Understanding Design Collaboration Between Designers and Artificial Intelligence: A Systematic Literature Review

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Recent interest in design through the artificial intelligence (AI) lens is rapidly increasing. Designers, as a special user group interacting with AI, have received more attention in the Human-Computer Interaction community. Prior work has discussed emerging challenges that persist in designing for AI. However, few systematic reviews focus on *AI for design* to understand how designers and AI can augment each other's complementary strengths in design collaboration. In this work, we conducted a landscape analysis of AI for design, via a systematic literature review of 93 papers. The analysis first provides a bird's eye view of overall patterns in this area. The analysis also reveals three themes interpreted from the paper corpus associated with AI for design, including AI assisting designers, designers assisting AI, and characterizing designer-AI collaboration. We discussed the implications of our findings and suggested methodological proposals to guide HCI toward research and practices that center on collaborative creativity.

Additional Key Words and Phrases: Design, Artificial Intelligence, Literature Review

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1 INTRODUCTION

Recent interest in design through the lens of artificial intelligence (AI) has significantly risen, with a steady surge of AI-driven ideas and techniques dedicated to a variety of design fields. For example, graphic designers leverage AI to amplify their knowledge of semiotics, typography, and layout to design visual works such as posters [59], banners [111, 204], and magazines [209]. UI/UX designers apply AI to create the user interface (UI) or user experience (UX) of websites [203], mobile applications [41, 122, 138, 149], and other digital tools [155]. Industrial designers use AI to enhance their skills in manufacturing, use of materials, and ergonomics to design furniture [164], vehicles [134], and more [99, 183, 191]. While AI will radically alter how design tasks get done and who does it, many researchers agree that the larger impact of AI will be in complementing and augmenting human creativity, not replacing them [34, 61, 151]. Thus, understanding human–AI collaboration for design tasks has been growing in prominence within the Human-Computer Interaction (HCI) community.

Designers, who create in response to a given problem in a specific context, constitute a special user group interacting with AI, as they not only consume the results of AI, but also co-create with it [211]. HCI research has discussed emerging challenges that persist in designing human-AI interaction encountered by designers and explored opportunities for designers to engage AI as a design material [47, 67, 185, 193, 194, 199]. For example, Yang et al. [192] collected and analyzed 2,494 HCI papers that mention Machine Learning (ML) to provide the landscape of HCI research in relation to ML. Their analysis revealed seven topics that describe where HCI has employed ML technical capabilities such as intelligent UI and sentiment analysis. Although prior work has laid a solid foundation for improving human-AI interaction from designers' perspective, they focused more on designing for AI instead of *AI for design*. Empowering design with AI is challenging, and little is known about how designers and AI can augment each other's complementary strengths in design collaboration.

To fill the gap, we conducted a literature review on AI for design following a mixed-method approach. First, we screened 2,574 ACM papers and included 93 papers in our final corpus based on the PRISMA framework. Second, we analyzed the corpus to reveal overall patterns in AI for design research, including *when* and *where* researchers have focused their attention and *what* they have focused on. Such a bird's eye view can help sensitize HCI researchers to the increasing breadth and depth of research in this area. Third, we applied a reflexive thematic analysis to understand the collaboration between designers and AI and identified three themes, including *how* AI can enhance what designers do best, *how* designers can most effectively augment AI, and *how* to support the partnership. These themes integrate disparate threads of prior research on AI across different design fields for the first time. Further, we envision potential research opportunities of enabling AI for design in a more explainable, moral, and adaptable way with designers. The the details of our corpus can be accessed at https://ai4designsurvey.github.io/.

2 BACKGROUND

As a preamble, we started by clarifying what "design" and "AI" mean in this work. "Design is a discipline of study and practice focused on the interaction between a person — a 'user' — and the man-made environment, taking into account aesthetic, functional, contextual, cultural, and societal considerations", as identified by the International Council of Design (ICoD) [129]. ICoD is the world's largest representative of professional designer entities founded in 1963 and is one of three international organizations on the steering committee that signed *The Montréal Design Declaration* [39]. Based on the definition, ICoD also listed a spectrum of specializations within the profession called 'designers', including graphic designers, industrial designers, fashion designers, interior designers, service designers, and UI/UX designers. Given that the act of designing is at the core of their practice, design disciplines are also related to artists, engineers, and architects. Specifically, while both designers and artists are creative, artists focus on self-expression and designers attempt to find a solution to the needs of targeted users. Both designers and engineers provide solutions to a problem but through different approaches; engineers base their work on science and technology while designers base their work on human behavior. As 'design' is a broad term, our work mainly associates design with *graphic design, industrial design, fashion design, interior design, service design*, and *UI/UX design* to narrow its scope.

AI is an umbrella term that encompasses a set of computational techniques that enable a machine to "make predictions, recommendations, or decisions that influence real or virtual environments", given a set of human-defined objectives [198]. Within AI, Machine Learning (ML) has emerged recently and transformed the field through breakthroughs such as computer vision and speech recognition. ML also contributed a modern meaning to AI, as it enables task completion by automatically learning knowledge from data [78]. In other words, instead of providing explicit instructions via programming, a designer can shape the behavior of the algorithm using examples of that behaviors [24]. Considering that ML is at the core of many current AI techniques, our work conducted the first systematic review of designer-AI interaction in the scope of ML-driven design ideas or techniques. We chose ML-driven design for two key reasons. First, given the wide adoption of AI in design using techniques such as optimization [92, 128] and predictive modeling [9, 170], the scope of our literature review should be constrained. Second, and more importantly, investigating ML-driven design can encourage more discussions on open questions concerning designer-AI interaction and provide more insights. For example, working with ML is perceived as "uniquely difficult" for UX designers, who usually face design challenges related to the uncertainty of AI's capabilities and the complexity of AI's output [194].

3 RELATED WORK

Before attending to our own research, we first reviewed existing work to lay a foundation for understanding: (i) How do HCI researchers approach human-AI interaction and designer-AI interaction? and (ii) What are technological advances in AI for design?

3.1 Understanding Human-AI Interaction and Designer-AI Interaction

Human-AI interaction describes the completion of a user's task with the support of AI. To improve human-AI interaction, HCI researchers have proposed principles, frameworks, and guidelines to understand the characteristics of such collaboration for over decades [6, 34, 35, 69, 109, 126]. For example, Amershi et al. [6] proposed 18 applicable guidelines for human-AI interaction, which are categorized into four groups, including initially, during interaction, when wrong, and over time. Cimolino and Graham [35] reviewed prior work about human-AI shared controls and contributed a four-dimension framework as an analysis tool, including AI role, supervision, influence, and mediation. Diverse qualities that well-performed human-AI interaction should be instilled have also been proposed such as transparency [49, 186], explainability [2, 103], and politeness [161]. Also, both actors of human-AI interaction, human and AI, have been explored and specified. In terms of AI, the potential values of different applications that employ AI inferences have been examined, such as conversational agents [208] and neural network games [212]. Regarding the other actor of the interaction, human, researchers have focused on how different user groups interact with AI, such as children [84, 179], clinicians [176, 195], artists [24], and data scientists [66, 177]. Among these user groups, designers are of emerging research interest [193, 199].

With respect to designer-AI interaction, two potential aspects can be considered: designers design *for AI systems* (but not necessarily have to be used by designers) and AI systems that were explicitly designed *for designers*. For the former aspect, HCI researchers have discussed challenges that persist in designing human-AI interaction encountered by designers [46, 47, 193, 194] such as failing to recognize the appropriate situations where AI might help [196] and envisioning novel features that exceed AI's current capabilities [194]. They have also explored opportunities for designers to "engage AI as a design material" [12, 67, 185, 199]. Such a concept was borrowed from physical design (e.g., craft) for interaction design [125]; the alternatives of a design choice are to a large extent defined by the materials a designer has to work with, which requires that a clear understanding of what AI can and cannot do should be formed [67]. Specifically, some research sought to understand how designers work with AI. For example, Windl et al. [185] contributed four approaches adopted by interaction designers when designing AI systems, including a priori, post-hoc, model-centric, and competence-centric. Some research proposed that unique attributes of AI can also be considered as design materials rather than obstacles. Benjamin et al. [12] derived three provocative concepts to explain how the uncertainty of machine learning can play a role as a design material, including thingly uncertainty, pattern leakage, and future creep.

When comparing to research efforts devoted to designing for AI, the latter aspect, AI for design, has only scarcely been touched by HCI researchers: Hwang [72] and Lu et al. [108] have investigated the types of assistance (e.g., editor and generators) provided by AI-enabled design support tools through a product analysis and a retrospective analysis, respectively. Motivated by such a gap in the literature, our work attempted to collect and analyze papers focusing on AI systems designed for designers and provide a systematic review of AI for design, as we see this as the best starting place for discussing what it means by better design collaboration between designers and AI.

3.2 Technological Advances in AI for Design

Recently, technological advances in deep learning open a floodgate of AI-driven ideas and techniques specifically for design [167]. Notably, generative adversarial network (GAN) [56] proposed in 2014 is one of the most widely-implemented AI techniques for design [58]. Through the adversarial process between a generator and a discriminator, GAN is able to generate high-quality samples that varied from the realistic images fed by users. In this regard, GAN has been frequently integrated into design support tools to generate inspirations such as UI designs [122, 207], stylized photos [30], and virtual terrains [57]. For example, Mozaffari et al. [122] proposed a style-based GAN to generate a diverse but focused set of UI examples based on an input image. MakeGirlsMoe [1] enables users to specify the desired features of female animators such as eye color and hairstyle and then create cartoon portraits. Another frequently-used generative model is Variational Autoencoder (VAE) [88], which was proposed in 2013. By applying VAE, Vinci [59] learns the behaviors of human designers when creating advertising posters to generate new posters while EmoG [155] helps design sketches of the character with expressions for storyboards by learning input strokes from users.

The development of convolutional neural network (CNN) [97] is another milestone for AI-enabled design. In 2016, Gatys et al. [54] proposed the first CNN-based model to support neural style transfer (NST), which renders a new image by combining the content of a photograph with the painting style of artwork. Subsequent efforts have integrated NST into design support tools in both academia (e.g., [26, 141, 159, 173]) and industry (e.g., Prisma [95], Deep Dream [121], and filters in Tiktok [5]). For example, Virtusio et al. [173] proposed Neural Style Palette, which allows users to interactively blend anchor styles extracted from a single style input to create their desired realizations. In addition to visual input, AI can use textual input from users to generate designs. For example, recent multimodal neural networks such as DALL·E [140] and Contrastive Language-Image Pre-training (CLIP) [137] allows creating images from textual input for various concepts expressible in natural language. In this work, we included the aforementioned AI techniques in our search query to collect related papers and construct our corpus, given that the major contribution in these papers should be AI-related or AI-based.

4 METHOD

In this section, we detail our approach to both data collection and analysis that construct our corpus. The details of the corpus are included in *Appendix*.

4.1 Data Collection

Our approach to data collection was based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework [132] and structured in four main phases, including *identification, screening, eligibility*, and *inclusion*, as shown in Fig. 1.

4.1.1 Identification. We first developed our search query by discussing it with researchers through multiple sessions of iterations and refinements. The search query is composed of primary and secondary terms; the primary terms cover synonyms and abbreviations of *artificial intelligence* and related AI techniques while the secondary terms help identify papers relevant to *design*. Specifically, the primary terms were inspired by previous reviews on human-AI interaction [35, 179, 208] and include "artificial intelligence (AI)", "machine learning (ML)", "deep learning (DL)", "neural network(s)", "reinforcement learning", "generation", "generative", "variational autoencoder(s)", "variational auto-encoder(s)", "style transfer", "natural language processing (NLP)", and "data driven". We searched these AI-related terms in the titles, abstracts, or author keywords of text. To explore design-related works from the retrieved results, the

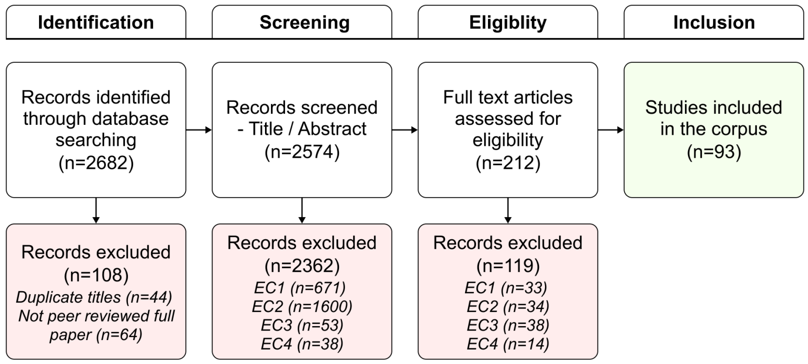

Fig. 1. The process of data collection following the PRISMA framework.

secondary terms were then used; "design" or "designer(s)" were searched in the titles, abstracts, or author keywords of text AND "designer(s)" was searched throughout full text.

To identify the data source, we followed the methodology proposed by previous literature reviews [208]; we first randomly retrieved 200 papers using the search query in total from five databases, including ACM Digital Library (ACM-DL), IEEE Xplore Digital Library (IEEE-XDL), ScienceDirect, Taylor & Francis Online, and Wiley Online Library. Two co-authors then reviewed 40 papers from each source and the qualification rates were: ACM-DL (15.0%), IEEE-XDL (5.0%), ScienceDirect (7.5%), Taylor & Francis Online (0%), and Wiley Online Library (2.5%). Specifically, 70% IEEE-XDL papers were based on AI but design did not play a salient role; 55% ScienceDirect papers mentioned designers but building designers or course designers who are beyond our research scope. As a result, we selected ACM-DL as the final source for our data collection due to its higher qualification rates than other sources. This decision was also made by considering that ACM-DL features a wide selection of reliable HCI works and the quality of the contributions. The ACM-DL database was last searched using our search query on June, 2022. Our search yielded 2,682 items. Items with duplicate titles (44 articles) and not peer-reviewed full papers (64 articles) were removed before screening the remaining 2,574 articles.

4.1.2 Screening, Eligibility, and Inclusion. After identification, screening and eligibility assessments were conducted by considering the following exclusion criteria:

EC1 The article discussed design in a broad scope (e.g., circuit design, architecture design).
EC2 The article did not directly aim at or involve designers.
EC3 The primary contribution in the article was not ML-based or ML-related.
EC4 AI for design is not the main topic. Instead, the article discussed designing for AI.

In accordance with the four exclusion criteria, EC1-EC4, two authors started screening by independently reviewing the titles and abstracts of a random sample of 515 articles (20%). During the process, the articles were assigned with 'include', 'exclude', and 'unclear' labels. We reached a good level of agreement (Cohen's Kappa > 0.8) and then discussed the mismatches to achieve a 100% consensus. Then, one author applied the exclusion criteria from the sample screening to the titles and abstracts of the remaining articles, resulting in 212 out of 2574 articles for full-text review. In terms of eligibility, two authors independently read the full text of each article and labeled them as 'include', 'exclude', or 'unclear'. They discussed and excluded 96 articles in total according to the four exclusion criteria. As a result, they identified 93 out of 212 articles to be included in our corpus.

4.2 Data Analysis

The data analysis of our corpus consisted of two parts. The first part focused on revealing overall patterns of AI for design in HCI by providing description statistics in terms of *publication year, publication venue, prominent work, application field*, and *contribution type* (Section 5). The second part focused on identifying the roles of designers and AI in design collaboration via a reflexive thematic analysis [15], which is a post-positivist approach that encourages researchers to be acquainted with the data as codes evolve when the analysis progresses. After engaging with the corpus during data collection initially, two authors independently reviewed the full text of the papers through three iterations. In each iteration, we went through the entire corpus and developed codes of themes openly in an inductive and theory-driven manner based on the semantic content of the papers. After each iteration, we collaboratively refined and revised the existing codes and discussed disagreements to achieve consensus. The codes developed from three iterations were then collated into potential themes, the papers relevant to each theme were gathered and recorded into spreadsheets. Finally, we conducted multiple rounds of reflection to derive a set of themes, including *AI assisting designers, designers assisting AI*, and *characterizing designer-AI collaboration* and their sub-themes as well as corresponding papers (Section 6). We also engaged in further discussions of explanatory memos.

5 FINDINGS: DESCRIPTIVE STATISTICS

In this section, we present the descriptive statistics of our corpus to show how the sample articles varied in publication year, publication venue, field of application, prominent work, and contribution type. Such descriptive statistics can help uncover overall patterns of the development of AI for design over time.

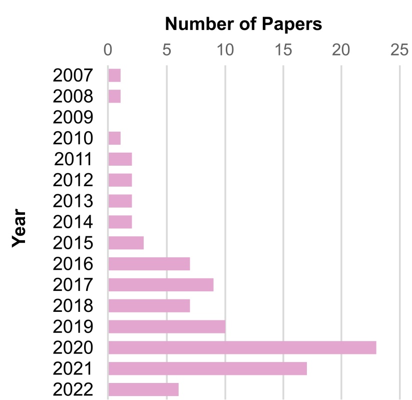

Fig. 2. Frequency of the papers about publication year.

Publication Year. We first examined the publication year of the collected papers in our corpus. Fig. 2 shows that these papers covered 15 years of the 16-year span we have surveyed (except for 2009). The first paper we could locate was published by Xu et al. [189] in 2007, in which an interactive evolution tool was developed to generate entertaining images based on generic programming. Starting from 2016, there was a steep increase in the number of papers specifically exploring AI for design, as more than 84.9% of the papers (n = 79) were published since then. This trend confirms our impression that the research interest concerning AI for design is growing radically and could be explained that such a surge was largely affected by the breakthrough of AI techniques at that time (e.g., GAN [56] in 2014, NST [54] in 2016). Also, the number of papers reached its peak (n = 23, 24.7%) in 2020.

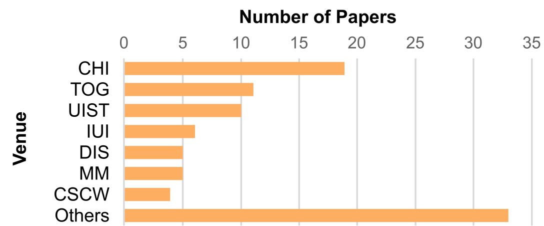

Fig. 3. Frequency of the papers about publication venue.

Publication Venue. In terms of publication venues, our corpus shows a characteristic of heterogeneity with 35 different venues in total, as shown in Fig. 3. Specifically, the ACM CHI Conference on Human Factors in Computing Systems (CHI) (n = 19, 20.4%) is the most common venue to appear for the collected papers, followed by ACM Transactions on Graphics (TOG) (n = 11, 11.8%) and the Annual ACM Symposium on User Interface Software and Technology (UIST) (n = 10, 10.8%). Overall, the dominant venues include human-computer interaction (e.g., CHI, UIST), computer graphics (e.g., TOG), and multimedia (e.g., MM) communities, reflecting the interdisciplinary nature of the topic of AI for design.

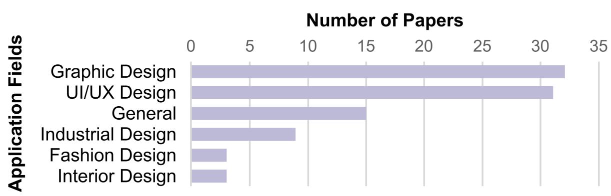

Fig. 4. Frequency of the papers about field of application.

Field of application. Fig. 4 shows the distribution of these papers regarding their application fields, including *graphic design, UI/UX design, industrial design, interior design*, and *fashion design*. Note that no papers have been found on AI for service design. We observed that papers in graphic design account for the majority (n = 32, 34.4%), which encompasses diverse topics extending through posters [59] and advertisement [163] to font [101] and icon [206]. The runner-up is UI/UX design (n = 31, 33.3%), echoing the huge demand for UI designs in the market nowadays [32]. The following field is industrial design (n = 9, 9.7%), and more than half of these papers attempted to save designers' effort in creating 3D modeling [27, 99, 114, 164, 182]. By comparison, interior design (n = 3, 3.2%) emerged as one of the rarest application fields. Interestingly, although their number is small, two of the three papers are highly cited: 227 [11] and 182 [200]. Similarly, fashion design attracted little attention (n = 3, 3.2%) which comes up as an emerging area not until 2019 when AI was introduced into fashion design for the first time [83]. We also found papers (n = 15, 16.1%) that address more general research topics around design such as design elements [127] and design phases [89].

Title and Year	Authors	Citations
Learning Visual Similarity for Product Design with Convolutional Neural Networks (2015)	Bell and Bala [11]	227
Make It Home: Automatic Optimization of Furniture Arrangement (2011)	Yu et al. [200]	182
Rico: A Mobile App Dataset for Building Data-Driven Design Applications (2017)	Deka et al. [41]	130
ReVision: Automated Classification, Analysis and Redesign of Chart Images (2011)	Savva et al. [147]	123
Learning Design Patterns with Bayesian Grammar Induction (2012)	Talton et al. [166]	86
Webzeitgeist: Design Mining the Web (2013)	Kumar et al. [94]	84
Learning a Manifold of Fonts (2014)	Campbell and Kautz [23]	72
Learning Visual Importance for Graphic Designs and Data Visualizations (2017)	Bylinskii et al. [22]	67
Deepfont: Identify Your Font from an Image (2015)	Wang et al. [181]	61
Probabilistic Color-by-Numbers: Suggesting Pattern Colorizations Using Factor Graphs (2013)	Lin et al. [105]	55

Table 1. Most cited papers of AI for design research (Top 10).

Prominent Work. We also measured the impact of the included papers based on their number of citations from ACM-DL and found that they are with varying levels of impact (Table 1). The average number of citations for all the papers is 19.9 (SD = 37.7) while 18.3% papers (n = 17) have not been cited yet. Besides, 14 of the top 15 most cited papers were published in UIST (n = 6), TOG (n = 5), and CHI (n = 3). Specifically, the most influential work [11] in our corpus was cited 227 times by June, 2022. It contributed a CNN-based visual search algorithm that matches in-situ images with iconic product images for interior design. Other highly cited work includes optimizing furniture arrangements automatically [117, 200] and collecting datasets of UIs to support data-driven design [41, 94].

Contribution type. Fig. 5 shows the contribution types [110] of these papers, including *algorithm, application, dataset, theory*, and *evaluation*. Note that multiple types of contribution can be contained in one paper. The primary contribution type is algorithm (n = 62, 66.7%). Among these studies, deep learning (n = 55, 59.1%) was the most utilized computational method. Application (n = 31, 33.3%) is the second most frequent contribution type, with 11 for UI/UX design and 9 for graphic design. The following contribution type is dataset (n = 23, 24.7%) and notable examples include Rico [41] of mobile UIs and AdobeVFR [181] of text images. More than half of the dataset papers are also accompanied by the contribution of algorithm (n = 13, 14.0%). In contrast, the remaining two contribution types, theory (n = 3, 3.2%) and evaluation (n = 2, 2.2%) were found relatively rare. All five papers were published after 2018, indicating increasing attention given to developing theoretical frameworks or design implications in this field.

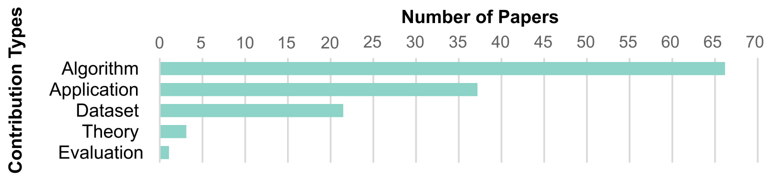

Fig. 5. Frequency of the papers about contribution type.

6 FINDINGS: DESIGNER-AI COLLABORATION

This section continues our presentation of findings, with items that emerged as part of our thematic analysis. These findings were structured as three themes regarding designer-AI collaboration, including (i) four abilities that AI can assist designers (ii) two ways that designers can augment AI, and (iii) five dimensions that characterize the partnership. The mapping of the themes on our corpus can be accessed at our AI4Design explorer, https://ai4designsurvey.github.io/.

6.1 AI Assisting Designers

AI is helping designers expand their abilities in four ways. It can help *discover* the requirements around the people and context designers are designing for, *visualize* hard-to-express ideas using retrieved references, *create* a spectrum of designs based on their ideas, and *test* the designs by predicting human judgements and preferences, as shown in Fig. 6 (A)-(D).

6.1.1 Discovering. AI can help designers understand the perspectives of the people they are designing for and unpack the context they are working in. Such ambiguity usually emerges from ill-defined user desire [36], as users often express their requirements and feelings vaguely [188] (e.g., “The new site must be ‘engaging’ and ‘inviting’.”, “I prefer a more ‘vivid’ poster design.”). To solidify vague requirements and unknown user needs, designers use various design methods [91] such as expert interviews and guided tours. However, challenges are still found in making sense of raw data when synthesizing insightful statements and highlighting key relationships, even for experienced designers [45]. To address the issue, AI has been used to navigate designers from ambiguity and discover what is potentially important to users in two ways, including *interpreting user comments* and *analyzing user behaviors*. Such assistance can give shape and form to subsequent ideation, pointing the way forward.

Interpreting user comments. By structuring and highlighting comments recorded from interviews with users, AI can assist designers in discovering users’ mindsets, behavior, and lifestyle. Design methods such as card sort [142] and thematic analysis [16] often require manually analyzing a large amount of text such as interview transcripts and support messages. AI can automate the time-consuming and error-prone analysis process of user tasks and requirements. For example, Meth et al. [118] leveraged NLP techniques to “semi-automatically identify user tasks from unrestricted natural language documents“ and organize them into two types of task models: the first model highlights different text passages according to task category (i.e., actor, activity, and data) while the second model combines the identified task elements into interaction flow to provide further structuration of each interaction step. In doing this, AI can help designers quickly elicit tasks that are required from users, providing a handover to their subsequent UI design.

Analyzing user behaviors. Another way for AI to help designers discover is by extracting underlying patterns from user behaviors observed when they live or work. Design methods such as peers observing peers often use digital tools (e.g., camera, sensor) to record user behaviors. Although comprehensive and detailed information can be collected,

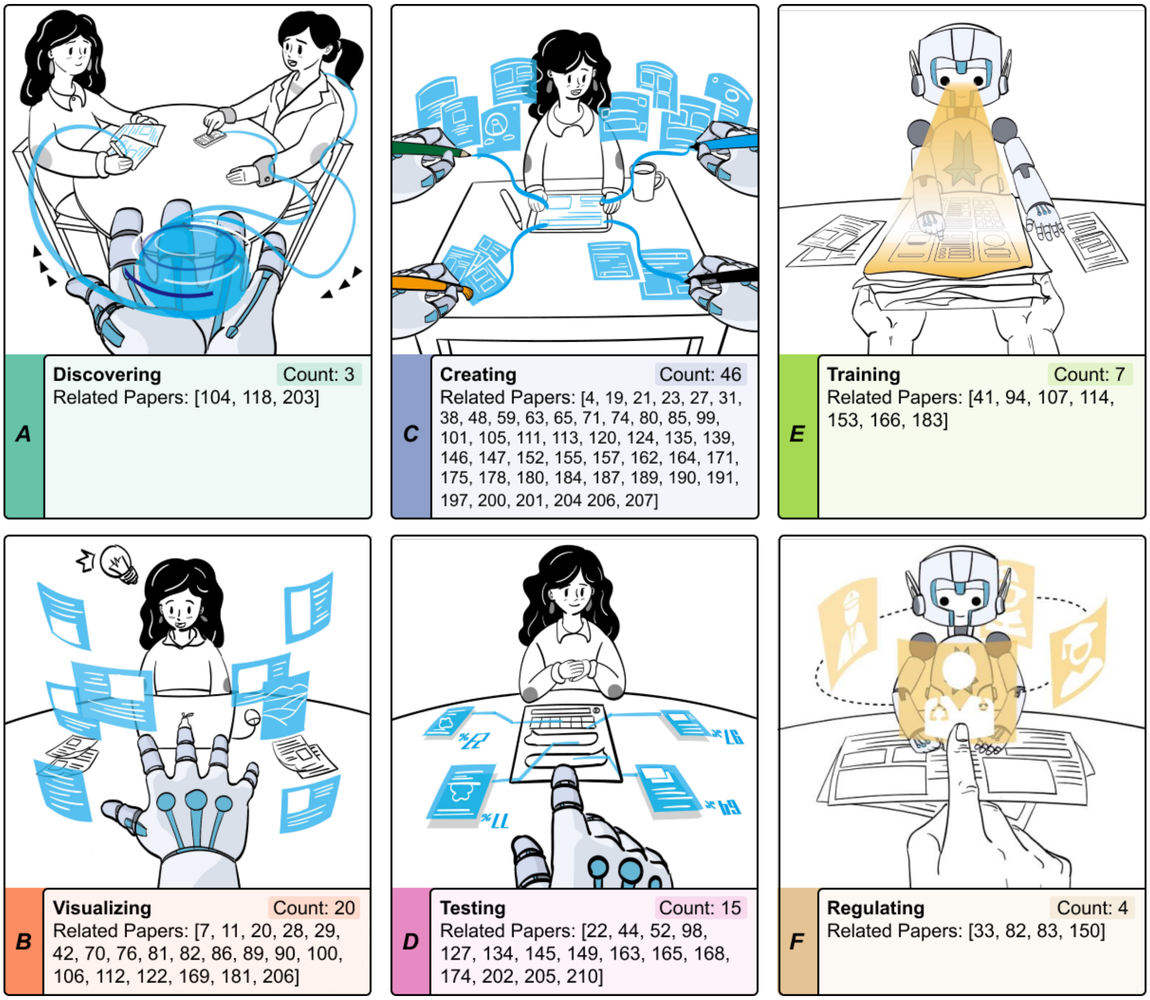

Fig. 6. Concept art of AI assisting designers in (A) discovering, (B) visualizing, (C) creating, and (D) testing, along with designers assisting AI in (E) training and (F) regulating. Papers related to each sub-theme are also listed.

subtle patterns in raw footage or telemetry data can hardly be captured with the naked eye. Also, human designers can only analyze the data of a limited number of users, which is typically suggested to be less than 12 users [93]. AI is able to extend designers' perceptions, allowing them to quickly and accurately compare differences and similarities in a large amount of user behavior data. For example, Zhang et al. [203] derived five behavioral personas from 3.5 million clicks gathered from 2,400 users of an actual product. They used a two-stage statistical machine learning approach: first, raw clicks were structured into clickstreams using hierarchical clustering to identify common workflows. These workflows reflect the representative behaviors of users when they are using the product to accomplish their goals; then, a mixed model assigns users with similar frequency of common workflows to a specific persona, resulting in five behavioral personas in total. Compared with manual analysis, this automatic method is efficient in counting "quantitative signatures" and revealing abstract patterns. Such data-driven persona construction is also scalable, as additional telemetry data can be included to help refine individual personas or track their evolution over time.

6.1.2 Visualizing. AI can augment designers' abilities to visualize hard-to-express ideas by collecting and curating various references in response to a given set of user requirements. References were frequently used by designers to find patterns that fit the current design context; they can draw a metaphor or an analogy from each reference to draw inspiration for their own designs [62]. In this way, ideas become more tangible and accessible. Design methods such as brainstorming [156] and moodboard [89] are used to collect and organize a flurry of references such as charts, drawings, and words. However, designers may face two challenges during the process: first, they can only walk through a limited number of references, where more related ones may be missed out; second, the references need to be carefully selected to stay away from design fixation and focus drift, both of which may hinder generating innovative solutions. To overcome these challenges, AI can assist designers in searching for references from a wide range of online sources or creating references by AI itself, providing both targeted and serendipitous inspirations [122] for designers. Such empowerment mainly reflects in *stimulating divergent thinking* and *promoting convergent thinking*.

Stimulating divergent thinking. AI can provide references to stimulate divergent thinking in designers, encouraging them to develop heterogeneous ideas and unexpected solutions as much as possible. Traditionally, design teams involve a diverse group of people and begin with a brainstorming of "thinking outside the box" [18]. During the process, a common challenge encountered by many designers is design fixation [75], that is, the mind's tendency to adhere to features of preexisting designs, which restricts them from generating a range of ideas with heterogeneity. This is especially likely to happen when the references have no significant difference from existing ideas. To avoid design fixation, AI can be used to push the boundaries of creativity, facilitating designers to think of sparking ideas they might not have initially considered. For example, StyleQ [76] was developed to increase divergent thinking in fashion design. As a designer uploads a design image, StyleQ can detect its fashion attributes (e.g., stripe, lapel) and suggest three styles related to the image. Each of the three styles is visualized with 15 representative looks. The designer can navigate a style and explore its representative looks and information about the attributes of each look. In this way, the original single idea represented by the uploaded image is extended to three different but related concepts to support inspiration-seeking.

Also, if designers get stuck due to design fixation, AI can bring in new perspectives and suggest alternative ways of thinking by providing references created by itself. For example, Cobbie [106], an RNN-based mobile robot, is able to participate in early-stage ideation to "ideate iteratively with designers by generating creative and diverse sketches". Specifically, when collaborating with designers in sketching, Cobbie can capture the image drawn by designers with a camera. Then based on the captured image, Cobbie can generate new sketches and draw them on paper. The results of their user study suggested that designers are satisfied with Cobbie in motivating exploration and provoking ideas.

Promoting convergent thinking. AI can also be used to retrieve references that promote convergent thinking, by which designers can delimit research space and constrain ideas within their known framework. Different from divergent thinking, convergent thinking aims at settling on a small set of ideas, selecting the one that truly merits effort, and developing it into a detailed solution [51, 148]. However, selecting a promising idea from an array of alternatives is a nontrivial task, which requires a wealth of context information to balance potential advantages and disadvantages. In this case, AI can provide relevant information about the retrieved references, allowing designers to evaluate each possible solution. Along with StyleQ, TrendQ [76] can help designers narrow down the boundary of trend styles which are recommended by StyleQ. Specifically, TrendQ visualizes four types of trends for all three styles over the season, including trending, declining, upcoming, and steady. Based on this information, designers can compare different styles to select the most popular one for further refinement.

After successfully selecting an idea, designers then evolve it into a fully-fledged state [43], where the idea is more polished and complete. To achieve this goal, designers usually collect references with similar contexts, where AI can also be helpful. For example, Bunian et al. [20] developed a visual search framework called VINS to retrieve UI designs which can be used to solidify existing ideas. Designers can input their ideas in the forms of abstract wireframes or high-fidelity examples. VINS first detects the types and location of the UI components (e.g., text, page indicator) contained in the input image. Then, VINS uses an attention-based neural network to learn the joint features of the input's structure and associated content. These features are used to guide retrieving UI examples that are highly similar to the input in both visual features and design context.

6.1.3 Creating. AI can assist designers in externalizing their ideas and transforming them into presentable forms. These forms include a broad spectrum of designs extending from mobile UIs and posters to household goods, interiors for offices, and clothing. To create such designs, a collection of design knowledge (e.g., the rule of thirds, Gestalt theory) and a set of skills specific to design implementation (e.g., sketching, modeling) should be acquired by designers. These design knowledge and skills are applied to design activities such as prototyping to validate their ideas and learn through making. However, designers may sometimes not be able to realize their ideas efficiently and accurately constrained by their physical capabilities. With the recent advances in deep learning, AI can help *generate drafts* based on designers' ideas within seconds, taking over laborious and tedious tasks. Also, AI can suggest the parts in a design that need further improvement and then automatically *refine* them.

Generating drafts. AI can help designers create by initiating a starting point. Such a starting point is usually presented as a form of low-fidelity prototypes, where design methods such as sketches, storyboards, and wireframes can be applied. When crafting such drafts, the goal for designers is to conjecture different solutions to find the one that can best express the ideas in their mind [36]. However, creating concrete drafts for abstract ideas is challenging, and starting from a blank canvas can often be overwhelming. AI can help designers generate drafts based on the verbal ideas [71, 206], visual elements [19, 59] they provided or the strokes [21, 99, 155] they started. For example, Scones [71] supports authoring sketches from designers' text instructions to help communicate their intent, which requires "significant training" and "additional, specialized expertise". Scones was trained with CoDraw and Quick, Draw! datasets and consists of a scene composition proposer and 34 object generators to generate and iteratively modify sketches. Vinci [59] can automatically generate advertising posters with visual elements such as product images uploaded by designers. By learning "the patterns in the design of human-created posters", which are modeled as background, embellishments, the product image, and text, a VAE-based deep learning model acts as a virtual bot that can mimic the behaviors of human designers to select design elements that match the product and organize them on a canvas. To improve traditional methods for 3D modeling in industrial design, Li et al. [99] developed Sketch2CAD which is able to transform "approximate sketches of human-made objects into regular CAD models". The system is based on a two-stage neural network, where the first stage predicts what CAD operations (e.g., extrude, bevel) may be adapted to produce the models, and the second stage segments the sketch, fitting specific parameters to instantiate the operation.

In addition, AI can deal with tedious and laborious details when creating, allowing designers to express their ideas more smoothly and focus on higher-level tasks. Zhang et al. [204] proposed a combinatorial approach of layout style learning, interpolation, and transfer to generate banners which can accommodate different display sizes and design styles. Such an automated multi-size and multi-style banner design take over layout tasks and thus release designers' creativity. Note that AI can be used to generate both references and drafts, the difference is that the drafts will be taken over by designers for further development while the references are only for inspiration.

Refining for the best. AI can assist designers in refining their design drafts through a series of iterations. Refinement is a quality that communicates a professional and delicate treatment as designers attempt to minimize flaws regarding visuals such as if a layout is balanced, angles are sound, or colors are harmonious [72]. Such a process can transform low-fidelity prototypes into medium- or high-fidelity prototypes with realistic and detailed designs. In this regard, AI can speed up the iteration by generating a refined design from the existing one based on well-known design guidelines. For example, Duan et al. [48] proposed to optimize the layouts of mobile UIs through a two-step approach. First, they extended the neural network model from Deep Menu to predict users' performance on manipulating mobile UIs. The performance includes task completion time and manipulating error rate. Then, they used the gradients of the model to automate layout modifications by adjusting the location and size of each element in the layout. With this method, AI helps designers save multiple rounds of iterations and design " an interface with better usability".

In addition to automatic refinement, AI allows designers to set constraints on the optimization, promoting the output design to be more consistent with their expectations. For example, Wang et al. [175] developed a data-driven method to enhance the desired color theme in an image based on user-specified colors. Specifically, designers can select a color theme and assign the colors by scribbling on any local regions of interest with desired colors to set additional soft constraints. In this way, the optimization of the image simultaneously considers "the desired theme, texture-color relationships as well as color constraints", suppressing potential problems (e.g., over-aggressive, commonsense violation) and satisfying designers' intents.

6.1.4 Testing. AI can enhance designers' ability to test their work by predicting human judgements and preferences to help understand the designs from the perspective of users. Results from initial tests can provide valuable insights to guide subsequent design iterations. Traditionally, to test what they have designed, designers apply design methods such as pilot [73] and co-creation session [77] to present their work in front of a small group of users and collect their honest, especially negative feedback. Although effective, these methods are usually time-consuming, costly [43], and more importantly, fail to provide instant feedback. To enable fast iterations, AI can be used to predict user behavior patterns based on extensive datasets collected from large-scale user studies, and test how specific designs align with these patterns. These AI-enabled tests fall into two categories, including *evaluating quality of experience* and *measuring quality of use*.

Evaluating quality of experience. AI can be used to test the user experience of designs. The concept of user experience reflects more subjective aspects of a design, such as fun and engagement, which suggest users' intrinsic motivation to use the design [115]. To assess user experience, different quality criteria such as the user experience questionnaire (UEQ) [96] are used to collect quantitative feedback from users. With the help of AI, qualities including aesthetics [134, 202], novelty [174], and personality [205] regarding specific designs can be predicted. In doing this, AI serves as a diagnostic tool that can remove redundant or unsatisfying details in designs. For example, Zhang et al. [202] developed statistical linear regression models to predict the perceived aesthetics of logos following "a group of metrics to evaluate some aspects in design principles", including balance, contrast, and harmony. Human ratings of these metrics of 60 logos are collected and were used to train the models. Similar examples include [174] which used statistical learning methods to calculate the novelty of visual design by comparing its visual features with designs that have been created before, as well as [205] which proposed a CNN-based network to score the personality of posters by investigating how different design elements (e.g., color, space) affect personality (e.g., futuristic, romantic).

Besides, evaluating user experience sometimes requires comparing different user groups, as their subjective feelings may vary due to their cultural backgrounds. Such a case is quite common for multinational enterprises that are entering foreign markets. In this case, AI can also be helpful in quickly understanding the unique preferences of different user groups with specific demographic information. For example, Pan et al. [134] proposed a deep learning model to "predict how customers across different market segments perceive aesthetics designs" of car designs. Trained with a large-scale vehicle image dataset and customer profiles, the model can predict how a customer perceives the aesthetic appeal of a vehicle design. Specifically, a customer is described by his or her demographic information, i.e., a series of labels such as gender, income level, and family size.

Measuring quality of use. AI can also help designers test the use of designs. According to a widely adopted definition [115, 123, 130], quality of use refers to the degree to which a design can be used to achieve specific goals effectively, efficiently, and satisfactorily. Compared with quality of experience, quality of use is more objective (e.g., efficiency, simplicity) and focuses more on the interaction between a user and a design. Measuring quality of use usually involves recruiting diverse users (e.g., crowdsourcing) and applying various tools (e.g., eye-tracking devices). To ease the burden of conducting such tests, AI has been increasingly applied by designers to simulate eye tracking studies [22, 52, 98] and tappability tests [149, 165] with a high level of accuracy. For example, Fosco et al. [52] proposed a deep learning approach to predict the visual importance across different design classes, such as posters, infographics, and mobile UIs. The visual importance shows how human attention distributes on the graphic designs and provides "insight into the effectiveness of the design" to communicate messages with users. Compared to traditional methods which require separate eye-tracking studies for different design types, the model can automatically classify the input design, generalize to the corresponding attention pattern, and predict visual importance accurately in real time.

Interpreting quantitative results from automated tools often depends on individual design judgements, AI can help increase the explainability of the results to support further decision-making and design optimization for designers. For example, Schoop et al. [149] proposed a deep-learning-based approach to predict users' perceived tappability of mobile UI elements. In addition to predicting the perception of real users, the model also provides "explanations of its predictions that offer insight for improving designs". To explain the predictions, both local and global explanations are used. Specifically, the local explanation generates a heatmap to show how strongly the other elements in the input screenshot influence the selected element's tappability prediction. The global explanation fetches a curated set of examples the model considers the most similar to the input but with opposing influences, providing actionable feedback to guide designers for further iterations.

6.2 Designers Assisting AI

Designers can serve two crucial roles when assisting AI. They can *train* AI with datasets to perform design tasks and *regulate* AI's behavior when interacting with designers, as shown in Fig. 6 (E) and (F).

6.2.1 Training. Designers can help train AI to gain design knowledge and perform assigned design tasks. In that effort, huge training datasets are created by designers to support AI understanding human designs. For example, Rico [41] is a mobile UI dataset, which contains 72,219 mobile UIs by mining Google Play Store. Given its large scale and high quality, Rico has been cited by more than half (n = 16, 59.3%) of the follow-up UI-related research work in our corpus, and 157 times in ACM Digital Library in total, is one of the most widely adopted mobile UI datasets. Specifically, designers can assist AI in learning both the *visual content* and *semantic context* of designs. In terms of visual content, designers can provide high-quality designs to help build up training datasets. For example, Sermuga et al. [153] constructed their UISketch dataset by inviting 967 participants, including 151 UI/UX designers, to draw sketches of 21 UI element categories. To evaluate the dataset, researchers split UISketch into sketches drawn by professionals and others. As a result, the model trained with sketches drawn by professionals gave 92.76% accuracy, which is higher than the model trained with sketches drawn by others and close to human performance which is 96%. The UISketch dataset was also open-sourced to facilitate the future conversion of UI sketches from low fidelity to higher fidelity.

Also, designers can add semantic information to datasets to deepen AI's comprehensibility of designs. When recognizing a design pattern, computational methods are often confused by elements with high similarity in shape and anatomy [153], such as button with text field and menu with card in UI design. These recognition tasks are easy for human designers and corresponding design knowledge can be better leveraged to annotate training datasets. Bunian et al. [20] utilized crowdsourcing to annotate their VINS dataset of mobile UIs. To ensure accurate annotations, the participants were asked to follow a set of UI/UX design instructions, which outline the collection of intended UI elements (e.g., icon, input field), along with their functionality and style guide. These instructions help AI recognize icon patterns and understand designs at a semantic level. In addition to UI/UX design, semantic information can also be applied to industrial design. Willis et al. [183] presented the Fusion 360 Gallery dataset, which consists of 8,625 CAD modelings. For each 3D model, designers provide a corresponding design sequence that documents how it was created through sketching and extrusion operations. From the dataset, AI can learn the necessary operations to construct 3D designs.

6.2.2 Regulating. Designers can help regulate AI's role and behaviors to fit in with their own design workflows. Current AI-infused systems may demonstrate unpredictable behaviors or follow a rigid process [6], which requires designers to change their behaviors to cater to AI. Examples include providing unexpected feedback that requires additional efforts to process [99, 152, 184] or deviating from traditional design workflow that requires additional tasks [55]. To help AI better fit in design workflows, designers' behavior patterns can be empirically studied to guide AI on when and how to perform specific tasks in design collaboration. For example, Chung et al. [33] investigated the types of support relationship which were inspired by the artist's support network and reflected on how AI-driven creativity-support tools (AI-CST) can mesh with it. Through an interview of 14 artists, they revealed seven support relationship types between artists and their partners who work to support the artistry, such as subcontractor, muse, and mentor. These relationships suggest what support is expected by artists and thus can inform the design of AI-CSTs. In one case, an AI-CST that has subcontract relationship with artists may be more easily accepted, as it would not disrupt high-level artistic ideas but realize the ideas with implementation support. Karimi et al. [82] studied how an AI-supported creative sketching partner (AI-CSP) can inspire designers while sketching in response to a specified design task. They mapped the participants' behaviors into three types of design creativity: combinatorial, exploratory, and transformational. These creativity types are associated with specific stages and goals in a design process: combinatorial creativity helps designers in the last stage to refine the sketch while exploratory and transformational creativity is more helpful in the earlier stages when designers are exploring or transforming ideas. Such findings can guide AI to take appropriate actions to assist designers at different design stages.

Also, designers can help AI improve its task performance in an unintentional way. When interacting with AI, designers' behavior data is automatically recorded and accumulated. With such data, AI can analyze the behavior patterns presented by designers and proactively adjust its behaviors based on what it has learned. According to the triple-loop model proposed by Seidel et al. [150], autonomous tools can keep learning designers' mental models, which refers to their goals, cognitive rules, and reasoning of the use of tools. When observing explicit feedback or intentional behaviors from designers, AI may change its own model as it relates to what designers want and how designers perceive. Such a change may result in the modification of the user interface or the design parameters being applied.

6.3 Characterizing Designer-AI Collaboration

Through design collaboration, designers and AI actively enhance each other's complementary strengths: the discovery, visualization, creation, and test skills of the former, and the comprehensibility and adaptability of the latter. Although these strengths are extended in different ways, designer-AI collaborations show common characteristics. Through the analysis of the 88 papers in our corpus, we highlight five characteristics, including *scope, access, agency, flexibility*, and *visibility*. When designing a specific designer-AI collaboration, finding an appropriate position in the spectrum of each characteristic can increase its efficiency and effectiveness.

6.3.1 Scope. Scope defines the range of design workflow in which the collaboration between designers and AI can cover. Ideally, designers and AI can be empowered by each other throughout the whole design workflow while currently, the empowerment only occurs in partial design workflow. Often, the broader the scope of the collaboration, the higher its generalizability. For example, designers may retrieve references for inspiration using various forms of input such as wireframes [29, 70] and high-fidelity prototypes [107, 122], at different phases in a design workflow. On the contrary, a majority of AI-supported tools only allow designers to input their ideas in a single form and thus designers have to switch between different tools for visualizing their ideas. In this way, the collaboration between designers and AI is applicable to a narrow range of design workflow.

The degree of scope can be reflected in two aspects, namely, the coverage of phases of a specific design workflow and the diversity of design workflow regarding different design fields. First, we found that AI can help designers in multiple design phases. For example, ICONATE [206] can support compound icon design by stimulating designers' divergent thinking and generating drafts for them. Given a text query (e.g., "eco tech"), ICONATE first provides a diversity of suggestions in the form of verbal words (e.g., "computer", "leaf", "tree") to inspire designers. Then, the combination of the words (e.g., computer+leaf) is developed into a draft design through automatic generation, which can be further modified by designers. By comparison, other studies focusing on icon design only assist designers in a specific phase, such as generating icons from photos [80] and automatic colorization of icons [162]. Second, the scope of the collaboration increases as AI supports more types of design workflows used in diverse design fields. For example, the unified model of saliency and importance developed by Fosco [52] is able to predict human attention on both natural images and graphic designs. In contrast, other studies that predict visual importance can only be applied to limited design workflows, such as information design [22] and UI/UX design [44].

6.3.2 Access. Access defines the level of design expertise required to be involved in the collaboration. The collaboration that only includes experts has lower access than the one that involves novices. For example, when designers use

EmoG [155] to sketch a character for storyboarding, they draw a few strokes and a character with different emotional expressions is generated. In the process, no expertise related to the golden ratio of the human head or the salient features for depicting emotions is required, and novice designers can get an outcome as good as experienced designers. The level of required expertise also varies among different AI models. To inspire designers, Malsattar et al. [112] uses Google Cloud Vision to detect the world from the perspective of AI who received no design-specific training. While in other studies [7, 28], the AI models were trained with a design-specific dataset to gain a professional understanding of design works before being applied to detect objects.

The degree of access depends on two aspects: dependency on design knowledge and design skills. In terms of design knowledge, certain collaboration requires more design knowledge in terms of design guidelines and principles from designers while others ask for less. EasyFont [101] is a novice-friendly system to automatically synthesize personal handwriting. A designer with limited experience in typography design can write a small set of Chinese characters and EasyFont will generate a handwriting font library in his or her personal style with huge amounts. In contrast, Attribute2Font et al. [180] requires design knowledge related to typography to generate font design. Specifically, designers are asked to specify their expected attributes such as serif, cursive, and angularity to get the intended fonts. In addition to design knowledge, design skills such as 3D modeling or building prototypes are sometimes set as a prerequisite to interacting with AI. SimuLearn [191] is able to combine element analysis and machine learning to create truthful morphing material simulators in real time. To take this approach, designers should know how to use computer-aided design tools and how to conduct 3D printing.

6.3.3 Agency. Agency refers to who dominates the interplay between designers and AI when performing design tasks. A designer-driven approach relies heavily on designers to control design tasks while an AI-driven approach depends on AI to automate design tasks with a high degree of freedom. Specifically, after inputting ideas in the forms of images [86, 100, 181] or sketches [29, 70], designers can allocate the task of reference retrieval to AI in its entirety. On the other hand, to ensure the retrieved references are consistent with given design requirements, designers can set inclusion criteria by adjusting the conceptual and visual similarity between the references and the input [82], which is more designer-driven.

The degree of agency is related to two factors, including how much two actors contribute to the design work and how the behaviors of the two actors are intervened in by each other. First, the actor that contributes the main part of the design work can be more dominant. For example, Vinci [59] applies a more AI-driven approach as it requires only product images from designers while AI generates advertising posters based on the input. In contrast, when using FlatMagic [190] to colorize the digital comics, AI only uses neural lines to enclose regions for designers' colorization, which is laborious and often slightly reflected in the final result. More critical work, such as color coordination, is conducted by designers. Second, the dominant actor usually has a significant impact on how and when the other one takes action. For example, when interacting with the generative model developed by Ueno and Satoh [171], although designers do not arrange visual elements on canvas directly, they can greatly influence how AI generates the layout of the graphics by parametrically varying the interpolation coefficient. We also found AI-supported design tools with AI that has more impact on human designers. For example, the model developed by Sung et al. [164] can "suggest complementary components and their placement for an incomplete 3D part assembly". The suggestion is entirely autonomous by AI while designers are only required to perform further modeling with the components selected by AI.

6.3.4 Flexibility. Flexibility describes how one actor responds to the changes conducted by the other one in the designer-AI collaboration. Such responsiveness can take the form of single-turn interaction, where AI generates a new output each time based on designers' input. We also found that multi-turn interaction is used in the collaboration, allowing AI to progressively modify the output generated in the previous turn to a new output when receiving designers' additional input. In general, high flexibility means that AI can interact with designers in multiple rounds to respond to their feedback in real time. For example, Vinci [59] is relatively highly flexible, as it is featured with an online-editing feedback mechanism that can capture the intention of each user modification on the existing output (e.g., the change of an embellishment's size or position) in real time and automatically tweak all generated posters based on the user's design preferences.

The degree of flexibility can be described from two aspects: if designers can examine real-time AI responses to their changes and if designers can retrieve intermediate states of a design. When receiving real-time responses from AI, designers can more easily iterate on their designs. For example, as designers draw a character in EmoG [155], the system suggests face sketches based on each input stroke, which contains sequential and positional information in real time. In comparison, if designers attempt to modify the handwriting font generated by EasyFont [101], they need to rewrite the whole set of Chinese characters (more than 200) that they inputted before. Besides, the collaboration is with a high level of flexibility if the intermediate states of the output can be retrieved to explore more possibilities for design. When creating icons in ICONATE [206], designers can bookmark in-progress icon designs for later reference. During the process, designers can select an already-saved bookmark as well as the AI-generated design variations of it, and improve a specific variation with AI. In doing so, they can easily turn back to the previous design status and begin a new turn of modification.

6.3.5 Visibility. Visibility refers to how easily the collaboration between AI and designers can be perceived in the design process. Such designer-AI collaboration can be either explicit or implicit. A typical way to present an explicit designer-AI collaboration is by visualizing AI as anthropomorphic entities. For example, Cheng et al. [31] developed an agent for designers to edit the shape, color, size, and texture of a visual design through conversations. Designers can easily recognize that they are using AI functions by observing the presence of the agent and communicating with it via natural language. Similar examples include design assistance for layout validation [38] and a physical robot for sketch inspiration [106]. By comparison, we also observed AI features that are implicitly integrated into design support tools. FlatMagic [190] is an AI-driven flat colorization support tool for digital comics. The UI of FlatMagic is implemented as an Adobe Photoshop plugin for color editing and the existence of AI is not explicitly reflected.

The degree of visibility depends on how AI features can be triggered and if the impact caused by AI is clearly annotated. Explicit designer-AI collaboration usually triggers AI features using clear commands. For example, when asking the design agent [184] to edit images, designers send their requirements through multi-turn textual commands. While in some cases, AI features are provoked by designers unconsciously. For example, SketchingInterfaces [184] allows designers to sketch low-fidelity UIs on a whiteboard and automatically translate the sketches into high-fidelity UI mockups. In this process, AI is activated automatically when detecting UI components on the sketch with a camera and no additional command is required from designers. Also, designer-AI collaboration is explicit as AI notifies which part in the final design was modified by it. Given a draft layout, the computational approach to UI design proposed by Dayama et al. [38] can visualize and annotate the UI components in the layout that are against design guidelines. Designers can then apply suggestions annotated by AI to the existing design to improve the layout and fix violations. In doing this, designers are aware of any subtle changes performed by AI. In comparison, FlatMagic [190] automatically optimizes flat colorization by detecting the potential region that designers may want to colorize. Such assistance is presented in an implicit manner, as the difference between the AI-enclosed region and the original region chosen by designers is often difficult to be perceived, and no annotation is provided to explain it.

7 IMPLICATIONS FOR FUTURE RESEARCH AND PRACTICE

Our review of AI for design research unifies designers and AI in design collaboration by leveraging the abilities of one actor to extend the abilities of the other. Also, identifying which of the characteristics regarding designer-AI collaboration is central to the desired results, how designer-AI collaboration can be utilized to address it, and what alignments and trade-offs with related characteristics, will be necessary. We now discuss the implications of these findings in terms of augmenting designer-AI collaboration by increasing the increase the explainability, ethicality, adaptability of AI, and understanding who the user is for specific AI tools in design contexts.

7.1 Augmenting Communication about Design Input and Output

To better support design collaboration, designers and AI should effectively communicate to plan and coordinate [102]. Through the analysis of our corpus, we have observed barriers to communication between the two actors: designers are provided with limited input modality to convey their ideas to AI while AI generates output without providing explanations that help designers understand its behaviors.

Multimodal interaction refers to a situation "where the user is provided with multiple modes for interacting with the system" [8] and frequently used modalities include visual, linguistic, gestural, and touch. Through multimodal interaction, users can have a flexible and powerful dialogue with the system [25]. According to our corpus, applying multimodal interaction to AI for design is still in its early stage, with only 15 papers in our corpus using input modalities other than visual, including linguistic (n = 7), touch (n = 6), and gestural (n = 2). Thus, we believe that multimodal interaction for design input is worth exploring to augment communication between designers and AI. Among diverse modalities, text-to-image has a great potential to empower designers, considering the success of AI techniques such as DALL·E [131] and Midjourney [119] applied to the field of art, which has a common ground with design [14]. Similar to that of art, design requirements can also be described as linguistic input, such as "*make the title stand out more*" and "*increase the spacing*" that were used to generate UI designs [87]. In addition to text-to-image, modalities such as hearing [160], smell [17], and taste [53] can also be used to support designer-AI collaboration, as each of them has unique advantages to convey certain features that are related to design work. For example, music can be used to express moods and emotions [160] that designers would like to embody in their work.

As one of the widely recognized principles for developing trusted AI, explainability also applies when AI is generating design output [211]. However, only one paper [145] in our corpus has investigated this issue, reflecting a lack of transparency in designers-AI interaction. As Lu et al. [108] suggested, designers may have limited trust in the output from AI, as they do not have control over the generation nor know how to interpret the output. Meanwhile, the uncertainty of AI capability also results in unique challenges for designers [194], who sometimes receive unexpected feedback from their AI partners before proceeding to the next step. Thus, future work should focus more on the explainability of AI for design to increase the probability that the AI's suggestions will be fully understood and appropriately adopted. For example, when retrieving UI examples for inspiration-seeking, AI usually extracts the visual features from the input and examples to compare the similarity between them. The visual features are visualized in the form of segmented layouts [20, 100]. Such segmented layouts can be used to explain the reason why the retrieved example is similar to the input from the AI's perspective and help designers decide whether to use the examples.

7.2 Addressing Ethical Issues Regarding Bias and Plagiarism

The emergence of AI for design comes with questions of delegation of morality to a machine: what kinds of morality do we want from AI discovering user needs, visualizing ideas, creating designs, or conducting tests? In our corpus, only a few papers discussed that while providing creativity, AI ethically confronts designers with limitations and biases originating from either humans or machines [112]. Thus, we propose that future work exploring AI for design can consider two ethical issues, including potential bias and suspected plagiarism.

When learning from designers' experiences, AI may be misled by the biases contained in the training data and then reflect on what it has learned in its output. Typical biases include sexism [154], racism [68] and geographical discrimination [136]. Such biases may be originated from harmful stereotypes [144] that designers unintentionally bring in when they draw datasets that will be used to train AI. To build moral datasets for AI training, designers should carefully review the designs they collect or create, according to existing AI ethics guidelines such as accountability and privacy [60]. Moreover, to reduce the risk of including unconscious biases rooted in cultural awareness, datasets should be established by designers with a wider range of cultural backgrounds. For example, when training AI to generate icons representing different occupations, designers should avoid using bad-designed icons which may suggest gender inequality such as social inequality and glass ceiling in their datasets.

Another ethical issue to consider is attribution and compensation for creative work in the AI era. For example, if the source design is uniquely associated with an individual graphic designer's style, one possible concern is the abuse of neural style transfer to plagiarize or impersonate other designers. Thus, AI can strengthen designers' testing ability by measuring the similarity between the source and the output, warning designers of potential risks of plagiarism in their designs. To achieve this goal, crowdsourcing studies can be conducted to ask designers to rate pairs of designs regarding the degree of similarity and infringement. With the rating statistics, AI can learn how to identify plagiarism while not interfering with reference retrieval when assisting designers.

7.3 Accommodating Different Designer Groups

Previous studies have suggested that different designer groups, such as novices and experts, work significantly different in how they think and what they perceive [13, 64, 116]. In our corpus, more than 60% of papers (n = 60, 64.5%) do not specify target designer groups in terms of the level of expertise in the full text. We propose that future AI for design research can focus more on accommodating different designer groups and developing AI-enabled tools according to their needs.

For novice designers, due to a lack of prior experience and professional skills, they usually receive more benefits from designer-AI collaboration than expert designers [99, 106, 164]. Nevertheless, user needs that are specifically related to novice designers should be considered. For example, novices are more intended to ask task clarification questions (e.g., "I'd like to discuss a bit, do they want to actually do something") to understand the nature of the desired solution as well as the relative priorities of the expressed requests [13]. Such questions can be addressed by AI who is able to analyze the design tasks and then retrieve similar cases as a reference, supporting designers to form a deeper understanding of their design problems. Moreover, although it enables "one-click" creation and adds the "wow" factor, using AI to generate design work can be less conducive for novices to grow into experienced designers, as design is an action-oriented profession and design knowledge is better obtained by knowing-in-action [40]. Future research on AI for design can explore how to engage in a design task as a knowledgeable partner; it provides different assistance based on specific scenarios or user intentions, whether active, reactive, or passive. For example, it suggests a new stroke when a user gets stuck or gives feedback when he or she finishes drawing an object.

Also, the difference between novice and expert designers in perceiving design problems in the early stage gains less attention. When compared to novices, experts define and structure design problems with "superior extent, depth and level of detail" [13]. Specifically, experts usually make more interconnections between the problem information and previous knowledge, identify sub-goals for the problem, and perceive richer information sources. Accordingly, we believe a promising direction to explore is to integrate designers' experience and knowledge that are applied in the early design stage, such as information from previous projects [3, 37] to understand contextual constraints [50] and develop design solutions [10], into the tools. Also, expert designers sometimes need "inputs from the outside". For example, experts are more intended to receive suggestions from a variety of professionals related to design solutions such as "engineers", "experts in electronic safety" [13]. This information can help deepen designers' understanding of the problem and develop workable solutions. Thus, future work can train AI with interdisciplinary knowledge rather than design knowledge alone.

7.4 Increasing AI-Supported Design Tool Adoption

Research advances regarding AI for design in academia can help develop creative industries, bridge science and art, and leverage technology for innovative social processes [158]. Despite its rapid progress in academia, many of the prototype AI-supported design tools included in our corpus have not succeeded in making practical influences on industry practices. Prior work [72, 108] explains that recent AI-supported design tools are mainly designed to be "overly-simplistic" , and mostly involved in the "hands-on stage" of design, thus are rarely adopted in practice. According to the analysis of our corpus, we also suggest that the reasons behind such a "research-practice gap" may in part be a result that the dominant contribution type of the papers in our corpus is algorithm (n = 63, 67.7%). These papers are more intended to introduce novel techniques or significantly extend existing ones. Accordingly, real-world design requirements from users would not be a priority for the researchers, but the novelty and frontier of the techniques. Thus, we suggest that HCI researchers can pay more attention to investigating how these research results can be applied in real-life practices instead of lab settings.

In terms of the papers that contribute applications, it is necessary for researchers to balance AI functionality and users' satisfaction. By considering the Kano model [79] which assigns products three types of attributes (threshold, performance, and excitement attributes), AI-enabled functions may be more suitable to act as excitement attributes in a design support tool. In other words, users probably don't know they want these AI-enabled functions but are delighted when they find them. For example, when looking at the entire design workflow, there are still many design tasks that can not be solved by traditional computational methods (e.g., understanding user needs, and developing novel solutions). Most of these tasks exist in early design stages [72] and often require design thinking [108]. In this case, AI, who is highly efficient in processing non-structured data, can be immensely helpful. When combining such excitement attributes with threshold and performance attributes, AI-supported design tools can be highly competitive and widely adopted.

Also, to increase creative practitioners' willingness to use these tools for the tasks they were designed to support, we believe drawing on existing theoretical frameworks of technology adoption [143] can also be a feasible method. Specifically, the technology adoption theories can be taken into consideration to shape the applications or be used as a measurement for evaluation in future studies. According to the recent study results [133] in the HCI community, creative practitioners care about multiple factors: "the tool's features and functionality, integration with existing workflow, performance, interface and user experience, support, financial cost, and even the emotional connection with the tool". Based on the analysis of our corpus, we observed that researchers are more intended to value the novel functionalities [106, 190] and superior performance [59, 155] of the tools than other factors. In addition to the aforementioned internal factors, external factors such as perceived pressure from peers [172] are also valued by practitioners. Thus, evaluations carried out for a long-period or in-the-wild for future AI tools should also take these factors into consideration.

8 CONCLUSION

This paper contributed a systematic review of 93 papers on design collaboration between designers and AI, published in core HCI venues from 2007 to 2022, and thus fills an important gap regarding the state of AI for design research in HCI. Our findings establish a roadmap for how researchers and practitioners can employ AI to effectively perform design tasks. The result of the review point to a number of research opportunities for AI for design research, notably the needs to support designers and AI communicating in a more explainable and transparent way, to investigate ethical implications of AI such as bias and plagiarism, to accommodate different user groups such as expert designers and novice designers, and to develop heuristics for AI to increase tool adoption. We hope that our literature review can help position AI for design research through the lens of collaborative intelligence and support designer-AI collaboration to boost creativity.

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A APPENDIX

ID	Title	Reference No.	Venue	Year
1	Artist Support Networks: Implications for Future Creativity Support Tools	[33]	DIS	2022
2	FlatMagic: Improving Flat Colorization through AI-Driven Design for Digital Comic Professionals	[190]	CHI	2022
3	GANSpiration: Balancing Targeted and Serendipitous Inspiration in User Interface Design with Style-Based Generative Adversarial Network	[122]	CHI	2022
4	Learning GUI Completions with User-Defined Constraints	[19]	TIIS	2022
5	Learning User Interface Semantics from Heterogeneous Networks with Multimodal and Positional Attributes	[7]	IUI	2022
6	Predicting and Explaining Mobile UI Tappability with Vision Modeling and Saliency Analysis	[149]	CHI	2022
7	Constrained Graphic Layout Generation Via Latent Optimization	[85]	MM	2021
8	Continuous and Gradual Style Changes of Graphic Designs with Generative Model	[171]	IUI	2021
9	Conversations with GUIs	[169]	DIS	2021
10	Explainable AI Based Interventions for Pre-Season Decision Making in Fashion Retail	[145]	CODS COMAD	2021
11	Exploring Automatic Fitness Evaluation for Evolutionary Typesetting	[139]	C&C	2021
12	FashionQ: an Ai-Driven Creativity Support Tool for Facilitating Ideation in Fashion Design	[76]	CHI	2021
13	Fusion 360 Gallery: a Dataset and Environment for Programmatic CAD Construction from Human Design Sequences	[183]	TOG	2021
14	Gesture Knitter: a Hand Gesture Design Tool for Head-Mounted Mixed Reality Applications	[120]	CHI	2021
15	Grid-Based Genetic Operators for Graphical Layout Generation	[157]	CSCW	2021
16	GUIGAN: Learning to Generate GUI Designs Using Generative Adversarial Networks	[207]	ICSE	2021
17	Interactive Layout Transfer	[38]	IUI	2021
18	InteractML: Making Machine Learning Accessible for Creative Practitioners Working with Movement Interaction in Immersive Media	[63]	VRST	2021
19	Learning Personal Style from Few Examples	[104]	DIS	2021
20	Screen2Vec: Semantic Embedding of GUI Screens and GUI Components	[100]	CHI	2021
21	UISketch: a Large-Scale Dataset of UI Element Sketches	[153]	CHI	2021

22	Vinci: an Intelligent Graphic Design System for Generating Advertising Posters	[59]	CHI	2021
23	VINS: Visual Search for Mobile User Interface Design	[20]	CHI	2021
24	Attribute2Font: Creating Fonts You Want from Attributes	[180]	TOG	2020
25	Creative Sketching Partner: an Analysis of Human-AI Co-Creativity	[82]	IUI	2020
26	EmoG: Supporting the Sketching of Emotional Expressions for Storyboarding	[155]	CHI	2020
27	From Lost to Found: Discover Missing UI Design Semantics through Recovering Missing Tags	[28]	CSCW	2020
28	ICONATE: Automatic Compound Icon Generation and Ideation	[206]	CHI	2020
29	Iconify: Converting Photographs into Icons	[80]	MMArt-ACM	2020
30	ImageSense: an Intelligent Collaborative Ideation Tool to Support Diverse Human-Computer Partnerships	[90]	CSCW	2020
31	Intelligent Exploration for User Interface Modules of Mobile App with Collective Learning	[210]	KDD	2020
32	Investigating Underdetermination Through Interactive Computational Handweaving	[4]	DIS	2020
33	It Is Your Turn: Collaborative Ideation with a Co-Creative Robot through Sketch	[106]	CHI	2020
34	KnitGIST: a Programming Synthesis Toolkit for Generating Functional Machine-Knitting Textures	[65]	UIST	2020
35	Learning to Select Elements for Graphic Design	[178]	ICMR	2020
36	MetaMorph: AI Assistance to Transform Lo-Fi Sketches to Higher Fidelities	[152]	OZCHI	2020
37	Optimizing User Interface Layouts via Gradient Descent	[48]	CHI	2020
38	Paper2Wire – a Case Study of User-Centred Development of Machine Learning Tools for UX Designers	[21]	MuC	2020
39	Predicting Visual Importance Across Graphic Design Types	[52]	UIST	2020
40	Scones: Towards Conversational Authoring of Sketches	[71]	IUI	2020
41	Sequential Attention GAN for Interactive Image Editing	[31]	MM	2020
42	SimuLearn: Fast and Accurate Simulator to Support Morphing Materials Design and Workflows	[191]	UIST	2020
43	Sketch2CAD: Sequential CAD Modeling by Sketching in Context	[99]	TOG	2020
44	SketchingInterfaces: a Tool for Automatically Generating High-Fidelity User Interface Mockups from Hand-Drawn Sketches	[184]	OZCHI	2020
45	Understanding Visual Saliency in Mobile User Interfaces	[98]	MobileHCI	2020
46	Wireframe-Based UI Design Search through Image Autoencoder	[29]	TOSEM	2020
47	Adversarial Colorization of Icons Based on Contour and Color Conditions	[162]	MM	2019
48	Artistic Text Stylization for Visual-Textual Presentation Synthesis	[197]	MMAsia	2019
49	Data-Driven Interior Plan Generation for Residential Buildings	[187]	TOG	2019
50	Designing and Prototyping from the Perspective of AI in the Wild	[112]	DIS	2019

51	Exemplar Based Experience Transfer	[111]	IUI	2019
52	GANs-Based Clothes Design: Pattern Maker Is All You Need to Design Clothing	[83]	AH	2019
53	May AI? Design Ideation with Cooperative Contextual Bandits	[89]	CHI	2019
54	Modeling Mobile Interface Tappability Using Crowdsourcing and Deep Learning	[165]	CHI	2019
55	Relating Cognitive Models of Design Creativity to the Similarity of Sketches Generated by an AI Partner	[81]	C&C	2019
56	Swire: Sketch-Based User Interface Retrieval	[70]	CHI	2019
57	And Now for Something Completely Different: Visual Novelty in an Online Network of Designers	[174]	WebSci	2018
58	Autonomous Tools and Design: a Triple-Loop Approach to Human-Machine Learning	[150]	CACM	2018
59	Computational Creative Advertisements	[163]	WWW	2018
60	Dream Lens: Exploration and Visualization of Large-Scale Generative Design Datasets	[114]	CHI	2018
61	EasyFont: a Style Learning-Based System to Easily Build Your Large-Scale Handwriting Fonts	[101]	TOG	2018
62	Learning Design Semantics for Mobile Apps	[107]	UIST	2018
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