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When and How to Use AI in the Design Process? Implications for Human-AI Design Collaboration

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ABSTRACT

As the potential for human-AI design collaboration increases, understanding the role of artificial intelligence (AI) in the design process becomes more important. *How does AI currently support the design process and how could it do so in the future?* To answer this question, we categorized existing AI design support systems (DSS) according to the Double-Diamond design process model, and found that they are mostly used in the later stages of the design process, focusing on generating design solutions. In contrast, very few systems focus on the early stages of the process, which include discovering and defining design problems. To explore this finding's alignment with designers' expectations in real-world design, we present a case study involving emerging AI technologies such as ChatGPT and robots. This study proposes that AI agents can potentially assist designers by providing inspirations, defining design problems with constraints, offering grounded metaphors, and exploring design materials.

KEYWORDS

Artificial intelligence (AI); design thinking; design process; engineering design; Human-Computer interaction

1. Introduction

There has been a longstanding effort to support design tasks with artificial intelligence (AI) techniques. Design work is, in fact, a good candidate for collaboration between humans and AI, due to the complementary strengths of humans and algorithms.

Human intuition is well-suited for abductive reasoning, a form of thinking that Dorst (2011) positions at the core of design work. Humans also can apply a breadth of prior experience to understand a design problem and they can continuously adjust their understanding of the problem as they interact with it. They are also capable of reflection-in-action, building abstract understanding through concrete interactions with materials relevant to a design problem they are working on (Schön, 1992).

Despite the messy, situated, and social nature of how humans design, Schön (1992) argues that AI can also perform important functions as a design assistant. The strengths of AI complement human design skills well, especially by providing scalable and repeatable outcomes. For instance, algorithmic search functions can be used to find and evaluate solutions quickly and consistently, and information retrieval algorithms can be used to search a massive dataset for information relevant to a problem. AI can also help a human designer explore a wider range of solutions than they would on their own (Song et al., 2022).

The benefits of AI design support can occur along different points of the design process, from initial problem framing to the detailed design of a particular solution. AI can also play a variety of different roles in support of the human design process. This paper thus approaches the research question: *When and how can AI systems support human design?*

We first approach this question by systematically examining the literature on AI design support systems (AI-DSS) through the lens of the Double-Diamond design process framework. Then, we survey AI-DSS research presented in the human-computer interaction (HCI) and design literature and categorize the surveyed papers along the four phases of the Double Diamond model. This allows us to understand where and how AI is currently thought of supporting the design process. We find that AI is not often used during the early phases of the design process and is mostly used in the second half of the design process. To explore how this finding aligns with designers in a real-world design situation, we present a case study of a human-AI design collaboration that examines designers' expectations of how AI tools might support design.

1.1. Related work

Several surveys have reviewed human-AI interaction research in a design context. Yang et al. (2018a) conducted a literature review to understand ways in which machine learning (ML) might improve user experience (UX) design. Based on an analysis of 2494 HCI papers, they generated seven clusters describing ways that ML could support UX,

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three of which they identified as understudied (sentiment analysis, neural networks, and social networking mining).

Jin et al. (2021) extracted 40 design heuristics from 1755 granted AI patents in the area of UX and suggested two case studies based on their taxonomy. In contrast to these two prior works, we focus on academic research papers, on design more broadly than just UX design, and on the phase of AI design support grounded in a formal design process model.

Our approach is most similar to that taken by Liu and Nah (2020), which examined the collaboration between designers and AI design application systems mapped on the Double Diamond model. However, Liu and Nah did not perform an extensive literature survey, but focused on a handful of industry AI design systems. In addition, their short report does not provide much information on the cases studied. In contrast, we provide a comprehensive survey of academic AI-DSS research across diverse contexts.

Beyond surveys, many researchers have examined the role of AI in human-AI design systems from a variety of perspectives. Yang et al. (2020) examined whether, why, and how human-AI interaction makes it difficult to design and innovate, focusing on UX challenges of AI systems. Their work also provides guidelines for improving and facilitating human-AI interaction design. Similarly, Yildirim et al. (2022) examined the challenges that designers face when using AI as a design material. They conducted design workshops aimed to understand designers' roles on cross-functional AI teams and how designers successfully worked with AI. Unlike these authors' work, our work does not address the question of how to support designers that need to work with AI systems. Instead, we study AI systems that are specifically conceived to support the design activity.

1.2. The Double Diamond design process model

Our study is grounded in the Double Diamond design process model. Developed by the UK Design Council in 2004, the Double Diamond model is a framework that helps organize activities occurring during the process of designing (Design Council, 2019). We chose the Double Diamond model as our theoretical framework because it is widely used in user-centered design (Howard et al., 2008; Kim, 2020) but has not been extensively applied to map AI-DSS. Figure 1 shows the four phases in the Double Diamond design model: (1) Discover, (2) Define, (3) Develop, and (4) Deliver. As the shape of the diamonds suggests, Phases 1 and 3 are divergent, whereas Phases 2 and 4 are convergent.

What are some of the tasks that human designers perform in each phase of the Double Diamond model? In the *Discover* phase, designers explore the problem's boundaries and understand users' needs and challenges. They broadly consider variables that influence the design problem. In the *Define* phase, designers attempt to clearly frame and define the design problem that they are attempting to solve. Designers identify themes and crystallize insights. In the *Develop* phase, designers come up with solutions to the design problem they identified in the previous phase. They ideate about the solutions and explore diverse design options divergently. In the *Deliver* phase, designers evaluate, narrow down, and test the proposed solutions. They also generate prototypes to answer specific questions about possible solutions. To understand how AI supports—and could support—each phase of the design process, we applied the Double Diamond design process model as our main theoretical framework.

1.3. Procedure

The overall study procedure is illustrated in Figure 2. We first conducted a systematic review by screening topical papers using the PRISMA framework (Page et al., 2021). Then, we mapped the AI-DSS we found across the four phases of the Double Diamond design process model. Based on this categorization, we conducted an affinity diagramming activity to

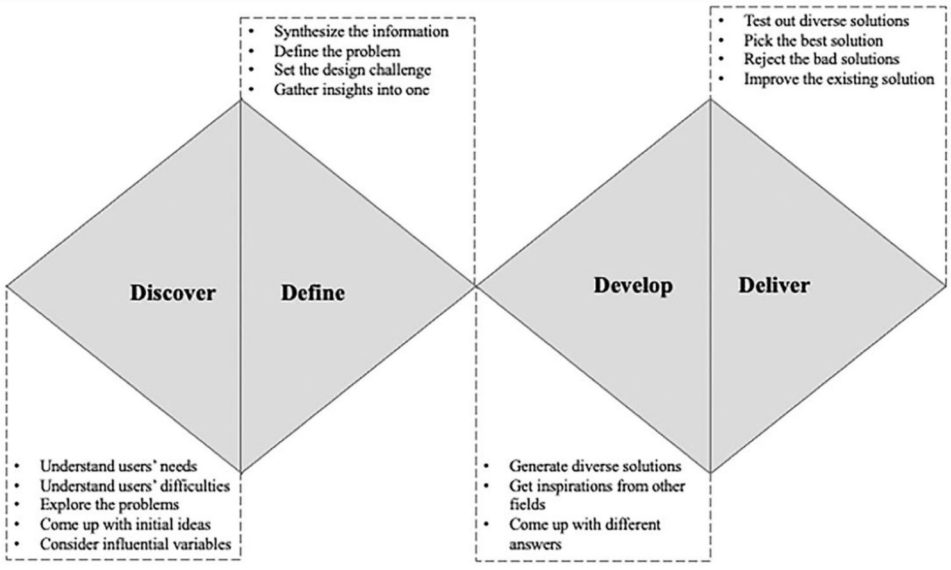


Figure 1. Double Diamond design process model is a framework organizing activities occurring in the design process. This figure shows the four phases in the model: (1) Discover, (2) Define, (3) Develop, and 4) deliver. It emphasizes the divergent and convergent aspects of each phase.

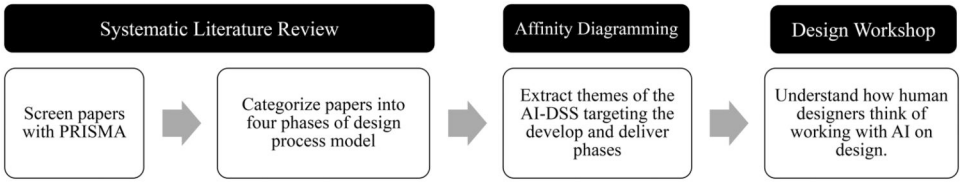


Figure 2. To answer our research question, we first performed a systematic literature review applying the PRISMA framework and categorized papers into four phases of the Double Diamond design process model. Based on the categorization, two researchers extracted the themes using affinity diagramming. Then the design workshop was followed in the real-world design situation to provide insights into what people with design expertise expect and want the AI agent to assist them with in the design process.

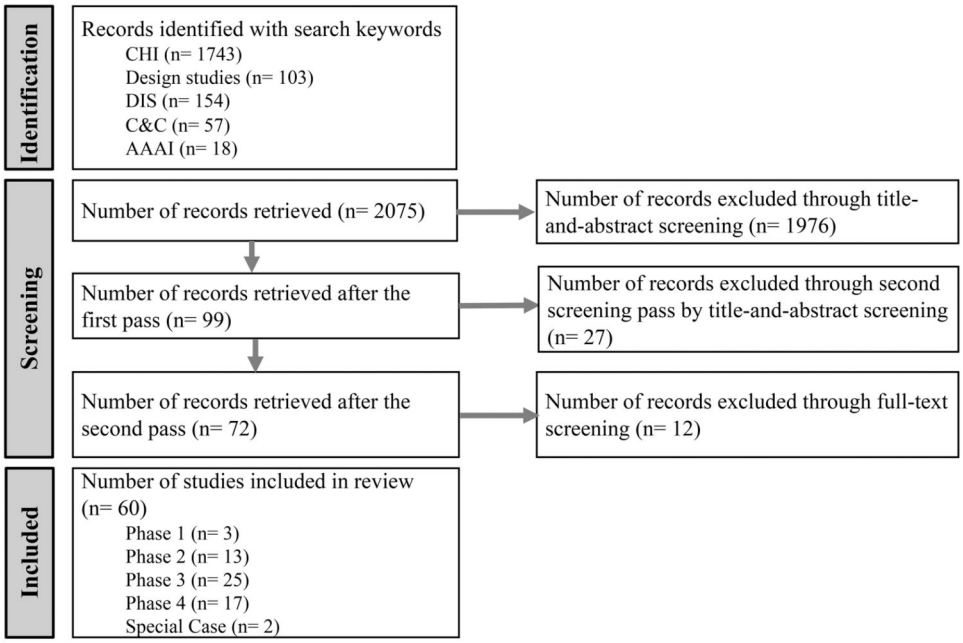


Figure 3. PRISMA flow diagram describes the procedure of systematic literature review. For the identification phase, papers were extracted using search keywords from five venues. After that, for the screening phase, papers were screened based on title and abstract. Researchers conducted the second screening pass by title and abstract. Then, full-text screening was followed. Finally, researchers categorized the screened papers based on the Double Diamond design process model.

extract common roles of current AI-DSS. We identified the roles an AI-DSS could play to assist human designers and in the design process. In light of these roles, we conducted a case study in our lab with the aim of exploring how human designers think of working with AI on design.

2. Systematic literature review

We performed a systematic literature review of research papers that dealt with AI to assist design tasks using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) method (Page et al., 2021). Similar surveys used venue filtering with exhaustive reading (Thomaz et al., 2016) or pre-defined keywords with Boolean search expressions (Kyriakoullis & Zaphiris, 2016). Often authors also apply additional inclusion and exclusion criteria.

2.1. Method

In this work, we use the PRISMA method, which has been used in a large number of prior survey papers (e.g., Hutton et al., 2015; McInnes et al., 2018; Stewart et al., 2015; Thieme et al., 2020), and provides a template for selecting papers in systematic reviews (Liberati et al., 2009). PRISMA divides the selection process into four stages: identification, screening, eligibility, and inclusion and it provides a checklist of 27 items to aid the work in each stage.

Our PRISMA strategies and selection process are depicted in Figure 3. We started by identifying candidate papers from six relevant venues, including the Design Studies journal, the Proceedings of the AAAI Conference on Artificial Intelligence, the ACM Conference on Human Factors in Computing Systems (CHI), the Designing Interactive Systems conference (DIS), and the conference on Design Computing and Cognition (DCC), using a set of Boolean strings, shown in Figure 4. To conduct the review, we ran our keyword searches on the archival databases of our selected venues (Figure 3).

Next, we used the set of inclusion and exclusion criteria from PRISMA and filtered the papers accordingly. The inclusion criteria involved considering papers from 1980 to the present that presented an AI system that supports design. Since the terms "AI" and "design" are used broadly and with varying levels of specificity across disciplines, we constructed operational definitions relevant to our research question to guide our search (see Table 1).

We define "AI" as computational systems that interpret external data, learn from such data, and use the learned

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1) AI AND "design support system"
2) AI AND Design
3) "design support system" AND "artificial intelligence"
4) designing AND AI
5) designing AND "design support system"
6) "machine learning" AND designing
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Figure 4. Boolean search strings used to initially filter papers in the selected venues. We ran our keyword searches on the archival databases of our selected venues and compiled the results into a master BibTeX file.

Table 1. Operational definitions of AI, design, and AI-design support systems.

Concept	Operational Definition
AI	Computational systems that interpret external data, learn from such data, and use those learning to achieve specific goals and tasks. Machine learning, feature learning, generative models (VAE, GAN) are examples of AI methods.
Design	The process and results of developing prototypes, products, and craftworks to satisfy certain goals and needs, serving both functional and aesthetic goals. Industrial design, product design, graphic arts, drawing, sketches, and fashion design are examples of design work.
AI-Design Support Systems	The systems that support design with AI technologies.

These definitions were constructed based on previous research and included in the inclusion area of PRISMA.

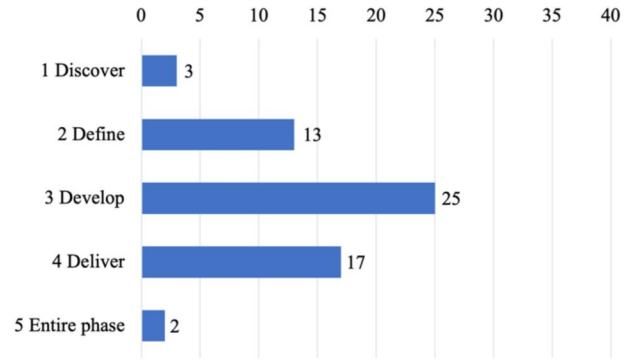


Figure 5. Number of papers attributed to each phase.

information to achieve specific goals and tasks (Yang et al., 2020). Machine learning, feature learning, and generative models, for example, were considered AI methods. In contrast, pure visualization tools that had no AI component and pure computer aided design (CAD) tools were excluded because we were examining design support systems that provide more than just visualization or modeling assistance.

Our definition of "Design" included the processes and results of developing prototypes, products, and craft works to satisfy certain goals and needs (Norman, 1988). Those that included both aesthetic and practical functions were considered within our definition. For instance, work in the areas of industrial design, product design, graphic arts, drawing, sketches, and fashion design were considered "Design." However, video editing and music composition are examples of activities not counted as design in this study.

For the exclusion criteria, we excluded papers that were missing AI or design components. We also excluded papers that had AI and design components but didn't match our operational definitions of AI and design. Additionally, we excluded duplicate papers that dealt with the same system. Patents, extended abstracts, survey papers, and preprints were also excluded. As for books, we only included the book chapters and cited them individually. When an extended abstract and the full paper dealt with the same system, we only counted the full paper.

Based on these inclusion and exclusion criteria, two researchers filtered and screened the papers (Figure 3). Initially, the papers were screened based on their titles and abstracts. We repeated the title-abstract screening process twice to filter papers. Then, we conducted a full-text screening process. The final number of studies included in the review was 60 papers. Lastly, researchers categorized 60 papers into four phases of a double diamond design process model. We carefully analyzed the content of each paper and identified which phase of the design process it mainly addresses.

2.2. Results

The final set of included papers consisted of 60 papers, which were broken down across each design phase (Figure 5). We found a total of three papers targeting the first phase, Discover; 13 papers targeting the second phase, Define; 25 papers targeting the third phase, Develop; and 17 papers targeting the last phase, Deliver. Two papers were categorized as special cases because they were relevant to more than one phase in the process. These results indicate that most (70%) of current AI-DSS supports designers in the second "diamond" of the Double Diamond model. In other words, current systems support designers in later stages of the process where humans generate and evaluate design solutions.

To better understand the specific support that AI-DSS do in each phase of the design process, we conducted an affinity diagram. We applied the affinity diagram because it is a structured method to organize a large number of data or ideas into meaningful categories. The main purpose of the affinity diagram activity was to extract common themes and aspects of support that AI-DSS provide for each phase of the design process. Two researchers made sure to have a common understanding of this goal.

Next, to gather information for the affinity diagram, we wrote down one-sentence summaries explaining how AI supported the design for each system presented in 60 papers. This summary was written in the online Microboard with the sticky notes that each note represented one system (Miroboard, 2023). Then, researchers grouped the systems that shared similar supporting roles. We looked for similar

or relevant features of the supporting role between systems. To ensure a clear understanding of each sticky note's content, researchers exchanged their thoughts when grouping the ideas. While grouping the systems, we wrote a descriptive heading on top of each group that represents a common theme. These headings served as the main categories. After this, we moved to the blank page of Miroboard and placed each group of systems with its corresponding headings.

Once all groups were in place, we reviewed the arrangement to ensure that the supporting roles within each group were related to one another. We adjusted the placement of sticky notes or reassigned them to different groups if needed. During this review process, we sometimes revisited the full-text papers to ensure that our understanding and grouping aligned with the content of the paper. Table 2 shows the results of the affinity diagramming.

2.2.1. Discover

We identified three systems that targeted the Discover stage of design. These works were generally targeted at improving designers' access to a large amount of data relevant to user

Table 2. The extracted themes from affinity diagramming based on the results of categorization of AI-DSS for each phase of the design process.

Model phase	Main activities of designer during phase	Supporting role of AI-DSS	References
Discover	• Explore the problem • Collect data that describes user needs	Increase access to large amounts of user data	Alomar et al., 2021; Todi et al., 2021; Vaccaro et al., 2018
Define	• Specify the design problem and constraints	Support qualitative coding	Marathe & Toyama, 2018; Rietz & Maedche, 2021
	• Describe target user • Find structure in raw information	Provide user representations (personas, storyboards)	Lin & Martelaro, 2021; Zhang et al., 2016; Zhu et al., 2019; Vandenberghe, 2017; Shi et al., 2020
		Broadly support information structuring	Koch et al., 2020; Yan et al., 2021; Wright et al., 2006; Bae et al., 2020; Gilon et al., 2018; Swearngin et al., 2018
Develop	• Generate multiple solutions	Simplify the mechanics of developing a solution	Boulanger & Smith, 2001; Chinowsky & Teicholz, 1993; Dayama et al., 2020; Eckert et al., 2000; Kumar et al., 2011; Katsanos et al., 2008;
		Leverage raw inputs for design solutions	Bevilacqua et al., 2013; Brazier et al., 2001; Cooney, 2021; Fails & Olsen, 2003; Hammond et al., 2008; Keshavarzi & Rahmani-Asl, 2021; Mo et al., 2021
		Construct or optimize a solution with the user	Guzdial et al., 2019; Katan et al., 2015; Law et al., 2019; Quiroz et al., 2007; Wang et al., 2017
		Generate solution alternatives	Alcaide-Marzal et al., 2020; Preston et al., 2017; Chirkin & König, 2016;
		Inspire users' creativity	Chan et al., 2016; Koch & Oulasvirta, 2016; Lee et al., 2010; Sun et al., 2014
Deliver	• Evaluate solutions • Prototype solutions	Augment designers' ability to generate, collect, or analyze feedback on a design	Krause et al., 2017; Rodgers & Huxor, 1998; Tizani et al., 1994; Yen et al., 2020
		Generate high-fidelity prototypes	Guo et al., 2021; Noyman & Larson, 2020; Suleri et al., 2019; Villalon et al., 2009
		Refine the existing solutions, or evaluate issues in generated designs	Françoise et al., 2016; Ivory & Hearst, 2002; Lee et al., 2019; Prato et al., 2020
		Use predictive modeling to evaluate solutions	Ashbrook & Starner, 2010; Brown, 2020; Greenberg et al., 2013
		Simulate users	Löwgren & Nordqvist, 1992; Stahlke et al., 2019
Special Case		Support the entire design process	Rasmussen et al., 2019; Culverhouse et al., 1992

needs and preferences. In one example, researchers studied a set of ML classifiers to identify accessibility issues in user reviews, supporting the discovery of such issues for design (Alomar et al., 2021). Two other works used a chatbot to collect preferences about graphical user interfaces (Todi et al., 2021) and fashion designs (Vaccaro et al., 2018).

2.2.2. Define

We found thirteen systems that targeted the Define stage. These projects aimed to help designers condense, make sense of, and construct definitions out of data describing a problem. Several of these directly targeted common methods used by designers to define a problem. For instance, two papers—Marathe and Toyama (2018) and Rietz and Maedche (2021)—used AI to support qualitative coding, applying rule-based, supervised, and simple natural language processing methods to apply human-defined codebooks to unseen data.

Several systems supported methods designers use to develop user representations from data. Four of these systems targeted the development or use of user personas. For example, Lin and Martelaro (2021) utilized pattern recognition techniques to synthesize "pseudoclients" that express style preferences for fashion design clients. Similarly, Zhang et al. (2016) and Zhu et al. (2019) used clustering methods to support the generation of user personas from data. Vandenberghe (2017), meanwhile, argued for the use of chatbots to make personas interactive. Finally, Shi et al. (2020) developed a system that used deep autoencoders to help designers generate emotional characters in storyboards from a few strokes.

The third cluster of systems more broadly supported the definition of structure in unstructured information. Koch et al. (2020), for example, used a semantic labeling algorithm to help users translate vague ideas in a digital mood board into concrete text. Yan et al. (2021) developed an algorithm to help interface designers automatically identify segments of goal-oriented activity in user interaction logs. Wright et al. (2006) developed a virtual sandbox for visually structuring and developing hypotheses out of information, backed by data-mining techniques including analytic, linguistic, and knowledge-based services. Within the context of mind-mapping, Bae et al. (2020) specifically targeted design fixation using suggestions generated by random walks over a knowledge graph. Along those lines, Gilon et al. (2018), developed an interactive logic and semantic-based search engine to expand designers' understanding of specific needs through distant product analogies.

Finally, in a slightly different vein, Swearngin et al. (2018) developed a system to generate vectorized UI building blocks from example screenshots, using classical vectorization and constraint optimization techniques. We argue that automatically defining the building blocks on which to construct a UI from design precedents is a form of problem definition, similar to defining a working principle or constraints over possible solutions.

2.2.3. Develop

The largest category we identified was made up of the 25 papers that targeted the third stage of the Double Diamond process. Many of these systems focused on simplifying the mechanics of developing a solution. For instance, Boulanger and Smith (2001) created an interface to guide and simplify decision-making when designing a bridge using a hierarchical model of task parameters. Dayama et al. (2020) used mixed integer linear programming to generate grid layouts for user interface wireframes. Kumar et al. (2011) used a structured prediction technique to translate the content of one website into the style and layout of another. Eckert et al. (2000) used a shape model to generate cutting shapes from verbal and numerical descriptions, as a way to facilitate communication between knitwear designers and technicians. Chinowsky and Teicholz created an interface for humans to evaluate and provide feedback to automatically synthesized architectural layouts (Chinowsky & Teicholz, 1993). Finally, Katsanos et al. (2008) used latent semantic analysis and hierarchical clustering to propose an information schema for a website.

Six papers used machine learning techniques to help designers handle raw inputs like sketch and gesture. Some of these focused on converting raw design inputs into a computational context. For example, Keshavarzi and Rahmani-Asl (2021) used computer vision methods to vectorize floor plan sketches and convert them into parametric building models, optimized using genetic algorithms. At a more basic level, Hammond et al. (2008) studied probabilistic models for sketch recognition that could support, for example, more natural CAD input. Cooney (2021), meanwhile, investigated co-creative agents that use technologies like style transfer and scene graphs to help citizens place objects in virtual scenes to visualize urban revitalization projects. Other work focused on helping designers to prototype user interfaces with intelligent input recognition components. For example, Fails and Olsen (2003) proposed an interactive machine learning tool that allowed designers to prototype image classifiers to support camera-based interfaces with minimal technical expertise. Mo et al. (2021) created an interactive tool that used hidden Markov models (HMM) and Bayesian optimization to help designers prototype gesture recognizers for gesture-driven interfaces. Finally, Bevilacqua et al. (2013) used classical machine learning and signal processing techniques like k-NN and HMMs to support real-time design of action-sound mappings for modular instrument design. Overall, all of these projects used machine learning to either allow designers to translate raw inputs into a design solution or prototype solutions with interactive components.

A number of papers developed systems to directly construct or optimize design solutions with a human. Quiroz et al. (2007) used an interactive genetic algorithm to evolve user interface layouts. Guzdial et al. (2019) studied taking turns editing human game level designs using different types of agents (Markov Chain, Bayesian Networks, and LSTM). Law et al. (2019) used local optimization with Pareto sorting to suggest improvements to a human's satellite system

designs. Katan et al. (2015) used interactive machine learning to create and customize gesture-controlled musical interfaces. Schmidt-Belz and Hovestadt (1996) presented a suite of tools, some of them machine-learning based, to support the generation of building plans using a mix of case based and knowledge based methods (Schmidt-Belz & Hovestadt, 1996). This includes generating part of the building plan itself, depending on the tool and context. Zhao et al. (2020) developed a system that automatically generates compound icons from text using a deep learning pipeline. Their method allows icon designers to explore style variations for different components in the generated design (Zhao et al., 2020).

Other systems focused on generating alternative solutions to present to the user. Chirkin and König (2016), for example, built an urban planning system that generated multiple solutions based on preferences it inferred from a seed design. Alcaide-Marzal et al. (2020) generated varieties of product shapes using shape grammar and a parametric modeler (Alcaide-Marzal et al., 2020). Preston et al. (2017) used topological combination techniques to automatically generate variations of hand-crafted visual markers that were designed to be both computer readable and aesthetically pleasing. To design the curriculum, automatic progression generation was utilized with partial ordering graph and graph coloring algorithm (Wang et al., 2017).

Finally, several authors use machine learning to intelligently present examples or other materials to inspire designers' creativity. For instance, Chan et al. (2016) investigated different levels of automation using clustering and topic modeling to organize suggested solutions paths for design problems; presenting the results to participants as brainstorming stimuli. Lee et al. (2010) developed an adaptive example gallery which used different sampling techniques to allow users to find similar or different examples when designing a website. Koch and Oulasvirta (2016) used cooperative contextual bandits to provide relevant materials to inspire designers via a digital mood board. In a slightly different approach, Sun et al. (2014) developed an adaptive rule-based system to detect creative activities in sketches. They used these segments to visualize a designer's thought process as a tree, which provided a source for designers to identify new paths of exploration when they got stuck.

2.2.4. Deliver

We identified 17 papers that targeted activities in the fourth stage of the double diamond process. In this stage, designers start to prototype and narrow down solutions, collecting feedback, and creating medium and higher fidelity prototypes as they work towards delivering a final solution.

In support of this process, four projects developed systems to augment designers' ability to generate, collect, or analyze feedback on a design. For example, Krause et al. (2017) used natural language features like specificity and sentiment to come up with a framework for improving crowdsourced design feedback. In a similar vein, Yen et al. (2020) built a system that used topic and sentiment models to help designers visualize and interpret product feedback. Two other papers provided automated design critique. Rodgers and Huxor (1998), for example, used a knowledge base to critique solutions based on user provided design requirements, helping them narrow down potential solutions. Tizani et al. (1994) used a knowledge-based inference engine to provide feedback relevant to fabrication and site construction earlier on in the design process.

A second group of papers targeting phase four focused on supporting or generating high fidelity prototypes at scale. For instance, Suleri et al. (2019) developed a system to detect UI elements in a low fidelity sketch and automatically generate corresponding medium and high-fidelity prototypes. Similarly, Guo et al. (2021) built a generative tool to reduce the tedious task of crafting and embellishing advertising posters from user-defined text and images. Villalon et al. (2009) took a slightly different approach, using a knowledge base to give the user information about construction and a specific fabrication tool (in their case a robotic arm) relevant to a design they were making. Finally, Noyman and Larson (2020) used generative neural networks to produce visualizations on a TUI that allowed designers to interact with high fidelity models of an urban planning environment.

Four papers used machine learning techniques to evaluate or identify issues in designs. Lee et al. (2019) developed a predictive pose model driven by comfort to visualize how humans would interact with physical designs. Similarly, Françoise et al. (2016) suggested the design support tool applying the hidden markov models (HMMs) to visualize humans' movement interactions in real time for interaction design. Ivory and Hearst (2002) described a machine-learning driven process for uncovering heuristics related to the quality of a web site design as the basis for improvement. Prato et al. (2020) used deep learning to offer fashion compatibility analysis and outfit completion recommendations with real data quickly enough to be used in a real application.

We found three papers that used predictive models to evaluate solutions. Ashbrook and Starner (2010) used a corpus of everyday motions to help designers predict whether a gesture design would trigger false positives without needing to do actual user testing with the product. Brown (2020) used surrogate models to evaluate building performance. Greenberg et al. (2013) built a classifier to predict the success of a crowdfunding project design.

Two papers simulated users to reduce the cost of user testing. Löwgren and Nordqvist (1992) use a knowledge-based system to automatically identify issues and provide comments in a user interface. Meanwhile, Stahlke et al. (2019) proposed using autonomous agents with different behavior profiles to simulate usability testing in games.

2.2.5. Special cases

We found two systems covering all phases of the design process. Co-notate is a research prototype system that enables the automatic synthesis of audio and video recordings with textual annotations that are simultaneously captured during design activities (Rasmussen et al., 2019). These recordings could help provide insights into the entire design process. Culverhouse et al. (1992) developed DESMATE that

captures the detailed activities of the engineer working in a design environment. The system increases the access to information that can be useful for the entire design process.

In our literature review, AI design support systems targeting the second half of the Double-Diamond design process (Develop and Deliver) were more predominant than those targeting the early stages (Discover and Define). We were curious how this finding would align with designers' expectations and imaginations of how AI tools might support real-world design situations. To explore this, we applied the scenario mapping method because this method can help us understand the diverse approaches taken by designers in terms of how AI can support design (Pruitt & Adlin, 2010). By analyzing and comparing specific scenarios generated by different designers, the purpose of the workshop was to gain insights and identify gaps for AI support, leading to designer-centered ideas.

3. Case study: What roles do designers imagine for AI-DSS?

We conducted design workshops to extract insights into what people with design expertise thought an AI tool might do to assist in the design process. We conducted workshops with two different types of emerging technologies in the context of design support—a physical robot and a large-language model driven chatbot (ChatGPT) (OpenAI, 2023). We chose emerging technologies to encourage participants to think more broadly than the roles that they might associate with more traditional tools.

3.1. Designing a Zen Garden with a physical robot and ChatGPT

The aim of our design workshop was to probe for roles that human designers imagined an AI support design in a simulated real-world design situation. To accomplish this, we asked expert designers to brainstorm scenarios where an AI would help a novice designer learn to design a tabletop rock garden. The scenario mapping method was applied because this method can help us understand the diverse approaches taken by designers in terms of how AI can support design (Pruitt & Adlin, 2010). We chose to frame the scenarios around novices as we felt this might present a broader range of opportunities than specialized practice over the course of a short workshop. However, we recruited expert designers who we hoped would have a comprehensive grasp of design activities and pain points that might emerge across the entire design process. We recruited seven participants with strong design backgrounds, in fields including UI/UX design, product design, and architectural design (Table 3).

At the start of the study, researchers verbally explained a set of design principles to consider while designing the garden. We used the problem of designing a Japanese rock garden, also referred to as a dry garden for the workshops because of its open-ended design possibilities with natural elements, such as rocks, sand, and plants (Slawson, 1985). Three design principles included negative space, horizontal structure, and vertical structure. Then, researchers let participants know how to control the robot using a simple point-and-click interface or converse with chatGPT. For the robot, the tabletop robotic arm was used. The robot was built on the Ufactory Uarm that can grab and move stones in the sandbox. The UArm is a 4-DOF miniature palletizer arm with a suction gripper well-suited for pick-and-place tasks. We instrumented the UArm's end-effector with a downward-facing Pi HQ camera and fisheye lens to capture high-resolution, wide-angle images of the entire sandbox. These images are used to track rocks in the sandbox and make decisions about where to pick and place rocks. Four of the participants were given control of a small robotic arm positioned next to the dry garden box, and three were given access to the ChatGPT chat interface (Figure 6). The robot was capable of text-to-speech and arm movements, while ChatGPT provided conversational answers through a text interface.

Table 3. Seven participants with strong design backgrounds including UI/UX design, product design, and architectural design were recruited.

ID	Background	Age	Gender	AI agent
P1	Architectural Design	32	Male	Robot
P2	Architectural Design	29	Female	Robot
P3	Design	25	Male	Robot
P4	Design	29	Female	Robot
P5	Product Design	31	Male	ChatGPT
P6	UX/ UI Design	26	Female	ChatGPT
P7	Architectural Design	31	Female	ChatGPT

Four participants were given control of a physical robot and three were given access to the ChatGPT interface.

After these explanations, researchers asked them to design their own rock garden while applying three design principles for 15 min. Participants were asked to identify any confusing or difficult moments they experienced while working on the garden. During this process, they considered not only their own frustrations but also the potential challenges faced by novice designers. Following that, they sketched out three primary pain points where AI support, such as robot and ChatGPT, might be helpful for 20 min. The researchers then instructed them to develop their scenarios based on those pain points. At the end, participants wrote down three scenarios on the worksheet used for the scenario mapping method.

3.2. Results

Altogether, we collected 21 scenarios describing ways that expert participants envisioned a novice working with an AI agent to design a rock garden. Scenarios were all recorded and transcribed by the researcher. Two researchers met for three meetings, during which they read the transcribed scenarios and categorized each one according to the definitions outlined in the Double Diamond Design process model (Section 1.3. and Table 2). Two researchers collaboratively organized the scenarios according to the four stages of the Double Diamond process model. We enumerate the scenarios we associated with each of the four stages here before discussing insights from this comparison.

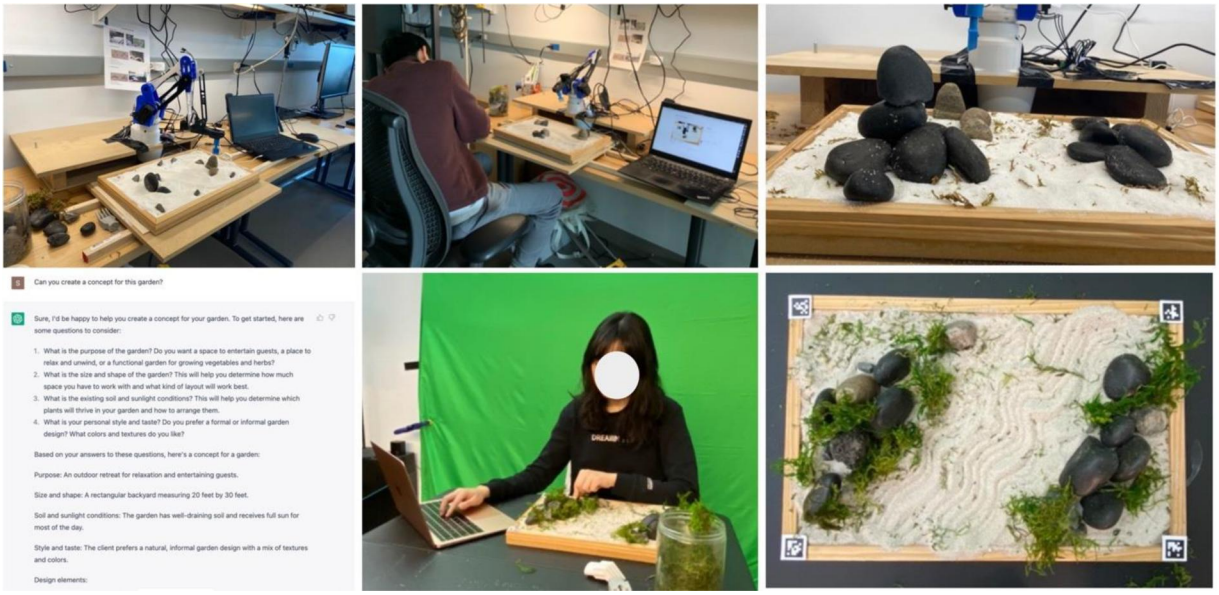


Figure 6. The study setting and results of the design workshop. A physical robot and a large-language model driven chatbot (ChatGPT) were used as the AI agents in this case study.

3.2.1. Stage one (discover) scenarios

Some participants mentioned ways the agent could help them explore the design problem, suggesting potential first-phase roles. For instance, multiple participants suggested that an agent could inspire them to help them generate ideas and gain a better sense of the design problem space.

- *Explain a problem*. P5 stated, "I did not know where to start, so I asked ChatGPT, 'How can I design the garden?'"
- *Explore design principles*. P4 mentioned that AI can help designers to explore different ways to approach the task through introducing them to a variety of design principles: "We have a designer who wants to create an aesthetically pleasant horizontal structure but doesn't know how to start. The robot can provide design options based on Gestalt or other design principles and give examples of the grid and show the person possible patterns based on design principles."
- *Discover inspirations*. P6 wanted the AI agent to discover potential sources of inspiration before she started designing: "I was first looking for the inspiration for the garden, so I asked ChatGPT where I can find the inspirations because there are a lot of resources that I can access."
- *Explain design materials*. P6 also wanted the AI agent to provide more information about designing with the combined design materials in the problem space: "I told the ChatGPT about the ingredients that I have—'Can you design the garden with sand, moss, and rocks?'—and ChatGPT answered with possible combinations such as Japanese rock garden, moss garden, rock garden, and beach garden."
- *Suggest a design concept*. P2 wanted the agent to help her develop a style to inform the kind of garden by suggesting high-level design concepts: "The designer wants to create a Japanese-style garden but doesn't know how to design. Robots can look up the successful precedents online and give proposals and let the designer choose."

3.2.2. Stage two (define) scenarios

Multiple participants mentioned the potential roles involving defining the design problem, which is phase two of the Double Diamond process.

- *Define design constraints*. P4 mentioned that the agent can help define possible design constraints: "The person doesn't know how many clusters they can fit, so the robot will scan the area, 'The sandbox is 12 inches by 9 inches. You can create up to 4 clusters in the box.' The robot gives numerical data."
- *Define design problems*. P5 also suggested that the AI agent can gather information to help define and constrain the design problem: "I don't know how small or how big the garden is. I wanted to get the dimensions of the garden. It would be more helpful if the AI told me how the model fits in the real-world context."

Other participants suggested that an agent could inspire them to get the sense of the design problem space:

- *Provide inspiration*. P5 wanted this inspiration in the format of images: "I just wanted to see the example pictures of the garden from ChatGPT."
- *Define the design concept*. P6 specifically mentioned that the AI agent could help them define the underlying design concept, such as defining the purpose of the garden: "I asked ChatGPT to create the concept for this garden because I wanted to write a brief description about the garden. ChatGPT proposed helpful questions like what the purpose of the garden is, how the shape of the garden affects people's feelings, and all the environmental conditions like sunlight and stuff. I was also asked about my personal style and taste of the garden. I wanted help to set up a detailed main concept for the garden."
- *Choose the design theme*. After receiving help from ChatGPT, P6 was inspired to choose an overriding theme

to frame her design that was suggested by ChatGPT: "The beach garden inspired me because it will be cool to set up this environment in the city where people can walk along this pathway. I started designing the rock patterns on the real beach and scraping the patterns of the waves and stuff."

- *Define the purpose of design*. Similarly, P7 mentioned that the AI agent could help define the garden's purpose and provide contextual details for its garden: "Because I was not sure about why I was designing this garden, particularly the purpose of the garden, I was unsure where it should fit in a wider spatial context. And the viewpoints specifically were not determined. I was not sure where I should start."
- *Explore design materials*. P7 also suggested that AI could help designers explore design spaces by providing supplementary information about design materials, thus fulfilling phase 2 roles: "What bothered me the most was the texture of the rock. I was not sure about the moss, either. AI can help me imagine the design balance between rocks and moss."

3.2.3. Stage three (develop) scenarios

Participants also suggested roles relevant to phase 3, which involved generating design solutions:

- *Generate solutions* P1 mentioned that AI could generate prototypes and solutions that human designers would find difficult to create by themselves: "The novice designer wants to place rocks in the perfect spots, but it is difficult to create symmetry. The robot uses the laser pointer to show the right places or even project all grids simultaneously."
- *Suggest solutions with motion* P1 also mentioned a similar idea about raking motion: "It is difficult for designers to create the perfect path. When designers put down all the stones, the robot reads all the stones and calculates all the possible paths, and the designer can follow the robot's movement."
- *Generate a prototype* P3 also mentioned that the agent can help generate a prototype: "Designers can collaboratively design one Zen garden with multiple robots. They can collect and make things together."
- *Provide grounded metaphors* P4 mentioned that AI agents could provide grounded metaphors to help designers work toward solutions: "The person wants to create a negative space but has no idea how. The robot projects images of nature with two different things: the sea and sand, the sky and mountain. And then it asks the designer to create a negative space based on the projected image."

3.2.4. Stage four (deliver) scenarios

Some participants mentioned that the agent could help designers evaluate the solutions that they come up with:

- *Assess the feasibility of a solution* P2 suggested that the agent can assess the feasibility of a person's design: "The designer already has a tentative layout for the garden design, but he doesn't have a dimension for the space. So, the robot can scan the empty space to survey dimensions and determine the feasibility of the designer's plan based on the information that robot gathered and provide relevant feedback or suggestions."
- *Provide feedback* P5 also wanted the AI to evaluate and provide the feedback on the design solution that the designer provided: "I asked ChatGPT about whether the designed garden was good or bad because I was not sure. I just wanted to get feedback on whether it's good for the community and people."
- *Narrate the design solution* P2 also mentioned that the AI agent can help interpret and narrate the design solution: "After the garden is built, the designer wants to enjoy the garden, and he wants the interpreter–the robot–to explain the story of each rock, like a museum curator."
- *Generate a high-fidelity prototype* P3 suggested ideas relevant to generating the high-fidelity prototype: "Designers can use robots after construction. They reduce the physical efforts and prevent injuries from lifting heavy rocks and they can support large-scale construction."

4. Discussion

According to our systematic literature review findings, most current AI-DSS primarily targets generating solutions for design problems (Figure 7(a)). However, our case study findings suggest that the expert designer's perception was

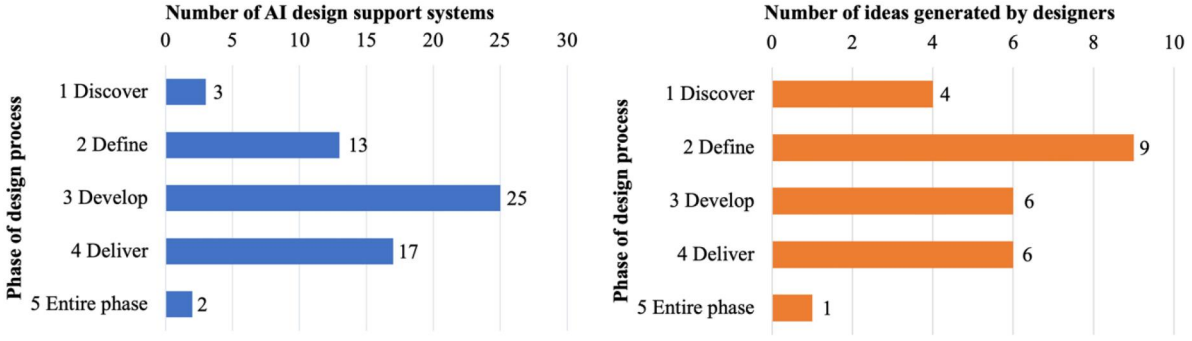


Figure 7. (a) Number of AI-DSS attributed to each phase in systematic literature review. (b) Number of ideas supporting each phase of the design process from the case study.

more evenly distributed across the design process. Indeed, several scenarios expert designers generated involved seeking AI assistance when exploring and defining the design problem (Figure 7(b)).

This suggests that AI-DSS in the early phases of the design process may warrant further exploration. The AI-DSS we identified in our literature review mostly supported the early phases by giving designers access to a broader range of information and user data. However, as we found in the design workshop, one might imagine ways that future AI-DSS could also help reframe design problems or encourage designers to explore design concepts, principles, and themes instead of simply providing a large amount of raw data. This kind of support could propagate down the process and ultimately influence how a human defines the purpose and details of a design. For example, an AI-DSS might propose an interpretation of a design problem or possible design constraints that focuses on the kinds of solutions a person develops. Conversely, an AI-DSS might provide inspirational materials that can encourage a designer to consider new ways of understanding the situation or identify new problems. This is because AI's distinct approaches to "thinking" can introduce novel and inspiring perspectives that may fall out of humans' sights (Jordanous, 2009; McCormack, 2008). For instance, when asking a machine learning model to calculate the "surprisingness" of different windows shapes, it concluded that having no shapes at all is the most surprising (25).

4.1. The gap between current AI-DSS and designers' expectations of AI

The possibilities that arise out of our findings raise the question: *What might explain the differences in the surveyed literature and participants' imaginations about AI-DSS?* There are several possible explanations. Our case study used new emerging technologies, such as ChatGPT and a physical robot, that were not widely adopted in design support systems. It is possible that technology-driven perspectives on AI-DSS may have constrained prior work to the kinds of tasks suggested by conventional systems. A robot's ability to provide physically grounded support, meanwhile, may inspire different roles, such as showing a designer how to rake patterns. On the other hand, large language model-driven chatbots like ChatGPT have the potential to dramatically extend the capabilities of AI-DSS beyond what was previously considered possible or exclusive to humans. For instance, ChatGPT can fluidly suggest contextually grounded rationale, critical thinking, and intuition to help a person find structure in an open-ended problem.

It is also possible that the wicked and undetermined nature of design problems (Buchanan, 1992) simply makes AI-DSS for the Discover and Define phases less tractable. AI technology might be less suited to handle ill-defined and less constrained tasks. AI-DSS might traditionally automate repetitive tasks with scalable methods. However, design problems involve multi-faceted aspects that require critical thinking and intuition (Darwich, 2016). Recent improvements in models of natural language, as we've discussed, may be poised to change this. By utilizing machine learning algorithms and natural language processing, large language models like ChatGPT have the capacity to enhance decision-making in design processes through the analysis of unstructured tasks (Hassani & Silva, 2023). To be clear, our point is not that new AI technologies are the correct lens through which to view the future development of AI-DSS. However, the rapidly changing landscape of new technologies might support designers and open research around less solution-oriented forms of design support.

Another potential reason for this difference is that designers and engineers have different backgrounds and skills that focus on different aspects of the design process (Maudet et al., 2017). For instance, when it comes to engineering design, the main goal is to find a convergent solution to the design problem concerning a set of requirements (Löwgren, 1995). This differs from designers who focus on understanding design problem space and exploring divergent design possibilities (Löwgren, 1995; Maudet et al., 2017). Our findings suggest that future AI-DSS can reflect these points. Conducting design workshops and ethnography with design professionals before system development can be a useful starting point.

4.2. Human-centered AI and human-AI teamwork perspectives

Our surveyed papers overall demonstrated that substantial AI-DSS performs non-creative and repetitive tasks to support humans' design. In other words, AI-DSS describes their values as taking charge of the laborious work and allowing designers to allocate their cognitive abilities more wisely and focus on solving the design problems (Hwang, 2022). For instance, according to our surveyed papers, creativity supporting AI-DSS provided a large amount of inspiring data, such as previous examples, to inspire designers' creativity (Chan et al., 2016; Koch and Oulasvirta 2016; Lee et al., 2010; Sun et al., 2014). Still, the role of AI in these AI-DSS is limited to providing a large amount of data and not directly interacting with users' creative and cognitive thinking processes. This approach might not be ideal for successful designs because it can limit the creative output of some designers by overly relying on previous examples (Sio et al., 2015).

Most recently, the rise of generative AI introduced abundant new forms of creativity support, enabling users to iteratively explore, prototype, and bounce ideas back and forth (Berger & Ploennigs, 2023; Cai et al., 2023; Chang et al., 2023; Petridis et al., 2023; Wallace et al., 2023; Wallace et al., 2021; Wang et al., 2023). How users utilize these tools has also transformed, with increased opportunities for users to interact with AI while performing design thinking and creative tasks (Devasia et al., 2020; Bernstein et al., 2023; Verheijden & Funk, 2023).

Despite these recent changes, the forms of interaction between designers and AI are somewhat limited. For instance, the most popular interaction patterns of recent AI-DSS are that designers seek out AI, and AI reacts to

designers' input by generating design solutions (El-Zanfaly et al., 2023; Yan et al., 2022). Aligned with our design workshop results, designers expect AI to engage more in their initial thought process in design. Our surveyed papers' findings demonstrated that AI is involved in a limited part of the design process and does not collaboratively interact with users. Our study suggests that there is a lack of attempts made to address a user-centric and collaborative human-AI teamwork perspective (Hwang, 2022). For instance, most AI-DSS did not consider designers' individual differences and assumed all designers had identical design expertise and capabilities. In addition, these AI-DSS do not have a customization function and were not designed for collaboration among multiple designers. Our study provides insights that future AI-DSS needs to consider more interactive involvement of AI and collaborative human-AI teamwork perspectives with a more human-centric approach.

4.3. AI in the production of culture and the arts

A concern that AI will replace humans' unique identities in the creative workspace has been raised for a long time (Van Esch et al., 2021). As our surveyed papers showed, AI can inspire creative works in unique ways, and the strengths of AI complement human skills. However, we need to be aware of several crucial ethical concerns when using AI in design.

Concerning that most AI-DSS directly generate design solutions, it may be challenging to determine the copyright boundaries. Humans struggle to detect creative contents such as poets, news, recipes generated by AI language models (Clark et al., 2021; Köbis & Mossink, 2021; Kreps et al., 2022). This raises the concerns about new forms of deception and manipulation (Jakesch et al., 2023). For an efficient Human-AI collaboration in design, it is important to guard the territory of humans' works and define AI's role clearly. Human-AI collaboration needs to be determined by humans themselves (Hwang, 2022). Our study suggests that future AI-DSS needs to consider the self-explanation and transparency aspect of AI (Salminen et al., 2020).

In addition, AI models are trained with a large number of human-generated examples. As more data is available, the better generative outputs become. Sourcing data to train better AI can lead to design that lacks the cultural context with racial or cultural biases. For instance, in AI-generated images, the algorithms tend to work for majority views and groups while excluding minority racial groups (Williams et al., 2018). In addition, demographic biases also exist in that AI-generated images do not reflect all demographic group, skewed towards young adults, especially white women (Salminen et al., 2020). More efforts are needed to mitigate this skewness and bias in AI design supporting systems because it can directly influence the generated design solutions. In future studies, it is crucial to consider a direction that enhances and complements human designers' work rather than undermining their efforts, ensuring the collaboration between AI and human designers.

5. Conclusions

This paper explores the assistive roles of AI in DSS, categorized according to the Double Diamond design process model. We surveyed and categorized existing AI-DSS based on HCI and design literature, extracting key themes about current AI-DSS opportunities. AI-DSS aids in the Discover phase by enhancing access to information and user data for designers. In the Define phase, AI-DSS collects information and data. During the Develop phase, AI-DSS supports designers by generating solutions, prototypes, feedback, and analyzing the design process. In the Deliver phase, AI-DSS facilitates automatic evaluations, simulates users, generates high fidelity prototypes, and provides refinement tools.

To gain insights into designers' expectations, we conducted a case study in a simulated real design situation using emerging technologies like ChatGPT and a physical robot, which have been less commonly used in design support. We argue for further exploration of AI-DSS in exploring design problems, as existing systems primarily focus on generating and developing design solutions. Emerging AI technologies like large language models may have the potential to pave avenues for future research in less solution-oriented design support.

Our work provides insights into the potential of AI in design process and human-AI design collaboration. Future work can concentrate on AI-DSS in the early phases of the design process because AI can assist designers in the early stages by introducing new approaches to design problems. In addition, our study suggests that future AI-DSS needs to consider a human-centric approach of AI with its possible ethical concerns to ensure effective collaboration between AI and human designers.

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