 by 11), 6 tools by 4–7 respondents (2 by 7, 2 by 6, 1 by 5, 1 by 4), and 27 tools by 1–3 respondents (3 by 3, 6 by 2, and 18 by 1).

The 39 AI tools were grouped according to type and reviewed in terms of capabilities. Among the tools, four were chatbots. Thirteen AI tools were image generators, accompanied by one tool for video generation, one for image and video generation, one for audio generation, and one for image, video, and audio generation. One tool was for 3D model generation, one for sketch-to-render generation, one for photo editing and image manipulation, one for texture generation, and one color tool. Other specific types were two architecture and interior visual and render generators, one game assets generator, one vector graphics and illustration generator, one graphic design and template tool, one font identifier, and one brand identity/content generator. Four tools offered collaborative whiteboard and AI workspaces. The list finally included one tool for translation and one for research summaries and note-taking.

The survey findings indicate that chatbots are mainly used for research, questions and answers, recommendations, opinions, information, and assistance, through conversations. *ChatGPT* ($n = 68$) remains a leading platform since its integration with *DALL-E* ($n = 15$) that has image-generation capabilities and other features such as adaptation and creating variations. A main feature of *ChatGPT* is its capability to maintain context across sessions, retrieving past conversations, making interactions feel continuous and genuine. *Microsoft Bing (Copilot)* ($n = 7$) was another commonly mentioned chatbot, differing from *ChatGPT* by offering a native Windows application and eliminating the need to use a web browser. *Google Gemini* ($n = 6$) and *Perplexity* ($n = 2$) were also referenced by participants.

The most commonly used tools for image generation included *Midjourney* ($n = 36$), *Vizcom* ($n = 17$), *Adobe Photoshop's Generative AI* ($n = 15$), *Adobe Firefly* ($n = 11$), *Stable Diffusion* ($n = 7$) and *Krea* ($n = 6$). *Midjourney* is a subscription-based tool accessed via Discord or web browsers, allowing users to generate four images using the prompt command "/imagine." These images can be regenerated, upscaled, or variated. It also features an image training function that enables users to upload visuals; AI analyses and describes the content, displaying how it interprets the visuals to support the creation of more targeted prompts. *Vizcom* uses sketches and reference images in combination with prompts, specifically aimed at creating images. Its stand-out features are the creation of product renders by editing generated images and adjusting prompt-based influence, making it particularly suitable for design-focused applications. *Adobe Photoshop*'s generative AI (e.g., Generative Fill) allows editing parts of an image using prompts, rather than generating images from scratch. *Adobe Firefly* excels at generating images from text prompts with a wide range of styles and visual effects. *Krea* operates in real-time for image creation and enhancement, enabling users to manipulate and develop images by integrating shapes, drawings, reference visuals, and prompts.

Usage purposes of AI tools

The survey included open-ended questions on the usage purposes of AI tools and the stages in which designers utilized them. Responses were collected in an Excel sheet and subjected to content

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analysis. The responses were first sorted by topic (e.g., exploration, research, and visualization). The processed data was then transferred to a Miro board for iterative reviews (done primarily by the first author and supervised by the second author) for placing the topics under themes on Post-its and converting them into a hierarchical category tree. This categorization resulted in the identification of specific usage purposes, emerging inductively from the content analysis of the data on reported practices, distributed under nine design-related functions, aligning with fundamental literature on the design process. Among the 85 respondents (responses from 3 participants could not be categorized due to ambiguity), 15 reported using AI tools for one function, 31 for 2, 27 for 3, 8 for 4, 3 for 5, and 1 for 6 functions. The weighted mean number of functions per respondent was calculated as 2.48 ($1 \times 15 + 2 \times 31 + 3 \times 27 + 4 \times 8 + 5 \times 3 + 6 \times 1 = 211$, $211/(15 + 31 + 27 + 8 + 3 + 1) = 2.48$), and the median was calculated as 2. The most common function for which AI tools were used was *idea generation and development*, mentioned by 59 respondents, followed by *visualization* (39), *research* (35), *presentation* (22), *inspiration and benchmarking* (16), *data analysis* (16), *organization and planning* (8), *persona/user journey/scenario generation* (8), and *automation* (4).

AI usage mapped on the double-diamond design model

To identify the stages of the design process in which AI tools are integrated, the identified usage purposes covered under the nine design-related functions were subsequently mapped onto the double-diamond design model (Fig. 1). This mapping revealed that AI tool usage is distributed throughout the design process, and some AI tools are integrated in multiple stages. For instance, an AI tool may be used in initial research, then for form exploration during idea generation, and finally for editing images and generating illustrations for presentation in finalization.

Phase 1 Discover: Thirty-one response statements corresponded to the *discover* phase and were related to *research* and *planning*. For *research*, designers reported using AI tools for problem exploration by gathering information and searching for specific answers, and for conducting literature review by document scouting and scanning, language translation, and content summarizing. For *planning*, designers reported using AI for planning the process and determining a timeline for the steps, formulating an initial brief, and documenting the process.

Phase 2 Define: Seventeen statements corresponded to the *define* phase and were related to *research, analysis*, and *problem statement*. For *research*, designers reported using AI tools for conducting market and user research during user needs identification. For *analysis*, designers reported using AI tools for statistical data analysis, information synthesis, and insight building. As for *problem statement*, designers reported using AI tools for building problem definitions and elaborating draft briefs.

Phase 3 Develop: Ninety-four statements corresponded to the *develop* phase, covering *exploration of solution space*, *user development*, *research*, *idea development*, and *planning*. For *exploration of solution space*, designers reported using AI tools for generating ideas, refining concepts, exploring forms, visualizing sketch ideas, seeking visual inspiration, and creating moodboards. For *user development*, designers reported using AI tools for developing personas, building scenarios, detailing lifestyle descriptions, and preparing user journeys. For *research*, designers reported using AI tools for market benchmarking, making ergonomic analyses, and consulting related standards and regulations. For *idea development*, designers reported using AI tools for developing script codes for parametric 3D modelling, automation of prototype modelling, systems engineering, mathematical calculations, UX development through UX copywriting, and prompt generation. Additionally, for *planning*, AI was mentioned to be used for setting timelines and detailing briefs.

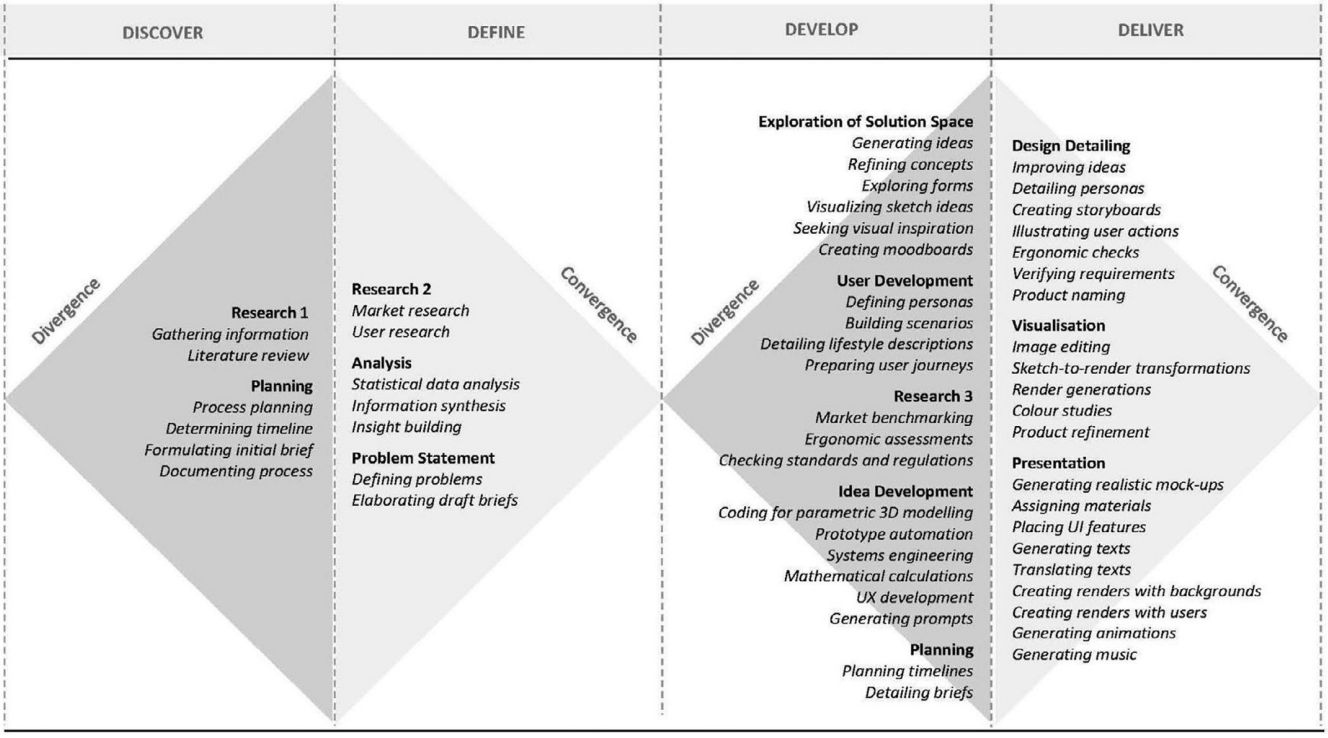


Figure 1. Usage purposes of AI tools inductively identified from the survey responses and subsequently distributed on the double-diamond design model.

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Phase 4 Deliver: Sixty-three statements corresponded to the *deliver* phase, covering *design detailing*, *visualization*, and *presentation*. For *design detailing*, designers reported using AI tools for improving ideas, detailing generated personas, creating storyboards, illustrating user actions, making ergonomic checks, verifying requirements, and naming the product. For *visualization*, designers reported using AI tools for image editing, sketch-to-render transformation, render generation, color studies, and product refinement. For *presentation*, designers reported using AI tools for generating realistic mock-ups, assigning materials, placing UI features, generating text, translating text, preparing renders with backgrounds, preparing renders with users, generating animations, and generating music.

Think-aloud interview sessions

Participants for the think-aloud interview sessions were selected from among the 67 survey respondents who had agreed to participate in the following stage of the research. The selection criteria included working in product development, using multiple AI tools in design practices, integrating AI tools in multiple stages of their design processes, and self-assessed proficiency in using these tools. A criterion matrix was prepared, resulting in the identification of 35 suitable candidates who were then contacted via email and invited to participate in the study. The study was carried out with the 10 candidates who responded and agreed to participate. The participants were based in various cities across Türkiye and had time constraints since they were working full-time. Therefore, the sessions were scheduled according to the convenience of the participants and conducted online. No difficulties were expected in the conduct of the online think-aloud interview sessions. Remote conduct and collaboration in design have been widely explored, with studies showing shifts but no decline in cognitive mechanisms involved (Lee and Ostwald, 2022; Lee, 2024). Various online platforms and software have been developed to ease online collaboration (Ye et al., 2022). Online meeting platforms for creative tasks have become highly familiar to designers, particularly since the COVID-19 pandemic in 2020 (Ozturk et al., 2021), when design education and practice had to be transferred into digital media for remote generation, collaboration, learning, and sharing.

Design task and research setup

Think-aloud interviewing, initially developed for studying psychological phenomena, requires participants to think aloud and verbalize their actions while performing a task (Leighton, 2017). As noted in the literature (Sarkar and Chakrabarti, 2013), design activities can be challenging to analyze in terms of the reasoning involved. As a method of investigation, verbal reports obtained through think-aloud applications enable researchers to trace the cognitive steps and design reasoning through the actions undertaken by designers and the resulting outcomes (Cross et al., 1996). For research purposes, it is recommended for the design task assigned to participants to be relevant to the research objectives, appropriately challenging, realistic, suitable for the participants' level of expertise, manageable in complexity and scope, feasible within the allocated time, and within the researchers' sphere of knowledge (Dorst, 1996). For this study, the researchers aimed for a design problem that would be within a familiar problem area for the participants, but not deeply explored by them in the past, allowing freedom in exploration. One hour was estimated to be suitable for the completion of the design task, in order not to cause fatigue, considering the task would also include interaction between the designer and researcher.

After considering several alternatives, the researchers finalized a design brief for a lunchbox concept accommodating various types of food and addressing the needs of a user persona, also to be developed by the participant. The lunchbox was expected to potentially include features such as lids, locks, and inner compartments. The design process was left free to allow participants flexibility in the way they would approach the task, enabling the observation of their interactions with AI tools throughout the process. Miro boards were prepared as the digital workspace for the sessions.

The online think-aloud session procedure was planned to incorporate activities besides designing, such as persona development that would require research, and visual representation that would require prompt generation and digital rendering. These activities could be followed in real-time through the use of screen sharing and access to the same digital interfaces in certain software. In this remote setting, it would not be possible to observe the paper-based or tablet-based sketching activity preceding digital and prompt-based generation, though the outputs would be directly made available in the medium (e.g., through Cam-scan). Miro was to be used as the submission platform, as it allows sketching made directly on its boards as well as access to multiple participants, making it possible for the researcher to be in the same medium during the generation of outputs and filling in the template boards. A pilot study was conducted with a graduate design student to investigate potential issues in the design brief, task procedure, and online session conduct. The pilot study was held via Google Meet and lasted slightly under 1 hour, as anticipated. Adjustments were made to the design brief and the concept submission template on the Miro board. The final version of the design task was written in both Turkish and English and included an introduction to the research, instructions for the session, and the design brief (Table 1). Each Miro board had the design brief and templates ready for the participants to fill during the session (Fig. 2).

Participants of the study

The participant group consisted of seven male and three female designers (Table 2). All participants were graduates of industrial design departments. The professional backgrounds of the participants varied, as well as their years of work experience. Nine were working as in-house designers, and one was working as a freelance designer. Five were involved in product development, and five were involved in digital product development.

Procedure

The sessions were conducted by the first author over Google Meet, within a span of 5 weeks during May and June 2024. The same procedure was followed for each session. After greetings and introductions, the researcher explained the aim of the study, session procedure, and design brief. The session continued following consent for participation and for the session to be recorded. Participants began working on the design task using the AI tools of their choice. Meanwhile, they were expected to articulate their thought processes aloud, explaining their reasoning in the actions they took (including but not limited to designing) and decisions they made. The researcher communicated with the participants over video cameras at both ends and observed their interactions from the shared screen that showed the design-related explorative and generative functions and their outputs in real-time. In its form, the session was not expected to induce cognitive load on the participants; it was anticipated that there would be moments of silence,

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Table 1. Instructions and design brief given to participants (reorganized for this article)

Introduction to the Research and Instructions

- The goal of this research is to observe designers during a design process. Therefore, the design process in this study will be entirely based on your individual preferences and working habits. You are free to structure and carry out your process in any way you choose.
- The use of AI tools is encouraged, and you may incorporate any tool you prefer at any stage of your design process.
- The design task is expected to take approximately 60 minutes. By the end of this period, you are expected to submit an advanced representation of a product solution.
- Throughout the session, you are asked to think aloud, verbalizing your thoughts and explaining your actions as you proceed with the design task. This will help us gain insight into your design reasoning and decision-making process.

During the session, the researcher will observe, take notes, and record your verbalizations. The researcher may occasionally ask you to elaborate on specific design actions, decisions or tool usage. These interactions aim to better understand your designerly thinking. All recordings will be used solely for research purposes during the analysis phase to examine how designers engage cognitively throughout the design process.

Design Brief: Design a lunchbox for a user group of your choice. This lunchbox must contain different types of food (soup, salad, rice, etc.) and be easy to carry. It should integrate seamlessly into users' daily lives, offering innovative features.

Requirements

- Consider the user group, their needs, and preferences. Describe their food preparation and eating habits, as well as the context of use for this lunchbox. Features of the product should consider the needs of the selected user group.
- Ensure that the solution is safe to use with food, heat-resistant, easy to clean, and spill-free.
- Suggest material, texture, and color, as well as details (e.g. locking mechanisms, moving parts).

Deliverables

At the end of the session, submit a persona description and a final design concept with drawings, collages, annotations, etc.

particularly during reviewing research output or composing prompt-based dialogues with AI tools. The researcher posed clarifying questions when necessary, for instance, when a participant went silent (e.g., during sketching, during prompt generation) or performed an action that required further explanation (e.g., using a search engine for research purposes). The researcher also took notes using pen and paper to record insights that were not documented as task output or verbally expressed. The sessions ended when the participants stated that they had finished, generally with the output of a final design concept. Session durations ranged from 50 to 115 minutes, with an average of 77.2 minutes. The collected data was qualitative in nature and included video recordings of the online sessions (772 minutes in total), detailed notes for each participant kept in a notebook (30 pages in total), and participant-generated outputs documented on Miro board templates (Fig. 3), including persona descriptions, idea generation outcomes, and final design concepts.

Data analysis

The analysis was mainly conducted by the first author, with regular consultations and cross-checking with the second author. The session recordings were initially reviewed four to five times to identify key design-related activities undertaken by the participants. These included the stages of the design processes they followed, outcomes of these activities (as documented on the Miro boards), AI tools used, participants' interactions with these tools, verbal explanations of actions, reflections on AI tool usage, and evaluations of the outputs. Notes taken during the sessions were also consulted for highlights and insights. Summaries of each session were made, describing the steps followed, actions performed, outcomes generated, and interactions with AI tools, including remarks and explanations made by participants during the process. The workflows of participants were then visualized as process diagrams, mapping their use of generative AI tools and any iterations (backward or forward loops) within the

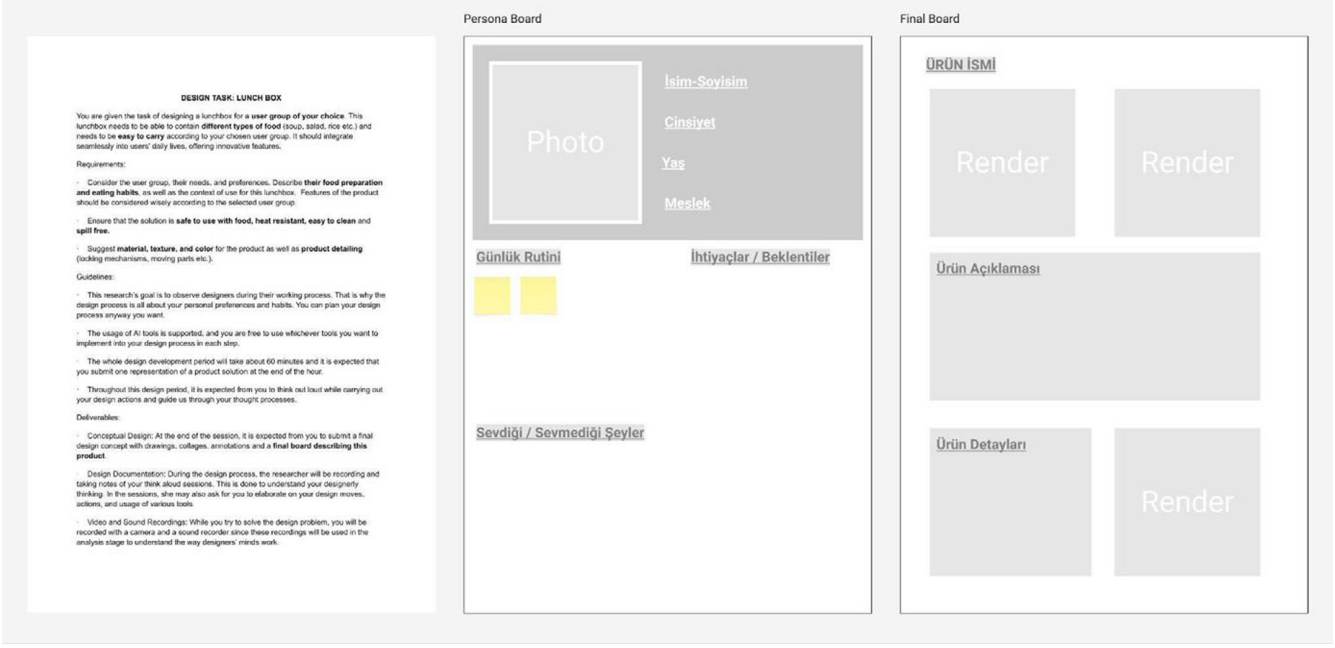


Figure 2. Miro board template (empty) used in the think-aloud interview sessions for the participants to fill in (Left: Description of the design task. Center: Persona board asking name, gender, age, occupation, daily routine, needs/expectations, likes/dislikes. Right: Final board asking name of product, statement of concept, product details.).

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Table 2. Participants of the think-aloud interview sessions

Participant (gender) Year of graduation (year of professional experience)	Current position/sector or domain	Meeting date	Meeting time	Session duration (min)	AI tools used in the session
P1 (M) 2023 (1)	In-house designer/Chassis-top body equipment	20/05/2024	21:00	85	Vizcom
P2 (M) 2016 (8)	In-house designer/White goods	31/05/2024	11:00	75	ChatGPT-4; Vizcom
P3 (M) 2017 (7)	In-house designer/Defense industry	01/06/2024	10:00	115	Vizcom
P4 (F) 2015 (7)	UX/UI designer/Software development consultancy	01/06/2024	14:00	50	ChatGPT (free version); Figma AI
P5 (F) 2020 (4)	UX designer/Engineering services company	03/06/2024	18:30	50	ChatGPT-4; Figma AI; Krea AI
P6 (F) 2022 (2)	Product specialist and game designer/Mobile game development company	08/06/2024	10:30	65	Adobe Photoshop AI; ChatGPT (free version)
P7 (M) 2022 (2)	Industrial and graphic designer/Design consultancy	10/06/2024	16:30	115	Adobe Firefly; Adobe Photoshop AI; ChatGPT (free version); Lensgo AI; Playground AI; Vizcom
P8 (M) 2024 (1)	Industrial designer/Engineering services company	11/06/2024	12:15	80	Adobe Photoshop AI; ChatGPT-4; Midjourney
P9 (M) 2022 (2)	Experience designer/Engineering services company	24/06/2024	18:15	70	Adobe Firefly; Adobe Photoshop AI; ChatGPT-4; Krea AI
P10 (M) 2024 (1)	UX designer and researcher/Engineering services company	25/06/2024	20:15	65	Vizcom

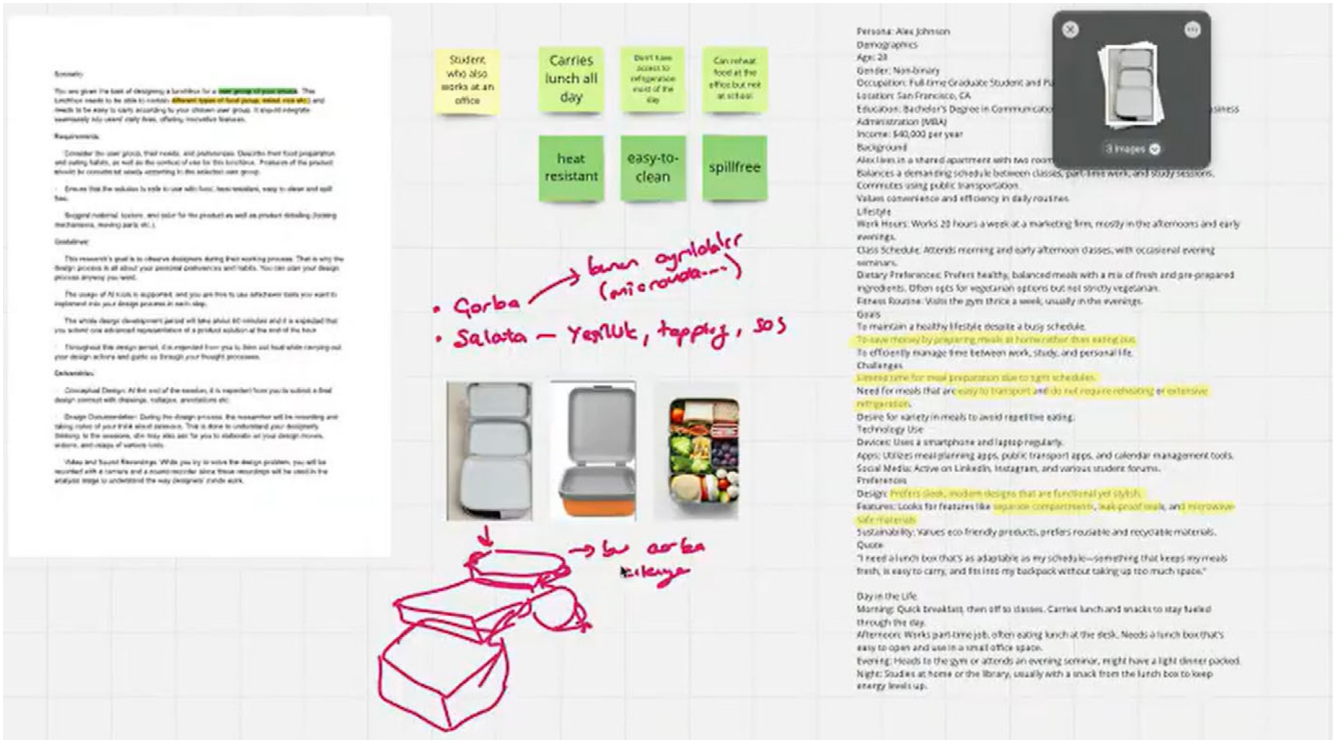


Figure 3. Example of a Miro board obtained at the end of a session (pilot participant).

process. The analysis identified five stages in the participants' design processes: *understanding brief and research*, *benchmarking*, *persona generation*, *ideation*, and *detailing and finalization*. These stages were determined based on variations in design-related activities as well as shifts in the usage of AI tools. The durations of each stage were calculated (Table 3).

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Table 3. Session breakdown in minutes for the design process stages

Participants/design stage durations (min)	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	Stage duration (min)	Stage duration (%)[a]
Understanding brief and research	0	3	9	7	8	11	7	10	5	2	62	8.03
Benchmarking	0	4	16	3	6	12	15	15	2	6	79	10.23
Persona generation	22	12	17	40	12	17	16	4	12	0	152	19.69
Ideation	50	11	45	0	8	5	42	20	23	42	246	31.86
Detailing and finalization	15	45	28	0	16	20	35	31	28	15	233	30.18
Total session duration (min)	87	75	115	50	50	65	115	80	70	65	772	100

[a]Lewis and Bonollo (2002) report the percentage distribution of total time dedicated to five major stages of the design process: task clarification 12.2%; concept generation 27.5%; elaboration and refinement 8.8%; detailed design 17.1%; communication of results 34.5%. Goldschmidt and Rodgers (2013) report the percentage distribution of total time dedicated to nine major stages of the design process: studying the brief 5%; planning the process 4%; collecting information 6%; looking at examples 6%; consulting with others 13.5%; analyzing and comparing 6.5%; thinking about solutions 32%; evaluation 2.5%; and preparing final presentation 24.5%.

Finally, the process diagrams and corresponding AI tool usage from all participants were synthesized into an overall double-diamond design model (Fig. 4), grouping designerly activities and compiling the AI tools employed across the stages.

Designers' integration of AI tools in the design process

The first diamond in the design model represents exploration of the problem space. Initiated with the design brief, this phase encompassed *understanding the brief and research*, *benchmarking*, and *persona generation*. It concluded with the development of a user persona, alongside product specifications and/or project constraints and objectives. Participants collectively spent 293 out of 772 minutes on this phase, constituting 37.95% of the total duration.

Typically, participants began by reviewing the design brief and identifying requirements to inform the following steps. This stage sometimes included reflecting on past projects and processes they had personally conducted. Following this, participants planned their design processes and tentatively allocated time to specific activities. As the design brief required the development of a persona, the subsequent step involved research to identify and define a target user group. This step was often supported by a search for inspiration and the generation of mood boards. In many cases, the persona was detailed with a scenario or user journey. Defining the attributes of the persona led to the specification of product requirements, which in turn prompted further technical, market, and user research. This stage generally included benchmarking for relevant brands, lunchbox-type products, and analogous solutions from other product categories (e.g., organizer containers). At the end of this research, participants typically articulated product specifications and performance expectations. In some cases, these were

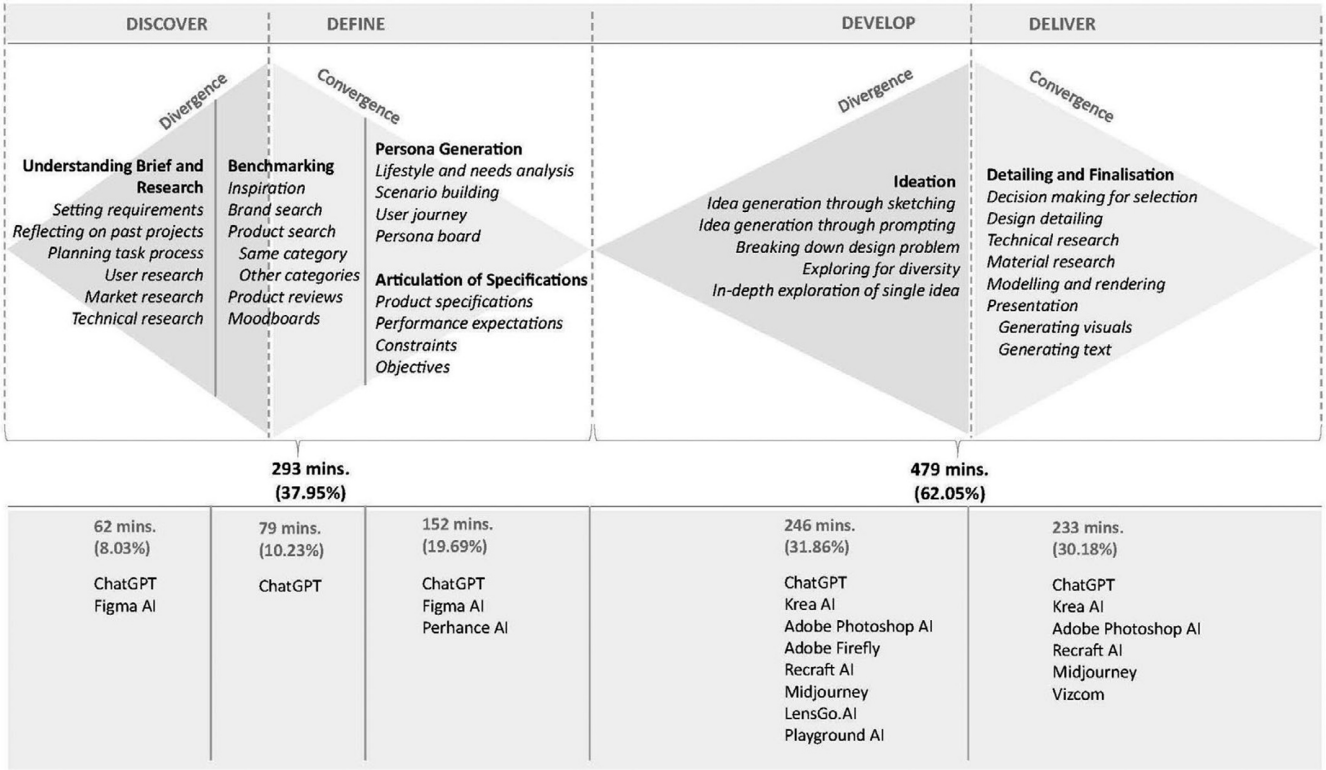


Figure 4. AI-supported design process of the think-aloud session participants mapped on the double-diamond design model.

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accompanied by project constraints (e.g., avoiding food odors that might disturb colleagues) and objectives (e.g., designing lids that can also function as plates) that expanded on those already stated in the brief.

Despite the wide range of designerly activities conducted in this phase during problem exploration, AI tools were less varied, and their usage was relatively limited in duration. The most commonly used tool was a generative AI chatbot, which supported user, technical, and market research, benchmarking, and lifestyle and needs analysis for persona development. A design and prototyping software and a character generator app, both with AI-powered features, were used for the specialized purposes of persona and user journey representation.

The second diamond in the design model represents exploration of the solution space. This phase included *ideation*, *detailing, and finalization*, resulting in the delivery of a final design concept. Participants collectively spent 479 out of 772 minutes on this phase, constituting 62.05% of the total duration.

Participants allocated more time to this phase, and AI tools were used more extensively and diversely; however, design-related activities were fewer in variety. The ideation stage was handled in different ways. Some participants began ideation by generating ideas through hand-drawn sketches (paper-based or digital), which they later elaborated and refined using AI tools. In other cases, ideation was directly prompted by AI tools, where participants described a persona and asked "What would this persona use?" or "How should such a product be designed?" This prompted the generation of rough ideas by AI tools in the form of texts or visuals, which were further developed by the participants. Idea generation was carried out following three approaches:

1. Divergence by breaking down the design problem into smaller components and resolving them separately (e.g., container, lid, lock, carrying case),
2. Divergence through lateral exploration, by searching for alternative and diverse solution ideas, and
3. Convergence through vertical exploration, where an immediate idea was explored in depth.

Due to time constraints, participants often made quick decisions during the finalization stage to select a final concept. Some participants dedicated time to develop a digital model of the final concept and produce rendered images. Some participants struggled to select a final concept, and concluded the task by submitting a set of ideation outcomes instead. Generally, technical and material research was included for design detailing of the outstanding ideation outcomes, and their presentation on the Miro board was prepared with a legible rendered sketch and a descriptive text. Exceptions also occurred; in one case, a persona was not generated for the task, and in another, the session was concluded with the generation and submission of the persona only.

In the second diamond, the same generative AI chatbot was used again, particularly in idea generation, additional research, and design detailing. Different versions of the chatbot were used to generate both texts and visuals for the presentation of the final design concept.

Participants additionally made use of drawing and modelling software, AI-powered image and video generating and enhancing tools, as well as image search platforms for sourcing visuals to train the GAI tools. Participants used these tools for iterations in the exploration of design solutions, searching for images, using them as prompts, generating sketches, enhancing them, generating further sketches based on what the AI tools provided, and generating prototypes based on these. A total of nine image content creation and enhancement tools were used by the participants. Five of these were used throughout the second diamond. Proficient participants used multiple AI tools simultaneously for obtaining visuals in different styles, or alternated between AI tools during a specific task for higher performance. They also prepared their AI tools for the delivery of the final design concept by training them with images and preparing image backgrounds and props for enhanced product renders.

Designers' engagement with AI tools

The integration of AI in the design process required the engagement of designers with AI tools, revealed as the designers' attitudes, communication styles and interactions. These were identified from the ways in which participants described the tools, explained their capabilities and evaluated the output; the content and style of the generated visual and verbal prompts; and ways of using these tools in terms of strategies and actions, accompanied by specific verbal comments and displayed behaviors.

Attitudes. The various attitudes displayed by participants toward AI tools were divided as negative (n = 3), neutral (n = 4), and positive (n = 3) (Table 4). Participants with a negative attitude tended to reject, ignore, or hesitate to engage with AI tools. They were skeptical about the AI tools' capabilities and the skills they could acquire through training. They preferred to remain present in the design process, rather than giving control to AI applications. They expressed frustration, anticipated low-quality outputs, and avoided using them. They also mentioned that they had to compromise on aspects of their initial ideas to achieve an end result generated with AI tools. They expressed concerns regarding how these tools could block their creativity due to limited tool capabilities, create ethical issues regarding ownership, and make them feel threatened as designers. Participants with a neutral attitude seemed to blend their own expertise with the capabilities of AI tools, instead of selecting one over the other. They selected, refined, and curated the outputs from their preferred tools, mainly relying on their own judgment and expertise. Participants with a positive attitude demonstrated awareness of the capabilities and skills of AI tools and were willing to leverage them fully. Their expectations were to receive information, get inspiration, visualize ideas, and render drawings. They acknowledged how these tools could aid them rather than being a threat.

Communication styles. In terms of generating images or writing prompts, participants' communication styles were categorized as brief-explainers (n = 5), balanced communicators (n = 3) and over-explainers (n = 2) (Table 5). Brief-explainers were those expecting results from writing short and straightforward prompts. This was mostly seen when these participants used AI tools to gather

Table 4. Quotes from the think-aloud sessions exemplifying participant attitudes toward AI tool usage (participants not indicated for anonymity)

Attitudes	Quote (excerpt from interview, translated from Turkish)
Negative	"I used it in a way that allowed it to take over my profession, and I didn't get exactly what I wanted."
Neutral	"It actually gives ideas for the next close steps. I think it speeds up the process by pointing out small details."
Positive	"I actually filter the information that AI gives me based on my past experiences and knowledge, I eliminate unsuitable ideas and let in ideas that will support me."

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Table 5. Persona descriptions, examples of prompts and design output from the think-aloud sessions illustrating participant communication styles with AI tools (participants not indicated for anonymity)

Communication Styles	Persona and prompt (translated from Turkish)	Design output
Brief-explainer	**Persona description:** A white-collar worker who works in finance, aged 36, goes to work between the hours of 8 am and 6 pm. He needs to eat his lunch in the office and also carries some snacks and his breakfast. **Example prompt usage:** "Lunchbox, design, minimal, soft color, white and green."	
Balanced communicator	**Persona description:** Deniz, an office worker between the ages of 25 and 40, works in an office. Likes balanced meals with a mix of protein, vegetables, and grains. Likes the color navy blue, dark grey, black. **Example prompt usage:** "Divisions inside the lunchbox are too much; make it three. Also make it foldable and %100 silicone and blend it with this reference image." "Share some pictures of Deniz's lunchbox."	 
Over-explainer	**Persona description:** An 8-year-old girl named Ece, who requires a lunchbox that is fun and colorful with her favorite cartoon characters, easy to carry and use, durable, and has many different parts that are made from healthy materials. **Example prompt usage:** "A blue and silver lunchbox with three compartments on the front, with one open lid at the top left corner, two rectangular containers inside of it, product photography in the style of white background, light turquoise color theme, stainless steel."	

information as if they were search engines. In some cases, the participants did not have a clear idea of what they were looking for; therefore, they used such short prompts for inspiration.

Balanced communicators were those who engaged in a conversation with AI tools in order to understand a subject and develop ideas based on it. These participants addressed the brief by collaborating with AI, collectively generating refined ideas. Although the participants did not fully control or predict the AI's contributions, they still edited the outcomes based on their own judgment and expertise. Over-explainers were those expecting AI tools to

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represent the ideas in their minds as closely as possible; therefore, they wrote detailed prompts to improve the outputs. These prompts could involve long descriptions in complete sentences, in some cases including irrelevant or divergent information. Some participants trained their AI tools by adding images, and even asked from AI tools to generate new prompts for them.

Interaction types. The ways in which participants interacted with AI tools in their design processes divided them as over-reliers ($n = 1$), collaborators ($n = 5$), and commanders ($n = 4$) (Table 6). Over-reliers were those who seemed confident in and dependent on the capabilities of AI tools. These participants asked AI tools what to do (in terms of design action and design idea), and how to do it (planning the next steps). They used AI tools to identify problems for them, as well as generate design directives and visuals for design solutions. Some participants sought for confirmation or approval for their design decisions, as well as for their actions. They tended to directly use the AI output without intervention; this included the submission of final design concepts, directly obtained from generative AI tools. Collaborators were those who were aware of AI's limitations and capabilities, and made their demands of the AI tools accordingly. They trained AI for the task, with prompts and visuals, as well as by assigning roles to AI in different stages (e.g., asking AI to think like an industrial designer). They believed AI tools were slowing down their design processes and therefore developed strategies to cope with this in their limited session time. Some participants worked in parallel with the AI tools, meaning they carried out design ideation on their own while also prompting AI tools and waiting for their output to compare and negotiate. Commanders were those who used AI tools to enhance their performance as designers. They believed that AI speeds the process, but can make mistakes and hamper creativity. Therefore, they preferred to maintain control of their design processes and were critical of the AI outputs, making the design interventions and final decisions themselves. They assessed alternatives for function and efficiency. They were skilled in AI usage; they used tools in parallel at the same time for the same task, as well as used diverse tools sequentially for specific purposes to complete the task. They also saw the design process as an opportunity to invest in the training of their AI tools for future reference.

Bearing in mind that the number of participants is low, the distribution of participants according to attitude, communication style, and interaction type categories allowed observing certain patterns (Table 7). All three participants with a negative attitude toward AI interacted with AI tools as commanders, while two of them were also brief explainers in terms of communication style. Two out of four participants with a neutral attitude toward AI interacted with the tools as collaborators and displayed balanced communication. Two out of the three participants with a positive attitude toward AI interacted with the tools as collaborators and were over-explainers, while the third participant was the only over-relier on AI tools in terms of interaction and was a brief-explainer in terms of communication style.

Table 6. Quotes from the think-aloud sessions exemplifying participant interaction types with AI tools (participants not indicated for anonymity)

Interaction types	Quote (excerpt from interview, translated from Turkish)
Over-relier	"I usually use AI agents to observe whether they think like me, and if not, I look at what is missing to include. If I don't use it, I feel like I am losing my valuable time."
Collaborator	"I can create many outputs based on generated prompts and edit the results subtly or in detail to match my ideas before I model them for finalization."
Commander	"I thought it would change what I had in mind. I know what it is in my mind, but if I try to get it done, something different will come out."

Discussions

The survey findings indicate a rising interest in the adoption of AI technologies and integration of AI tools within professional design processes, with a variety of AI tools available. The younger generation of designers are coordinating multiple AI tools with general or specific purposes for a wide range of functions (i.e., text editing, image generation, sound generation, video editing, planning, research) across the design process. The design process is conducted as a complex series of functions, not only limited to the divergent and convergent act of designing for an output, but also involving the management of the process and communication of the outcomes.

Table 7. Distribution of participants according to attitudes, communication styles, and interaction types identified in the think-aloud sessions

Attitudes			Communication styles			Interaction types		
Negative	Neutral	Positive	Brief explainer	Balanced	Over-explainer	Over-relier	Collaborator	Commander
×			×					×
×			×					×
×				×				×
	×		×				×	
	×		×					×
	×			×			×	
	×			×			×	
		×	×			×		
		×			×		×	
		×			×		×	
$n = 3$	$n = 4$	$n = 3$	$n = 5$	$n = 3$	$n = 2$	$n = 1$	$n = 5$	$n = 4$

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Following the data analysis of the think-aloud interview sessions, the literature was reviewed for studies on design activity timelines for short- and long-duration design tasks. The general agreement is that designers follow a solution-oriented process (Lawson, 2005), meaning they start thinking on solutions early in the process, as a means of understanding the problem, making it difficult to distinguish thresholds between activities, as the process involves iterations (Goldschmidt, 2016). Studies on design tasks indicate them as a session composed of episodes (Teixeira et al., 2017), where a session representing a design task expects a design concept output in the form of a sketch or model based on a given brief, and each episode is a design-related activity (e.g., problem formulation, research, ideation, representation) in the pursuit. The timeframe obtained from the think-aloud sessions displays an aligned percentage distribution of time allocation to non-AI-supported designerly activities described in the literature. For example, 31.86% of the total session time was dedicated to ideation; Clayton (2000) reports time distribution in a design process for idea/concept generation as 38%, Lewis and Bonollo (2002) report as 36.3% (concept generation+elaboration and refinement), and Goldschmidt and Rodgers (2013) report as 32%. This may indicate that the designers have conducted the design task as would be expected in a regular design process in terms of procedure and pace; besides, they have developed and submitted a persona for problem framing, alongside the design concept. The AI tools have been used in supporting design-related activities, rather than undertaking activities on behalf of designers, or adding to their workloads with the introduction of extra activities related to AI tool usage (e.g., prompt generation).

It was observed that designers' AI tool usage incorporated ways of strategic partnership, such as parallel working for different activities (e.g., preparing presentation frame while AI tool renders image, as an example of human–AI cooperation, in reference to Li et al., 2022), parallel working for same activity (e.g., hand-generated sketching for an idea while AI is also working on image generation for the same idea based on prompts, followed by iterations between the outputs, as an example of human–AI collaboration, in reference to Cabrera et al., 2023), and work distribution for a goal-specific activity (e.g., giving research directives, synthesizing information compiled by AI, generating a persona and using AI to represent it, as an example of human–AI symbiosis, in reference to Mahmud et al., 2023). These findings bring a new perspective to participation style and task distribution as factors in collaboration style within Rezwana and Maher's (2023) Co-Creative Framework for Interaction Design. The designer divides the process into a series of activities and distributes the work; the designer assigns some work exclusively to AI, while exclusively undertaking other work, running in parallel and to be compiled later on. Some work is carried out by both parties, through serial turn-taking toward outputs to be combined, or in parallel to create alternatives that compete and to be used for output enhancement.

The think-aloud interview sessions confirmed that the experiences of participants were significant in implementing AI tools in the design process (Gmeiner et al., 2023; Tang et al., 2024). Experience levels influenced the participants' design competences (in terms of skill sets and strategic abilities), process conduct (in terms of stage planning and time management), involvement of expertise and domain knowledge, and personal motivation and interests. The more experienced participants were observed to break down the design task into planned and managed stages, giving weight to exploring the problem space as well as the solution space. These participants were more strategic in the way they addressed the design brief toward its finalization, prioritizing particular stages of the process in which they felt more competent and confident, contributing with their knowledge, bringing a different perspective to the brief, or differentiating from available design solutions. They were quicker in decision-making and more open to using AI as an assisting generative tool. Those with personal interest and prior experience in using AI tools were informed of the capabilities of these tools. They were able to use the tools purposefully for various tasks, carrying out interactive generation in coordination with multiple tools, steering them for the realization of their informed design decisions, thus resulting in the production of satisfying outputs.

Participants with less experience could tend to skip or rush through initial stages, jumping to premature idea generation. Strategically, some gave up on the goals they had set for themselves at the onset of the session, due to time constraints. These participants interacted with AI tools at a minimum level, generally conducting the earlier stages on their own and leaving AI tool usage to the later stages of the design process. This could be due to resistance to consulting AI tools, as well as not being fully informed on the usage of AI tools and their capabilities. Difficulties were observed in determining project objectives from the brief, diverging in idea generation, and, as a result, differentiating from already available mainstream products. When these difficulties were coupled with limitations in designerly skills (e.g., sketching, detailing), and the participants did not see their preparations (e.g., research, modelling) as vital in training the AI tools, treating them instead as an agent generating an output by chance (e.g., based on keyword instructions), AI tool usage typically produced unsatisfactory output.

Quality in design output is known to require time (Shah et al., 2003), and as the design task was of short duration with the goal of offering a workable design concept, feasibility of the output was not investigated as part of the study. It was observed, though, that participants considered project requirements during problem framing, and the outputs mostly conveyed solutions addressing them. Lunchbox design concepts incorporated solutions such as compartmentation, tiers, locks, handles, and leak-proof lids, as well as additional solutions that participants offered based on how specifically they framed the problem, such as sleeves to carry and keep warm, lids that doubled in function as plates, and collapsible containers for ease of storage when empty. The concept representations were mainly generated based on a series of iterations between participants and AI. In one strand, this involved hand-generated sketches that were then rendered using AI. In another strand, this involved detailed prompting and training with example visuals, which, when reaching a satisfying result after rounds of regeneration, was sketched or modelled by the participant, and then rendered using AI (Table 8). The accuracy of the representations mostly depended on the sketching and modelling skills of the participants; in some cases, the representations obtained using AI lost perspective or proportion (e.g., lid not matching container in dimensions), but still made sense in terms of function and configuration.

Conclusion

The research described in this article investigated how professional designers integrate AI tools across different stages of the design process and how they engage with these tools in carrying out goal-oriented designerly activities. The research consisted of two consecutive studies, a survey and think-aloud interview sessions that complemented each other in establishing strategies and patterns of

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Table 8. Examples from a participant's iteration of AI-supported solution exploration and image generation for a lunchbox design concept

			
Images generated by participant using Playground AI. Concepts based on prompts; example images obtained through benchmarking and regeneration.	LensGo.ai reference image edited by the participant in Photoshop AI, aiming to produce a metal lunchbox inspired by the brand Stanley.	Final hand-generated digital sketch by participant, based on exploration carried out.	The submitted lunchbox design concept, obtained by rendering the final hand-generated sketch on Vizcom.

AI tool usage throughout the design process. The respondents of the survey provided answers given in reference to their professional design practices for processes conducted over extended periods of time. The respondents reported using a variety of tools for an extensive pool of design functions. In the think-aloud interview sessions, although a limited number of participants used a limited number of AI tools over a tight schedule, the goal-oriented design task allowed observing the interactions of designers with AI tools and the delivery of outputs in real-time. From the survey responses, we identified the design functions for which AI tools are used and placed them on the double-diamond design model framework. We also identified participants for the following study. From the think-aloud interviews, we observed strategies of the designers in interacting with AI tools for divergence and convergence in exploring both the problem space and the solution space, building further on the framework (Fig. 5).

We established from both studies that AI tools are used throughout the design process for the exploration of both problem and solution spaces. The think-aloud sessions confirmed that exploration of the solution space is given more time, and AI tools are primarily perceived as a means for visualizing concepts during idea generation and representation. However, the findings indicate that AI tools are also being used for analytical purposes while exploring the problem space, as well as for synthetic purposes while exploring the solution space, underlining the iterative and reflective nature of the design process. Designers give importance to preparatory activities for problem framing preceding idea generation, supported with AI tools, such as research, benchmarking, and persona generation. Idea generation is carried out through iterations between the designer and AI tools, with further elaboration and refinement as ideas are passed to and fro through conversations, sketching, rendering, image generation, and enhancement. Activities following idea generation are also supported with AI tools for informed synthesis and decision-making through design development, evaluation, and presentation.

Designers' competences and experiences significantly influenced how they perceived AI tools and implemented them within their processes. Those with greater interest in AI had already explored a variety of tools for distinct purposes and therefore demonstrated the ability to use them in combination across different design stages, alternating or coordinating their use based on specific task requirements, and also training their AI tools for future reference. Notably, a distinctive usage pattern emerged, where some designers worked in parallel with AI tools on the same task, later comparing the generated alternatives to decide which direction to pursue. AI tools with multiple capabilities were preferred, as such a tool could be used in coherence for different functions across the design process. AI tools with specific, task-based capabilities were used when the design decisions were fixed and ready to be represented. Additionally, certain professional sectors in which some participants were employed showed more advanced integration of AI tools. These sectors exhibited a stronger awareness of the range of tools relevant to their domain-specific needs and demonstrated a more sophisticated use of AI in their workflows.

Designers who participated in the research are all from industrial design undergraduate programs. They are working across different sectors such as product design, graphic design, interior design, game design, UX design, and engineering design, and in various roles, such as designer, researcher, systems developer, and software developer. They are working in design consultancies as well as small-, medium- and large-size production companies. Although the core design activities carried out for product design and development are aligned in general, based on our findings, we acknowledge that sectoral context may shape the observed engagement patterns between designers and AI tools, which therefore may not transfer uniformly.

The response rate for the survey was low (103 out of 3004, with 88 valid responses), which poses a limitation to the study. Besides a large percentage who must have missed or ignored the emails, there may have been invitees who do not work as designers, who do not work in product development sectors, or who do not use AI tools in their design practices, therefore choosing not to respond.

Around half of the survey respondents (46/88) were recent graduates of 2020 and later. Likewise, 6 out of 10 of the think-aloud session participants were recent graduates (2022 and forward). These rates indicate more interest in AI tools among the younger professionals. This may be related to the emergence and widening availability of these tools coinciding with the final years of their design education and early years in their careers, when they would be more exposed to or more interested in exploring new technologies and tools for their transitioning professions. The establishment of the AI-integrated careers of the young generation designers is still ongoing, and the transformation of professional practices in design is yet to be observed in the near future.

It should be noted that the coding and categorization of data collected from both the survey and think-aloud interview sessions were conducted primarily by the first author; the second author provided regular feedback and cross-checking, but no formal

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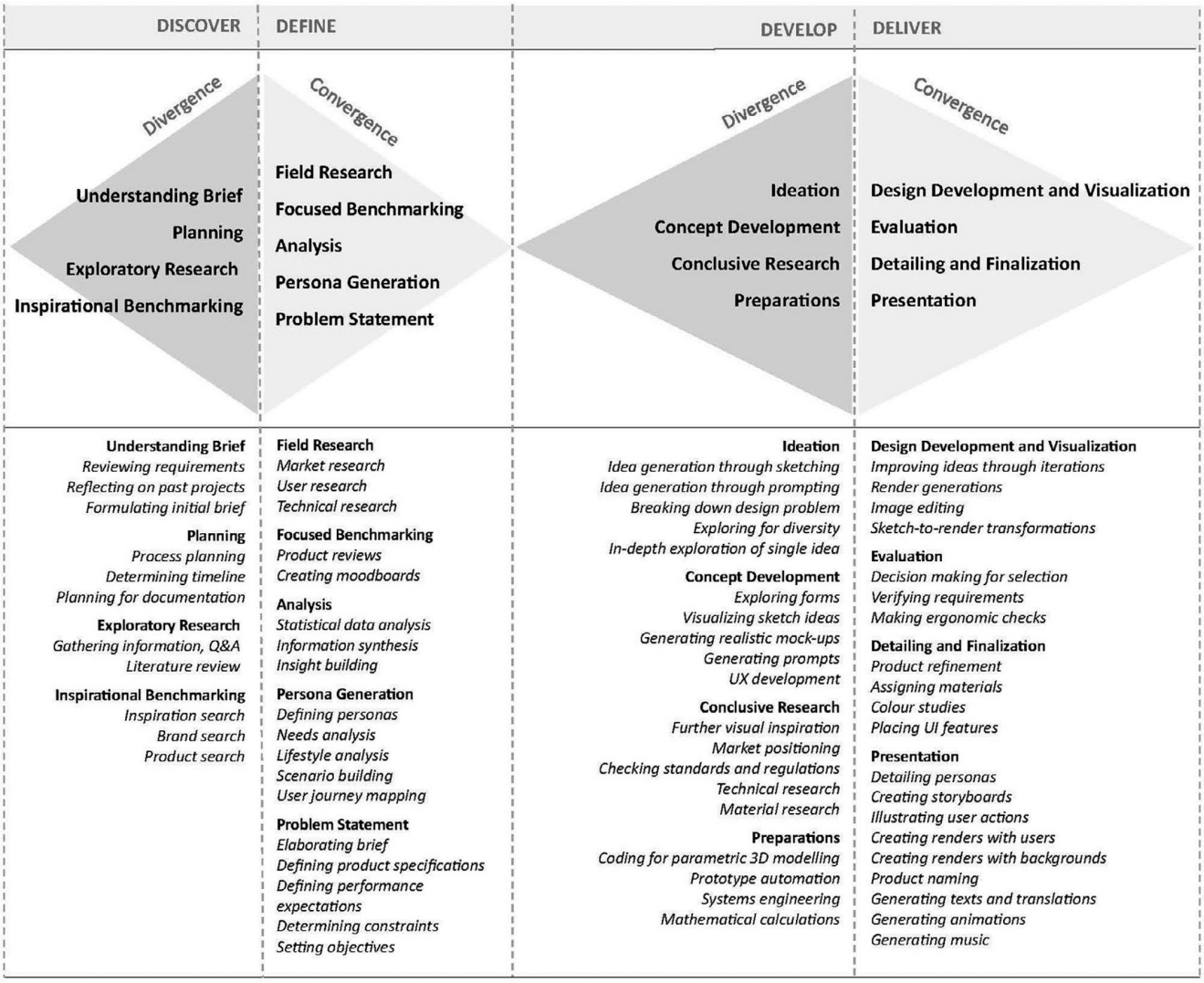


Figure 5. Designers' AI tool integration reflected within the double-diamond design model.

reliability metrics, such as e.g. Cohen's kappa or percentage agreement, were calculated.

While numerous AI tools are available in the field, it should be noted that the tools mentioned in this article were predominantly used by participants during the think-aloud sessions conducted in May and June 2024. Therefore, specific features or functionalities of these applications may have changed, although their overarching purposes are likely to remain consistent.

As concluding remarks, the findings imply that integrating AI across both phases of problem definition and solution development within the double-diamond design model supports a holistic design approach, ensuring alignment between the defined design problem and the design solution generated in response. In this context, AI can be positioned as a collaborative agent assisting designers in making informed design decisions and original design interventions. Building on this research, future research directions may include:

- A developed version of the design task, conducted over a longer period to better represent real-world design processes;
- Specific AI tools purposefully selected for the task, to reveal their roles within the design process and their impact on the outputs;
- Application of AI tools in particular stages of the design process for in-depth information on how they can be improved for specific purposes.

This manuscript was edited through personal communication with ChatGPT (GPT-4-turbo model), accessed via OpenAI's standard plan between April 13–23, 2025. The editing involved no addition or removal of content and was mainly for proofreading. Following this communication, the manuscript has been further developed and finalized by the authors only.

Data availability statement. The data have been collected with the permission of the participants, with the assurance of anonymity, and will be used solely for research purposes. More details on the processed data from both studies and their analysis procedures can be found in the MS thesis available at https://open.metu.edu.tr/handle/11511/111481.

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Ethical standard. This research has received approval from the Human Subjects Ethics Committee of Middle East Technical University on May 4, 2024 (Protocol No. 0317-ODTÜİAEK-2024). The collected data, including survey responses and session video recordings, are stored in the first author's digital archive to which only the first author has access. Participant anonymity in the reported materials has been provided through code assignments when referring to participants, and removing or blurring out any visual identifiers that may be indicative of participant identity.

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