Bridging the Gap Between UX Practitioners' Work Practices and AI-Enabled Design Support Tools

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ABSTRACT

User interface (UI) and user experience (UX) design have become an indispensable part of today's tech industry. Recently, much progress has been made in machine-learning-enabled design support tools for UX designers. However, few of these tools have been adopted by practitioners. To learn the underlying reasons and understand user needs for bridging this gap, we conducted a retrospective analysis with 8 UX professionals to understand their practice and identify opportunities for future research. We found that the current AI-enabled systems to support UX work mainly work on graphical interface elements, while design activities that involve more 'design thinking" such as user interviews and user testings are more helpful for designers. Many current systems were also designed for overly-simplistic and generic use scenarios. We identified 4 areas in the UX workflow that can benefit from additional AI-enabled assistance: design inspiration search, design alternative exploration, design system customization, and design guideline violation check.

CCS CONCEPTS

• **Human-centered computing** → **Interaction design process and methods**.

KEYWORDS

User Experience (UX), Human-AI Collaboration, design-support tools, data-driven design

ACM Reference Format:
Yuwen Lu, Chengzhi Zhang, Iris Zhang, and Toby Jia-Jun Li. 2022. Bridging the Gap Between UX Practitioners' Work Practices and AI-Enabled Design Support Tools. In *CHI '21 Extended Abstracts: Extended Abstracts of the 2022 CHI Conference on Human Factors in Computing Systems, April 30–May 6, 2022, New Orleans, LA.* ACM, New York, NY, USA, 7 pages. https://doi.org/10.1145/3491101.3519809

1 INTRODUCTION

In the tech industry nowadays, UI and UX design is a key element in the life cycle of product development. Not only do user interfaces contribute to the aesthetics of a product, but they also serve as an indispensable part of user experience and convey a company's branding and style.

However, UI design and development are time-consuming and error-prone [32]. Many researchers have worked on building design support tools to improve user interface creators' work efficiency. In the 1990s, early research projects such as the SILK system [23] and Garnet [34] were conducted for this purpose. Later, with the growth of UI and UX design as an individual profession, many commercial design and prototyping tools including PhotoShop, Sketch, Webflow, and Figma are developed to support graphical UI and interaction design. These tools have greatly helped designers in creating interfaces and prototypes for different use cases, contexts, and devices and are adopted by a wide range of organizations worldwide.

Recently, advances in machine learning (ML) have enabled data-driven approaches to support UI/UX design [19]. The introduction of large-scale datasets such as RICO [8] laid the foundation for training deep neural networks for user-interface-related tasks. Many research projects in areas including design search [17], UI generation [58], and UI understanding [27, 51] have followed. However, many of the AI-based research projects' impact remained within the academic research community and haven't succeeded in making practical influences on industry practices [19]. This phenomenon is common across HCI research and has been identified as the "research-practice gap". This term refers to the fact that HCI research findings, supposedly helpful for UX work, are rarely utilized by UX practitioners in the industry [5, 36]. Bridging this gap requires translational research that identifies practitioners' specific needs and provides translational resources for them to benefit from the latest technical advances and academic research findings.

In this work, to bridge the research-practice gap for AI-enabled UI/UX design support tools, we conducted a study with 8 UX practitioners with varying experience and backgrounds to learn about their work practices. We also used existing AI-based design support tools from the research community in the form of storyboards to gather feedback, understand user needs, and solicit design ideas. Through qualitative analysis, we identified 4 opportunity areas for AI to facilitate designers' work: (1) design inspiration search; (2) design alternative exploration; (3) design system customization; and (4) design guideline violation check.

We identified several gaps between current research projects and designers' actual needs. Current design support tools using ML mostly focus on graphical interface elements, while the design activities that involve more "design thinking" and less graphical elements, such as user interviews and user testings, are more helpful for designers to create enjoyable and usable designs. In addition,

CHI '21 Extended Abstracts, April 30–May 6, 2022, New Orleans, LA

ACM ISBN 978-1-4503-XXXX-X/18/06…$15.00
https://doi.org/10.1145/3491101.3519809

existing models generate outputs that are too generic and not specific to designers' problems domains or their companies' design styles. Designers need to invest substantial efforts in customizing these generic outputs to fit their purposes, and such efforts are so great that many of our participants claimed these model outputs are barely helpful. We believe these issues come from the fact that most ML models in this area work in overly simplified scenarios and fail to take many real-world design factors into account.

2 RELATED WORK

2.1 UI/UX Design in Practice

UI and UX design have established their status in both the tech industry and academia over the past decades. Practitioners working in the UX community around the world have grown significantly over the years. According to an estimation by Jakob Nielson, the population of UX professionals worldwide grew from about 1,000 to 1 million between 1983 and 2017. They estimated that in 2050, the number will increase by another 100 fold until it hits 100 million [35].

UI and UX design practices have evolved over the years. Within the HCI research community, empirical research has been conducted to understand designers' work. A 2014 study investigated practitioners' and academic researchers' different attitudes towards UX measurement through contextual inquiries and mass surveys [24]. In 2017, a literature review mapped the trends of UX by analyzing over 400 academic empirical study publications [41]. The study found that researchers more often investigate artifacts and services, but discuss less about the underlying technology. Usability studies, surveys, and interviews were most commonly employed in the surveyed projects. Research of UX practice has also contributed to identifying improvement opportunities in UX pedagogy [14, 43]. In addition, design researchers have also been involved in empirical research of UX design practice to theorize UX design [48].

However, few of the present empirical studies are conducted to find design and development opportunities for AI-enabled tools that support designers' work. A relevant piece of research work in this domain looked at opportunities to facilitate UX research using AI [3]. They surveyed 49 practitioners with experience in AI, UX, or both and conducted 13 semi-structured interviews with UX experts. One biggest difference between our study and theirs is that they specifically looked at UX research, while we investigated broader UX work with a slight focus on UX design. Their results emphasized the contrast between UX's empathy-focused approach and AI's data-driven approach and came up with broad directions to facilitate UX research with AI. Differently, we took a look at UX practitioners' workflows and habits to identify specific areas where the support from novel AI-infused tools can be beneficial. Regardless, many of their findings are generalizable for our problem domain and provided much inspiration for our study.

2.2 UI/UX Design Automation

UI work is time-consuming and error-prone [32]. Since the 1990s, researchers have been building tools to facilitate UI design. Early ones were designed to help programmers to increase productivity in building interfaces such as [23, 33]. Later, with the rising popularity of UX design as a dedicated profession on its own, many commercial products that support digital graphic and interaction design have been developed, including the early generic Adobe Photoshop, to the later specialized Sketch, Webflow, and Figma which specifically support UI/UX design and prototyping.

Recent advances in AI have enabled data-driven research for user interfaces. Lately, researchers introduced RICO, a large UI dataset containing 72k unique interfaces collected from 9.7k Android apps spanning 27 categories [8]. It also provided user interaction traces with the apps. Datasets such as SWIRE [17] and UISketch [46] also laid foundational work for conduction design support research involving hand sketches.

These datasets enabled new research areas including design search, UI generation, and user behavior modeling. Researchers have looked at using deep learning networks to generate layouts, with inputs including random 2D graphic elements [26] and user-specified constraints [25]. In addition, the Akin project explored the generation of UI wireframes from a given UI design pattern using deep learning [10]. Moran et al. also used an ML approach to generate mobile app prototypes based on sketches [30]. Deep-learning-based retrieval [17] and generative [18] models that utilize user sketches as inputs have also been developed. Data-driven approaches for understanding UI elements have also been explored through multiple projects [27, 51]. A major limitation in them is that they fail to create applications that utilize designers' agency. Instead, most ML models, especially generative ones, work independent of human input and seek to replace human designers on tasks. While such systems present great research contributions, acknowledging that designers won't be replaced by AI in the near future, these research prototypes are not as useful in real life by designers. In this work, we took a human-centered approach and worked on identifying opportunities to use ML models in complement to designers' agency and creativity.

An adjacent body of research looks at supporting designers in creating AI-enabled systems and products [52, 55, 56]. These works examine the design process for systems involving AI and aim at understanding and supporting designers' ideation, design, and prototyping for such systems. Prototypes such as ProtoAI [49] are being built to support designers' prototyping of AI-infused systems. While they provide valuable inspiration for our research, there are substantial differences in our approaches. Instead of helping the design process of AI-involved applications (design AI-enabled systems), we seek to help designers work on all applications, whether they involve AI or not, by integrating AI into their design tools (design *with* AI-enabled tools).

2.3 Human-AI Co-Creation

With the advancement of ML, many researchers have explored human-AI co-creation in creative domains including writing [4, 12, 22], music [29], drawing [7, 15, 20, 37], etc. In these systems, AI serves as humans' collaborators. AI usually makes recommendations based on users' goals and intentions, whether they are explicitly stated by the human users or predicted by the machines. Most recent AI-based design-support systems such as [17, 18] use ML-based techniques. In the rest of this paper, we will use ML to refer to the particular technical backbones, while use AI to represent systems and applications building on a variety of ML models.

We see facilitating UI/UX design with ML as a special instance of human-AI co-creation, different from the majority of existing directions in this area. The general goal remains the same and many design principles in human-AI co-creation, such as mixed-initiative interactions [16], are applicable. However, UI/UX designers usually face more constraints. For example, many companies have their own branding styles and visual guidelines that designers need to conform to. Furthermore, most design projects start with an organizational or business goal, such as increasing user activity, to achieve through design. These goals are generally implicitly brought into the design process and not explicitly tied to visual metrics that most ML models focus on. What makes UI/UX design more distinctive from other open-ended creation tasks is that after the creation process, established validation metrics are commonly applied to evaluate the designed interfaces and interactions.

3 METHODOLOGY

3.1 Study Procedure

In this need-finding study, our goals were: (1) understanding UX practitioners' work practices and challenges, (2) getting practitioners' feedback on existing research prototypes using AI to facilitate UX work, and (3) identifying future design opportunities for AI-enabled design support tools. To fulfill these goals, we conducted retrospective analysis and speed dating with 8 UX practitioners. These participants were recruited through social media advertisement and through a snowball method [13]. A description of participants' demographics is shown in Table 1.

In each study session[1], we first asked questions regarding designers' work practices through one or two previous design project examples. Then, we used 4 speed-dating storyboards showing scenarios of using AI to facilitate their work practices to solicit their feedback. The speed dating session was followed by questions regarding their ideas and concerns for using AI to automate their workflows. Lastly, we finished the interview with questions regarding differences between UI and UX design to find opportunities beyond UI manipulation with the help of AI. All interviews were conducted online and lasted around 60 minutes. Each participant was compensated $15 for their time. We recorded all interviews with the permission of our participants and used the tool Grain [1] to transcribe them for analysis.

3.2 Retrospective Analysis

Retrospective analysis is a powerful tool to reconstruct study participants' behaviors, rationales, and emotions for recorded events used by the HCI community [44]. By using recorded events, the method is able to put research participants in the context where they would normally carry out the studied procedure. Different from contextual inquiry [45], retrospective analyses don't observe participants during the actual event, which minimizes interruption and is suitable for studies of events that have happened in the past.

In our study, our questions about designers' work practices are suitable for a retrospective analysis study. We asked participants to refer to previous digital design and research files while explaining the behavior, rationale, and ideas in the design processes for each

[1]The study protocol has been approved by the IRB at our institution.

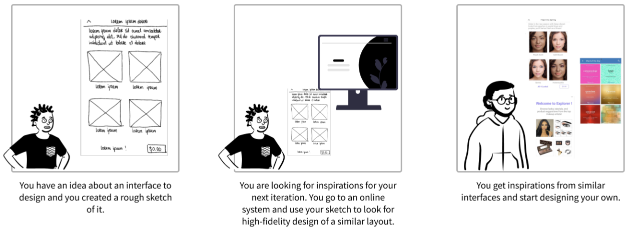

Figure 1: An example storyboard for a sketch-based design example retrieval tool used during interviews. Created with Open Peeps by Pablo Stanley.

project. Participants illustrated how they generated inspirations, concluded insights, and made design decisions. The interview questions centered around concrete examples of insights and decisions in the previous projects, allowing participants to recall more details of their projects and provide more useful information.

3.3 Speed Dating

In addition to retrospective analysis, we conducted speed dating with practitioners. Speed dating is a technique where researchers show users multiple possible design solutions and gather feedback [6]. Its usefulness lies in that after seeing many alternative solutions, users can have a better understanding of their true needs independent of the example solutions they looked at. This helps the interviewers to learn about users' true needs, which even users themselves often didn't realize.

In our study, we presented each participant with 4 storyboards of scenarios using AI-enabled design-support tools. We concluded 4 representative scenarios based on previous research literature: *(1) design inspiration search*, *(2) design mock-up generation*, *(3) iterative styling improvement*, and *(4) rapid exploration of design alternatives*. Each storyboard we created corresponds to 1 use case. One example storyboard is displayed in Figure 1. When creating the storyboards, we selected images of system prototypes from previous literature such as [17, 18]. A more detailed description of our storyboards can be found in Table 2.

After we presented each storyboard to the participant, we asked about their thoughts on each scenario's usefulness in their own daily work. We also followed up with questions on how the interviewee would change the scenarios when appropriate. Most importantly, speed dating can help users identify real needs that potentially lie outside of the given storyboard examples [6]. We followed each discussion with questions prompting our interviewees to think of additional areas they think AI can help with any potential concerns they would have.

3.4 Qualitative Analysis Methods

Two authors of the paper conducted a qualitative analysis of the interview transcripts using thematic analysis [42] and affinity diagramming [38]. The first round of analysis was open coding on interview transcripts using the tool Grain [1]. Two authors collaboratively went through the recordings, highlighted portions of the transcripts that are relevant to our research topic, and wrote a

Table 1: Demographics of Study Participants.

ID	Gender	Education	Industry	Job Title	Yrs. of Experience	Company Employee Count
P1	Female	Master's	Healthcare	UX Designer	1-3	1,000 - 10,000
P2	Female	Master's	Info. Services	UX Designer	1-3	> 10,000
P3	Female	Master's	Info. Services	UX Researcher	3-5	> 10,000
P4	Female	Master's	Entertainment	UX Researcher	Less than 1	1,000 - 10,000
P5	Female	Bachelor's	Government	Program Lead	1-3	1,000 - 10,000
P6	Female	Master's	Info. Services	UX Designer	1-3	> 10,000
P7	Female	Master's	Info. Services	UX Designer	1-3	> 10,000
P8	Female	Bachelor's	Info. Services	UI/UX Designer	1-3	> 10,000

Table 2: Speed Dating Storyboard Details.

ID	Use Scenario	Description	Inspiration
1	Design inspiration search	Designers use interface layout sketches to search for inspirations	[17]
2	Design mock-up generation	A system generates mid-fidelity design mock-ups based on designers' high-level natural language description for the interface	[18]
3	Iterative styling improvement	Designers use natural language to instruct interface element styling changes	N/A
4	Rapid exploration of design alternatives	After specifying a few constraints in an existing design, a system can generate multiple interface alternatives.	[50]

descriptive text for each highlight. The goal of this round is to identify relevant and valuable information in the transcripts. Then, two authors imported all of the open codes into Figma and conducted the second round of coding. The second round was the beginning of the inductive thematic analysis. During this round, two authors gathered open codes that are relevant to each other, formed clusters, and wrote a summary text for each cluster. Each summary text represented a specific idea discussed by our participants about detailed processes or issues they face in their design workflow. The third round of coding followed the second one as two authors grouped and summarized the previous summary texts. Each of the new, higher-level summary texts represents a design opportunity or a more general issue identified in our interview data.

4 FINDINGS

4.1 Design Opportunities

From our analysis, we were able to identify four areas in UI/UX designers' work that can potentially be supported by AI. For some of these opportunities, there have already been researchers working on them; the limitations of existing work in these areas will be further discussed in this section.

4.1.1 Design Inspiration Search. UI/UX designers use many references to generate inspiration for their own design. The references are not limited to examples, also can be guidelines and best practices. During our interview, P2 mentioned that "experienced designers are experienced because they have all the examples and inspirations stored in their mind". Similarly, P8 expressed that "as a designer, you need to have some patterns in your memory, but that requires experience". Designers need references to see what patterns fit the current design context and need to weigh the pros and cons of each reference before combining them into a desired one. We learned that in practice, designers usually curate their own reference libraries to find inspirations for their own design. They usually search for reference examples similar to their design goals based on **functionalities, problem domains, and visual styles**.

However, designers often have difficulty finding many relevant examples with these metrics. Sometimes, designers do now know what keywords to use or are constrained by the limited number of keywords they come up with. At the same time, designers expressed the need for a large number of references to generate good ideas, which is in line with suggestions for designing creativity support tools from previous literature [40]. This creates the opportunity for facilitating design inspiration search with AI. A possible solution is to explore different modalities to search other than keywords. Designers want to find similar designs based on functionalities, problem domains, and visual styles. Previous work has utilized visual styles as a modality for searching. For example, Swire [17] enables designers to search for high-fidelity interface examples using hand sketches.

Nevertheless, little work has enabled search based on the app's problem domains and functionalities. Such new directions create novel technical challenges. We need to build ML models that can understand an app's problem domain or interface elements' functionalities. In addition, designing such apps requires a deeper understanding regarding different dimensions of similarity useful for searching and the degree of similarity designers desire for the search results to be inspiring. This calls for more empirical studies of designers' particular habits in using tools for the ideation and generative design process.

4.1.2 Design alternatives exploration. Designers usually look at different design possibilities and test out alternative solutions. In interviews, designers expressed interest in using AI to automatically generate alternatives for an existing design as exploration. P2 specifically pointed out that this will be more helpful for graphic elements such as color, layout, and font instead of more high-level ones such as ways to fulfill a user's need. More specifically, P6 mentioned that such exploration would be most helpful if the alternatives can be a bit "outside the box" and creative, to stimulate more creativity from the designer. They imagined adding a certain degree of randomness to the output result can help introduce this creativity when exploring alternatives. This calls for new ML model architectures that add an additional layer of randomness over the generated results, similar to variational autoencoders [21]. Designers also want to have control over the degrees and forms of randomness to create results that fit their purposes.

4.1.3 Design system customization. The introduction of design systems in many companies created opportunities and challenges at the same time. On one hand, they improve designers' and developers' efficiency by providing a library of standard visual components (e.g. buttons, forms, navigation bars) that conform to the company's branding styles. Designers and developers can directly use them since most of these components have already been designed, programmed, and tested. However, on the other hand, there are occasions in which design systems actually reduce designers' efficiency. In our interviews, 5 out of 8 participants talked about scenarios where these standard components do not fit their specific design purposes and they have to customize or redesign them in their work. This creates a burden for both designers and developers and undermines the potential outcomes the design could have achieved.

For customized elements, designers sometimes need to check other teams whether their redesign conforms to the company's style guidelines. Since these elements are new, developers also have to write code from scratch to implement them, which significantly increases their workload and developers are usually reluctant to do it. In these cases, interactive systems that automatically adapt customized widgets or components to the company's design styles and guidelines will be tremendously helpful. Possible solutions include borrowing concepts from image style transfer algorithms [11] and applying them to UI widgets. However, our interviewees indicated that having Figma files as generative model outputs will be more useful than images, which creates unique requirements for model architectures. Regarding implementation code generation, existing research such as GUIS2Code [9] and Chen et al. [2] can already facilitate similar tasks after building the desired design.

4.1.4 Automatic design guideline violation check. During the interview, P2 expressed that some designers "are not paying too much attention to inclusiveness (e.g., accessibility), but it is very important". They proposed that if some AI systems can provide friendly reminders for "simple things like the color contrast, … keyboard navigation, and a lot of other details (related to accessibility)" it would be greatly helpful. There has been much research using ML to understand screen elements [27, 51] and check visual design guidelines [54]. By utilizing such models, it's possible to build applications that automatically detect violations of accessibility design guidelines and prompt designers to make improvements. Another potential direction is to model users with varying levels of ability, test the app with the agents to simulate user testing sessions, and apply ability-based design principles [53]. More importantly, such research opportunities are not limited to accessibility guidelines and can be expanded to universal usability guidelines [47] or other forms of design guidelines outside accessibility.

4.2 Gaps Between Existing Tools and Designers' Needs

Compared to using generated design results from existing ML models, designers prefer to get inspiration from existing apps and create their own designs for several reasons. Firstly, designers don't have control over the generation process, combined with the fact that the generative system didn't provide any rationale behind the result, designers do not trust the system's output. P6 explicitly mentioned "I don't have that trust in the system, so I would question why the system suggests this. I need several stems of solutions so I can…have that control to compare at least some of them". Also, designers expressed that existing model outputs, such as the sign-in mock-up pages from [18], tend to be too generic, thus cannot be easily adopted by designers to suit their own needs. As discussed in Section 4.1.3, designers spend more time adapting the initial design to company styles and guidelines than creating initial mock-ups, while current generative models can only support the latter. On the other hand, existing apps are more likely to have been through user tests and conform to best practices and guidelines. They can serve as better examples for designers.

Besides, current ML models are rarely helpful for design activities that do not involve graphical interface elements, the ones described by designers as involving more "design thinking". From an ML standpoint, interface elements are easier to manipulate due to the simplicity of their data representation; however, designers articulated that in UX work, those activities that involve more design thinking, e.g. user interviews, brainstorming sessions, and user testings, are more important for creating usable and enjoyable designs. During our interview, P6 mentioned that "for more complex features, the rationale behind designing something is more important than the visual elements and layouts". Coming up with such rationales requires a deep understanding of users' intentions and needs. It makes up a great portion of designers' daily jobs, however, most current AI-enabled UX design support tools overlooked it.

Also, existing ML models are not helpful in generating outputs that are context-specific to the designers' problem domain. For example, existing models only work best for generic interfaces that are common for many apps, e.g., sign-in pages, card list pages, user profile pages. For example, when a designer wants to design a list of all doctors available in an area for a healthcare app, existing ML models would not understand contexts such as the information to display for each doctor or the order to list the doctors. However, these are all important design decisions to be made by designers. We argue that current ML models usually work in an overly simplified scenario and don't take many real-world parameters into consideration. This leads to exceedingly generic design solutions that require too much customization done on the designer's end. Some study participants argued that such customization effort is so much that the generic generated results are almost not helpful for them.

Moreover, one of the main tasks for UX professionals in their daily jobs is to convince other non-UX team members of their work's value and quality. This task is closely related to their design generation process since value and quality are usually communicated by illustrating designers' design decisions and the underlying rationales. However, current ML models act on a model to replace designers in generating design interfaces, instead of complementing designers' agency and creativity. If designers use AI-generated design results, it's largely impossible to justify a model's design with rationales because they are not much involved in the generation process. One possible solution to this issue is to include additional model inputs such as explicit design decisions and user insights to generative ML models. Also, in our interviews, P8 expressed that when an ML model generates a design, it would be helpful for the model to provide some supporting evidence, such as well-known app examples that adopted a similar design layout. By incorporating such evidence, designers as well as other team members could have more confidence in the generated results. Researchers can get inspiration from the area of explainable AI [28, 39], especially those investigating generative models [57], to build ML models that generate explainable UI design.

5 FUTURE WORK

Continuing this work, we will conduct interviews with more UX practitioners to further understand user needs and identify gaps and opportunities in this area. Also, user-centered design activities such as participatory design workshops [31] will be greatly beneficial to solicit designers' ideas and feedback when designing new AI-enabled UI/UX design support tools. Regarding system development, we imagine more explainable and context-aware ML models that target pain points in designers' existing work practices will be created. Based on these models, interactive tools that facilitate effective human-AI collaboration in UX practices will be built and studied. We invite the community to join us in exploring these identified design opportunities and making an effort to further bridge the gap between academic research and UX practice so that research work in this area can create more concrete and profound real-world impacts.

6 CONCLUSION

Through a need-finding study with 8 UX professionals, we reported areas where AI applications can come into play to support UX design work and several gaps between current research projects and designers' actual needs. This paper contributed empirical findings of UX practice and identified research opportunities in designing and building future AI-enabled UX design support tools.

ACKNOWLEDGMENTS

This research was supported in part by a Google Cloud Research Credit Grant and an Asia Research Collaboration Grant from Notre Dame International. We would like to thank our anonymous reviewers for their feedback and study participants for their participation in our studies.

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