Generative AI in User Experience Design and Research: How Do UX Practitioners, Teams, and Companies Use GenAI in Industry?

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ABSTRACT

User Experience (UX) practitioners, like UX designers and researchers, have begun to adopt Generative Artificial Intelligence (GenAI) tools into their work practices. However, we lack an understanding of how UX practitioners, UX teams, and companies actually utilize GenAI and what challenges they face. We conducted interviews with 24 UX practitioners from multiple companies and countries, with varying roles and seniority. Our findings include: 1) There is a significant lack of GenAI company policies, with companies informally advising caution or leaving the responsibility to individual employees; 2) UX teams lack team-wide GenAI practices. UX practitioners typically use GenAI individually, favoring writing-based tasks, but note limitations for design-focused activities, like wireframing and prototyping; 3) UX practitioners call for better training on GenAI to enhance their abilities to generate effective prompts and evaluate output quality. Based on our findings, we provide recommendations for GenAI integration in the UX sector.

CCS CONCEPTS

• **Computing methodologies → Artificial intelligence**; • **Human-centered computing → Empirical studies in HCI**; **HCI theory, concepts and models**.

KEYWORDS

Generative Artificial Intelligence, GenAI, Industry Practices, User Experience Design, User Experience Research, Company Policies, Human-AI Collaboration, Interaction Design

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1 INTRODUCTION

User experience (UX) plays a pivotal role in creating successful digital products [30, 59]. The design and development of these products typically follows a user-centered approach, which includes a wealth of activities like user research, requirements definition, brainstorming, wireframing, graphic design, prototyping, and user testing. UX practitioners, including UX designers, user interface (UI) designers, UX researchers, and other roles associated with UX, can have diverse skill sets and often contribute to different activities or steps while working closely together with other UX experts [11].

UX practitioners have been interested in leveraging artificial intelligence (AI) and machine learning (ML) in their work practices for years [1, 14, 31, 91]. Current research has proposed that adopting AI into UX design, and into human-computer interaction (HCI) practices more generally, can bring many benefits. Some such benefits include fostering creativity [9], automating mundane tasks [14], improving the scalability of design processes [75], supporting decision-making [3, 14] and human-human collaboration [63], and speeding up and optimizing activities like sketching [21, 35], wireframing [68], and usability and user testing [22, 23].

Now, with the recent wave of *Generative Artificial Intelligence (GenAI)* and tools like ChatGPT[1], Midjourney[2], and DALL-E[3], many industries are looking to adopt them widely. According to a recent survey, companies see GenAI as the most transformative technology in a generation, with 90% of the surveyed companies increasing their investments in GenAI [79]. UX practitioners are especially looking to adopt GenAI tools in their work [e.g., 26, 67, 74, 82], likely because many UX activities involve producing text and images.

However, we currently lack an understanding of how UX praciti-tioners in the industry are actually using GenAI, and what policies and practices have been developed in companies and their UX teams. We argue that this understanding is crucial for developing efficient and responsible GenAI-enhanced UX practices. While prior work has looked into AI-related industry practices before [e.g., 14, 46, 84], there is not much research on how *GenAI* has been adopted into UX processes [66], especially at the company and team level. We argue that an investigation is needed due to the recent, massive wave of GenAI that is currently shaping many industries[4].

Therefore, in this work, we aim to understand the processes, attitudes, and challenges of GenAI use in the UX sector. Our primary research questions were:

- **RQ1:** How are companies allowing GenAI use in their UX departments and what policies are in place?
- **RQ2:** How are UX practitioners and UX teams integrating GenAI into their work practices?
- **RQ3:** What are the current challenges and needs regarding the integration of GenAI into UX industry practices?

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[1]https://chat.openai.com/
[2]https://www.midjourney.com/
[3]https://openai.com/dall-e-3
[4]GenAI has existed for a much longer time, but in the context of this paper, we refer to the most recent wave of GenAI, including text generation tools like ChatGPT, and image generation tools like DALL-E and Midjourney.

To this end, we conducted online interviews with 24 industry UX professionals. To ensure rich insights and the inclusion of different perspectives, we recruited participants from various backgrounds. Participants came from eight different countries, had varying levels of seniority, and served in different UX-related roles, including designers, researchers, and managers. All participants were employed by different companies, and we included companies ranging from start-ups and small businesses to large corporations.

Using qualitative content analysis, we identified 10 themes which we categorized under three major dimensions: GenAI Policies and Adoption in Companies (RQ1), GenAI Adoption and Practices in UX (RQ2), and Challenges and Needs Regarding GenAI in UX (RQ3). Our main findings include: 1) There is a significant lack of formal company policies regarding GenAI, with companies informally advising caution or leaving the responsibility to individual employees, 2) There is a significant lack of team-level practices and collaboration in UX teams. Individually, UX practitioners report using GenAI widely for research-focused tasks, but commonly note limitations for design-focused activities, like wireframing, prototyping, and graphic design, and 3) UX practitioners identify challenges with writing effective GenAI prompts and assessing output quality, and voice concerns about other practitioners over-relying on GenAI. UX practitioners call for GenAI training, and request better support in GenAI tools for UX design. Based on our findings, we provide recommendations to UX practitioners, teams, and companies.

Through our engagement with industry experts, our work provides an overview on the current status of GenAI integration in the UX sector, highlights the challenges and needs that UX practitioners have regarding GenAI, and provides recommendations for the adoption of GenAI.

2 RELATED WORK

In this section, we review relevant existing research surrounding AI, GenAI, and UX. To understand the context and scope of our work, it is important to understand the difference between design *for* AI and design *with* AI. We review both of these concepts below; however, our work focuses on design *with* AI. Then, we review research that has made direct enquiries to UX practitioners about AI integration. We finish by identifying gaps in current research.

2.1 UX Practices *for* AI: How UX Can Improve AI-Enhanced Products

By "designing for AI" we refer to practices, research, and tools where the target of the design—the product—has an AI component. There is widespread interest in the research community to investigate how we can design for and foster human-AI collaboration and AI-enhanced products [85], and businesses worldwide are looking to utilize GenAI tools like ChatGPT in their products [34, 37]. It is widely recognized that AI should be human-centered [81], and that UX and HCI are needed to create responsible, explainable, trustworthy, and usable AI systems [45, 77, 78], especially because there are risks and concerns about AI among workers [76] and the public [69]. As a result, prior research has discussed the challenges relating to designing AI-enhanced systems [83, 85], proposed AI design guidelines and principles [4, 57], and proposed tools and methods to help designers understand AI capabilities [86].

2.2 UX Practices *with* AI: How AI Can Improve UX and HCI Practices

By "designing with AI" we refer to practices, research, and tools where the process of design has an AI component. AI is expected to fundamentally change the way we design things [25]. The HCI community has been actively exploring how AI, HCI, and UX come together, evidenced by a wealth of studies, opinion pieces, and workshops on the topic [e.g., 26, 53, 54, 64, 66, 67, 74, 82]). Researchers have proposed and created AI-enhanced tools to aid UX professionals, as well as proposed and evaluated AI-enhanced processes and methods, which we review next.

Prior work has built several AI *tools* and computational models for UX-related tasks. Much of this work focuses on *design* activities, including AI-based ideation [36], sketching and drawing [16, 35, 55], wireframing [10, 24], graphic design [90], layout optimization [17, 68], and prototyping [44, 50]. Other AI tools have been proposed to assist with *research* tasks, like analyzing usability test videos [23] and think-aloud sessions [22], recognizing the user's emotional state during usability evaluations [60], and automatically detecting design violations in graphical user interfaces Moran et al. [51].

With a focus not on specific tools but on *processes and methods*, researchers have studied how AI can be integrated into UX activities. Abbas et al. [1] surveyed existing literature on how machine learning is utilized in user experience design, and Dave et al. [15] conducted a survey on AI-based approaches to turn UI mockups into wireframes and prototypes, and such approaches have reported good results [6, 61]. Other work in this area has explored using AI/ML to, among other things, assist in creating design proposals [13], serve as a collaborative partner to foster self-reflection [73] and creativity [32] among designers, generate personas [5, 33, 62], and communicate data analysis findings to UX researchers [39].

Recently, some research has surfaced focusing on GenAI and ChatGTP. Tholander and Jonsson [67] explored how GPT 3 can be integrated into co-creative design processes for ideation and rapid sketching. Similarly, Al-sa'di and Miller [2] investigated the integration of GenAI tools, specifically ChatGPT 3.5, into the Design Thinking process.

2.3 AI Practices and Policies in Industry

While plenty of studies have recruited UX practitioners as their study participants, for example, to receive feedback on their proposed AI/ML tools or practices, there are—to our knowledge—only a handful of studies that have enquired about the UX professionals' actual, adopted industry practices regarding AI or ML.

Liao et al. [46] interviewed 20 UX practitioners who were working on *AI products* about explainable AI (XAI), contributing to the design of XAI. Similarly, Yang et al. [84] interviewed 13 UX designers who designed products that were utilizing ML, contributing to the design on ML-enhanced products. Chromik et al. [14] surveyed practitioners experienced in UX, ML, or both to understand how data-driven ML techniques could support their work. Dove et al. [19] surveyed UX practitioners to understand how ML could be used as a design material. Yildirim et al. [87] investigated how practitioners use the People + AI Guidebook [58] when designing AI-enhanced products.

Closest to our work is the research conducted by Lu et al. [48] and Li et al. [43]. Lu et al. [48] conducted a study with 8 UX professionals in 2021 to understand how AI/ML could support their design practices. They identified lacking support for activities that involve more "design thinking", such as user interviews and user testing. Interestingly, they also discovered that AI tools at the time generated outputs that UX professionals deemed too generic, without considering the designer's specific domain or the company's style. Most recently, Li et al. [43] interviewed 20 UX designers, focusing on the designers' individual perceptions and practices regarding GenAI. The designers believed that GenAI can enhance productivity and serve as an assistive tool to help with repetitive and generic tasks. However, designers also expressed concern over skill degradation and potential unemployment among junior designers. Overall, Li et al. [43] highlight the importance of integrating GenAI into UX design practices due to its expected impact on the industry.

2.4 Summary and Research Gap

In the realm of designing *with* AI, existing research has proposed a wealth of tools and practices for UX activities, like brainstorming [e.g., 13, 67], sketching and drawing, [e.g., 35, 55], wireframing and prototyping [e.g., 10, 44, 50, 68], and user testing and analysis [e.g., 23, 39]. While much of this research has had promising results, they are merely *proposed* ways to work with AI; we do not know if and how these tools and methods are used in the industry. There is surprisingly little research on actual AI-supported UX industry practices. Existing research in this area, even if fairly recent, has mostly focused on other types of AI/ML and not GenAI [e.g., 14, 31, 91], and almost exclusively focused on individual practices [43, 48].

Hence, based on our literature review, we can identify two major gaps in existing research:

- **Research Gap #1:** There is very little research on GenAI-specific UX practices in the industry. So far, we are only aware of Li et al. [43] who have investigated UX industry practices regarding recent GenAI tools like ChatGPT. However, they focused on UX *designers* and their perceptions of GenAI; there is need to explore UX practices more broadly and cover a wider variety of UX roles.
- **Research Gap #2:** We are not aware of any research on team-level and company-level practices, discussions, and policies regarding the adoption and use of AI/GenAI in UX industry practices. This is especially important because AI can have a significant impact on team settings [89], and impacts entire companies and industries [66].

With these remarks and research gaps in mind, we planned an online interview study with UX practitioners, where we enquired about not only the participants' individual practices and attitudes, but also about their company's policies and communication as well as the practices and discussions among their teams.

3 ONLINE INTERVIEW STUDY

To answer our RQs, we conducted an online interview study with 24 participants, all of whom worked professionally with UX. The study was approved by our institution's research ethics board.

3.1 Study Design

We chose to conduct our research through a semi-structured interview, as opposed to, for example, an online survey for multiple reasons. Interviews can yield exceptionally in-depth results from each participant, and they allow for flexibility; the interviewer can probe new topics on the spot based on the participant's responses whenever the need arises [42]. Moreover, our research was qualitative and consisted of a large number of open-ended questions; online surveys are typically not suitable for such enquiries, leading to high drop-out rates and low-quality responses [52]. Finally, due to the nature of our enquiry (e.g., relating to company policies and attitudes), we hypothesized that our participants would be more comfortable providing such details directly to a researcher as opposed to typing their answers into a survey.

We furthermore chose to conduct our interviews online, because it allowed us to reach out to UX practitioners worldwide and recruit a diverse sample of participants. We describe our recruitment strategies in the subsection below.

We designed our interview questions based on our review of existing literature and identified research gaps, as well as our research questions. In addition to demographic questions, we included questions about topics like their work team and their role in the team, company-level and team-level policies and discussions regarding AI, specific AI tools and practices and changes in workflow, and perceived strengths and weaknesses of AI in UX. The full list of interview questions is provided in Appendix A.

Our study and all of its materials were reviewed by our institution's research ethics board (REB). Once we acquired approval from the REB, we began recruiting participants.

3.2 Participants and Recruitment

We identified potentially suitable participants via LinkedIn and by reaching out to companies in multiple countries. Participants were eligible for our study if they 1) were at least 18 years old, 2) worked in the industry in a role related to UX, and 3) had completed at least one UX industry project. We invited individuals for the interview via email. Prospective participants could sign up for the interview by choosing a 60-minute time slot via Calendly[5], which automatically created a Teams meeting for the chosen time slot.

An overview of the participants' demographics is provided in Table 1. Our sample consisted of 24 participants (7 women, 17 men), with an average age of 36 (Min = 23, Max = 47). One participant had a high school diploma (4%), one had a bootcamp diploma (4%), eight participants had a Bachelor's degree (33%), nine had a Master's degree (38%), and five had a PhD (21%).

The participants had varying roles as follows: UX Researcher (8, 33%), UX Designer (6, 25%), Head of UX (3, 13%), Product Designer (2, 8%), Product Design Manager (2, 8%), UX Writer (1, 4%), Chief Product Officer (1, 4%), and Assistant VP of UX (1, 4%). The participants' experience in the field ranged from 1 year to 25 years. 22 participant (92%) had permanent full-time jobs, one participant was an external contractor at a company, and one participant was a freelancer. The companies our participants represented ranged from very small companies and startups (1–10 employees) to international corporations (over 10000 employees).

[5]https://calendly.com/

Gender & Country		Age Group		Title		Years in industry		Company size	
Male	17 (71%)	18 to 19 years	0 (0%)	UX Researcher	8 (34%)	1–2	6 (25%)	1–10	4 (17%)
Female	7 (29%)	20 to 24 years	3 (13%)	UX Designer	6 (25%)	3–4	3 (13%)	10–100	0 (0%)
		25 to 29 years	1 (4%)	Head of UX Design	3 (13%)	5–6	4 (17%)	100–500	6 (25%)
Canada	11 (46%)	30 to 34 years	6 (25%)	Product Designer	2 (8%)	7–8	2 (8%)	500–1000	2 (8%)
USA	4 (17%)	35 to 39 years	6 (25%)	Product Design Manager	2 (8%)	9–10	4 (17%)	1000–5000	2 (8%)
Finland	3 (13%)	40 to 44 years	7 (29%)	UX Writer	1 (4%)	10+	5 (20%)	5000–10000	4 (17%)
Iran	2 (8%)	45 to 49 years	1 (4%)	Chief Product Officer	1 (4%)			10000+	6 (25%)
Bangladesh	1 (4%)			Assistant VP of UX Design	1 (4%)				
Italy	1 (4%)								
Pakistan	1 (4%)								
Germany	1 (4%)								

Table 1: Summary of participant demographics.

3.3 Procedure

Prior to the online interview, the participants were informed about the overall goals of the research through an information letter sent to them via email.

At the beginning of the interview and after greeting the interviewee, they were informed that participation is voluntary, and they may decide to end the session at any time. We also emphasized that they could choose to skip questions for any reason. Then, based on the information letter sent to them in advance, we verbally asked them to confirm their eligibility, and then asked them to confirm their consent to participation in the interview, the recording of the interview, later analysis of their data, as well as the use of anonymous quotes in publications. Once participants agreed, we began the recording and proceeded with the interview.

We started the interview with demographic questions, an overview of which was presented in Table 1. After the demographic questions, we enquired about their company and team, like which industries their projects focused on, the size of their team, and their role within the team. Then, we enquired about company-level and team-level policies and discussions regarding AI, like whether there were any restrictions in place, if there were concerns or hesitation, what kinds of other policies were in place, and if and how AI was discussed in the company and within the team.

Next, we enquired about their specific AI practices, like which tools they use, for what kinds of tasks, how AI has changed their workflow, and then enquired about their attitudes, like level of trust in AI. We also asked how their use of AI potentially different from their colleagues, and what kinds of practices and AI use they had observed from others. In case the participant reported that they nor their team used any AI tools, we diverted to ask a different subset of questions at this point, which centered around their reasons for not using any AI tools and what would need to change for them to adopt AI into their work.

Finally, we asked the participants to list what they thought the strengths and weaknesses of AI in UX practices were, and asked them to specify any needs or recommendations that might help them use AI more effectively in the future.

At the end, we thanked the participants for their time and valuable insights. The interviews lasted for an average of 60 minutes. Participants were compensated with a Tango gift card (value around 22.5 USD), sent to them via email after the interview was completed.

3.4 Qualitative Content Analysis

Our main interview questions consisted of open-ended questions. We conducted an analysis of the participants’ responses with three researchers using qualitative content analysis (QCA) [72]. QCA is a method similar to thematic analysis, both of which consist of researchers familiarizing themselves with the data, and generating codes and themes via an iterative process [72]. While thematic analysis can be seen as a more interpretivist approach focused on developing nuanced themes, in QCA, themes can be more descriptive in nature and researchers give more meaning to the frequency of codes when developing themes [71]. To support this process, we utilized the collaborative tool Jamboard [6].

In the next section, we present our results in detail.

4 RESULTS

Our results are divided into the themes identified during our analysis, which are further categorized into three dimensions. An overview of the dimensions and themes is presented in Table 2.

4.1 GenAI Policies and Adoption in Companies (RQ1)

4.1.1 Theme 1.1: Lack of formal GenAI policies in companies. We identified a significant lack of formal policies among the interviewees’ employers. Most participants noted that there were no formal policies, guidelines, or even emails or discussions from management or higher-ups regarding GenAI. Most of these participants noted that it was a "personal decision" (P2) left to the individual:

> "It’s a personal choice at this moment. [My company] is not providing us anything in terms of tools. That hasn’t been a conversation yet.” (P8)

Some reported high-level remarks by team managers or other parties regarding GenAI use (e.g., "be cautious with data"), hinting at the vague and informal nature of these communications. Some reported that a certain level of caution was simply "expected" in the company culture, even though there was no clear communication about GenAI. On rare occasions, though, participants noted that policies were being set up or they were being discussed among the upper management, but the employees did not know anything yet.

[6]https://jamboard.google.com/

1. GenAI Policies and Adoption in Companies (RQ1)	
Theme 1.1:	Lack of formal AI policies in companies
Theme 1.2:	Current GenAI policies and measures in companies
Theme 1.3:	Cautiousness about GenAI in large companies
2. GenAI Adoption and Practices in UX (RQ2)	
Theme 2.1:	Lack of team-level GenAI practices and discussions
Theme 2.2:	GenAI in research-focused vs. design-focused tasks
Theme 2.3:	Common uses and tools for GenAI
3. Challenges and Needs Regarding GenAI in UX (RQ3)	
Theme 3.1:	Quality and correctness of output
Theme 3.2:	Dependency on AI
Theme 3.3:	Need for GenAI training
Theme 3.4:	Improvement of GenAI for design-focused activities

Table 2: Overview of dimensions and themes discovered from the interview data using qualitative content analysis.

Several participants reported that specific GenAI tools were blocked in their company, and some of them had built their own GenAI tools, or licensed commercial tools for privacy reasons:

> "With ChatGPT launched a year ago, within a couple of weeks, there was a note that said [ChatGPT] was blocked from all corporate machines [...]" (P3)

> "We can't access [the main ChatGPT with OpenAI] from a work computer [...] It's blocked. We are using a licensed copy of ChatGPT which is not connected to the data we feed into it. It doesn't train the open AI model." (P6)

Participants consistently highlighted their individual sense of responsibility, professionalism, and judgment. They noted, for example, that despite the lack of company policies, they "knew better" than to insert sensitive data into an external GenAI tool. Two participants stated:

> "When experimenting with AI, we needed to pay attention to not share any personal information of our customers or any sensitive company information" (P2)

> "GPT is not restricted in our company and I am not aware [of] any policies, but as a professional, I know not to share confidential data with chatbots." (P24)

4.1.2 Theme 1.2: Current GenAI policies and measures in companies. Those participants that reported any existing policies or actions by the company regarding GenAI use were almost exclusively motivated by, and centered around, data privacy. These included things like building their internal GenAI tools to ensure data privacy and security (and to enable the use of company data with GenAI), providing guidelines or "best practices" for GenAI use especially regarding what data is allowed to be included, setting up a dedicated governance team to oversee AI use within the company, relaying rules and restrictions via communication channels (e.g., Slack) and in-person meetings, internal training on privacy measures and GenAI use, as well as recent policies focusing on client safety, data collection, and data storage.

4.1.3 Theme 1.3: Cautiousness and Data Privacy Concerns about GenAI. Many participants talked about data privacy concerns in their company, potential conflicts between AI and their current policy statements, and how AI can result in "intellectual property breaches" (P2), which also led to much longer approval processes:

> "[GenAI] is labeled higher risk. It's already taken pretty much the year for [GenAI tools] to go through the regulatory process. But now, because it's at high risk, they're going through even more." (P16)

> "We are expected to keep user information confidential. We cannot adopt [GenAI] because it's not part of our policy statements and data privacy. So general policies all apply [on GenAI]." (P9)

> "Asking for an AI tool in [my] company, usually takes more time than regular tools, since it needs to go through security and legal terms to be approved in addition to the regular process which involves checking the requirements and budget." (P6)

It is also worth noting that the industry in which the company was involved in likely played a role in the level of caution. The most notable restrictions were reported by participants' whose employers were in finance and banking. One of them mentioned:

> "I think the number one concern for the implementation of AI in any company is privacy and security. And that gets multiplied by 10 when you're talking about a financial company. The company wants to make sure that it's due diligence to the highest level before the implementation of any [AI tools]." (P17)

In the same vein, one participant mentioned that their company's engagement with AI was in its infancy, and any actions and discussions about GenAI were "driven by individual initiatives rather than structured directives by the company" (P7). This, again, hints at the individual responsibilities of employees rather than structured efforts by companies.

Some participants noted working around these restrictions by using GenAI tools at home. Such participants noted, though, that they strictly used GenAI for activities like preparing drafts and presentations, which did not involve sensitive details about the company or their clients, hinting again at their individual sense of responsibility. One participant explained:

> "GPT is restricted in the company, but I do some generic work like creating drafts, summaries, and emails with this tool on my personal computer." (P16)

Participants representing small startups generally reported a more relaxed attitude, saying that "we are very open to using AI tools, and my boss is always impressed with the output" (P12) and "we don't have any policy around AI because we are a very tiny startup" (P18). Another participant working for a startup mentioned that their company is interested in experimenting with more AI tools "since they like to increase productivity" (P10).

4.2 GenAI Adoption and Practices in UX (RQ2)

4.2.1 Theme 2.1: Lack of team-level GenAI practices and discussions. We noted a significant lack of discussions and practices regarding GenAI among teams, teammates, and supervisors. Some participants directly reported that they do not discuss the matter:

> "We never talk with my coworkers about AI tools policies, but we are all aware of how to use them and not to share any sensitive data. [...] We don't communicate how the team achieves the outcome; as long as they care about confidential and sensitive information and the outcome is acceptable." (P24)

> "We haven't openly discussed with the team that how they use AI and what tools they are using." (P11)

> "GPT is popular [in the team], but we don't openly talk with coworkers that GPT edits this work. [...] I don't think my manager has any problem with me using it." (P14)

> "I'm not sure about my coworkers [...] because we usually don't talk about this topic at work. I just know they are using some AI tools in their work process, but no more details." (P10)

In other cases, the lack of team-level practices was highlighted by the participants' inability to talk clearly about their team members' practices, resulting in speculation or vague remarks. When asked about whether their team members are using GenAI, for example, one participant said "I assume they are" (P7), another said "I don't know about my coworkers, they might use [GenAI], but we haven't talked." (P21), and a third said "It is mostly on an individual basis, so people just kind of adopt them where they see fit" (P9). Some participants were provided sgeneral or vague comments on their teams or colleagues' GenAI adoption, for example that "the design team is using [GenAI] plugins in Figma" (P11), and "my coworkers use some visual tools for image generation" (P20).

4.2.2 Theme 2.2: GenAI in research-focused vs. design-focused tasks. We identified a trend where UX practitioners working in more research-focused roles reported more comprehensive use of GenAI than those working more exclusively on design-related tasks.

In design-focused areas, participants reported using GenAI commonly in the early stages, like brainstorming and iteration and presenting their ideas to others (e.g., using Midjourney to generate visual representations of ideas), to speed up their work and develop ideas. Some designers also reported using GenAI for specific tasks like "Adobe Firefly for creating icons" (P15).

That said, many designers stated that they had tried to use GenAI tools for further, perhaps more advanced areas of their work, but that they did not find the current tools mature and helpful enough:

> "It feels to me that the AI design tools aren't quite capable of creating something that is meaningful enough. [My] design work relates to challenges about very specific technical things instead of [the product] being just a website or something. [...] I have used [computational methods] for something in the past, like algorithms that create color schemes, but it is often the case that the challenges we face are much more complex than that." (P1)

> "[I was] using Midjourney for designing a banner, but it didn't work that well. And I guess our prompts weren't good enough. But it was good for ideation, not for the complete work." (P5)

In contrast, GenAI was much more widely used in research-focused tasks, like designing studies, generating drafts, formatting and analyzing data, and summarizing results and prior research. Generally, participants perceived GenAI to be more mature in these areas. For example, participants reported using GenAI for "documentation" (P12), to "help with UX writing" (P22), to "come up with interview questions" (P6, P10), and to "reframe study questions" (P21). Another participant said that "GPT is really helpful for summarizing articles and find related work" (P17). One participant explained what they did with GenAI:

> "We did user research and we documented all of our [data] into Miro and then had the Miro AI create summaries and findings based on [data]. And it worked very well. There was one obvious factual error [in the findings], so you can't like simply trust it, but overall it did a very good job and also helped us in the creation of the report." (P1)

4.2.3 Theme 2.3: Common uses and tools for GenAI. In our study, ChatGPT was the most popular GenAI tool, mentioned by every participant during the interview. Regardless of a participant's position level and exact role, everyone reported using (or having used) ChatGPT in their personal lives and work routines on some level.

In addition to ChatGPT, in the area of research, participants mentioned using Copilot, Grammarly, and AI transcription software like Otter and Fireflies in their work routines. In the area of design, UX designers, graphic designers, and content designers relied on image generation tools like MidJourney, Adobe Firefly, and Microsoft Designer. Furthermore, participants highlighted that generative AI features have been gradually integrated into designers' commonly used software, such as Figma, Photoshop, Adobe Illustrator, and Adobe XD, either as plugins or new features within the software.

We identified the most common tasks for which our participants used GenAI. The majority of related statements were provided in the context of research-focused activities (as pointed out in Theme 2.2), although some were focused on design activities, and some were more general in nature. Many relevant quotes have been provided in the previous themes; we build on them briefly here.

Summarizing content. UX practitioners commonly used GenAI to summarize various types of content. This included, for example, "summarizing meeting notes" (P8, P22), "summarizing articles and giving a human answer" (P7), or more generally "summarizing or simplifing texts" (P19), and "summarizing information" (P6).

Brainstorming and visualization. Participants reported brainstorming and ideation as a common use for GenAI. One participant said that GenAI was akin to "quickly brainstorming with someone" (P12), and another said that "[GenAI] allows a good conversation starter for especially the brainstorming side of things" (P6). One participant praised image-generation tools like MidJourney and Microsoft Designer specifically for their "fast iteration" of ideas (P10). Another participant also mentioned that "Midjourney is good for ideation, not for completing the whole work" (P5).

Writing and creating drafts. UX practitioners commonly reported usign GenAI to assist with writing, especially in creating the "first draft" (P1), while also noting that it did not do all the work:

> "In the beginning of projects, I use [GPT] pretty extensively to create the first draft of something. [...] It often requires revision, but it saves me from that first step of actually writing, the first [version]." (P6)

> "It's helped me along in the [writing] process, but it hasn't helped me all the way to the end." (P7)

Data analysis. UX researchers commonly used GenAI to analyze data and identify common findings. One participant mentioned that they "had the Miro AI create summaries and findings based on [data]" (P1), and another said that they sometimes used it to "synthesize data" (P3). Another participant explained more thoroughly:

> "It was like 75 open ended survey responses and I [...] strip them of [the participant number] and dump them into ChatGPT, and asked [ChatGPT] to generate 5 insights based on the 75 responses." (P6).

Being an assistant. GenAI was commonly described as a general "assistant" that completes various specific and sometimes tedious tasks, often answering a serendipitous need like "finding good alternative words for a presentation" (P7), "framing things and helping organize your mind" (P11), and similarly, "helping work through the things I'm thinking through" (P6).

4.3 Challenges and Needs Regarding GenAI Use in UX (RQ3)

4.3.1 Quality and correctness of output. UX practitioners were critical of GenAI's ability to produce accurate content, saying that GenAI "just comes up with stuff without support" (P14), has "glaring errors" (P3), and "has bias in its data analysis results" (P21). One participant highlighted concerns about AI bias on a deeper level:

> "There are a lot of stereotypes, and biased information that get into the database of the GenAI machines that impact the generated outcome." (P18)

As a result, many participants reported being distrustful of the output, needing to validate the produced outcomes, and proposed to treat GenAI's output more as a "suggestion" (P12) or a "second opinion" (P11), that can be wrong just like a human. Due to the errors, one participant demonstrated frustration and questioned the use of GenAI: "what is the point if I have to validate the AI tool's outcome again?" (P14).

4.3.2 Over reliance on GenAI. Our participants highlighted concerns about individuals potentially becoming overly reliant on GenAI. The potential consequences of excessive reliance on generative AI applications that were mentioned by participants included inefficiency, reduced autonomy, and a potential disconnect from individual problem-solving capabilities. Some participants explained:

> "People trying to use AI for everything that it is not needed, and they spend more time on the right prompt instead of doing it on their own." (P23)

Another participant expressed their concern with over-reliance on AI which can potentially lead to a reduction in individuals' autonomy and self-reliance:

> "If people are over reliant on AI tools, as an educator, my concern is that they can't think for themselves." (P19)

Two senior UX researchers expressed their concerns about the potential consequences of junior researchers, who may not have extensive experience in their field, relying too heavily on GenAI:

> "I worry about junior researchers, who don't have a lot of experience, over-relying on AI models because I know what a bad piece of data looks like and I know what bad research design looks like [but they might not]." (P6)

> "I've seen people use [GenAI] because they just want to get away with not doing mundane work. For example, we have a system where researchers share insights [by writing online] posts. I had one [junior employee] who started writing the posts in ChatGPT, and I immediately noticed this because the text was so boring. And I told them, no, you cannot do this, you have to write yourself, make it succinct and interesting. It's like this doesn't accomplish the task, people are gonna tune out when they see this AI generated content. It's not interesting." (P7)

4.3.3 Need for GenAI training. Participants indicated needs and interests to learn more about the capabilities of current GenAI tools, improving their abilities two write prompts and interact with AI, as well as improving their skills to assess GenAI output. One participant wondered if "thinking and putting time to make the prompt" (P16) was worth the effort, and another was convinced that people "spend more time on the right prompt instead of doing it on their own" (P23). Some participants specifically highlighted the need for training:

> "Giving prompts is hard and time-consuming. [...] People have to learn how and where to use [GenAI] and then use it in a correct way." (P5)

> "I think I use only 5% of the capability of ChatGPT, and it's so helpful for me. I'd love to explore more. [...] I just need some courses to understand the underlying technology a little bit better because I think that would help me learn more about its limitations, and then also help me approach the output a little bit more critically." (P6)

Another participant elaborated that not being properly trained on GenAI might contain risks with regards to confidentiality:

> "It's important to understand how to utilize AI with customers' data without going over the border with intellectual property issues." (P2)

4.3.4 Improvement of GenAI for design-focused activities. Our participants highlighted shortcomings in current GenAI tools especially with regards to design-focused tasks, highlighting that GenAI tools need to be more "user-centered" (P24), consider the "designer's perspective" (P2), and generate more "meaningful" output (P1). Participants requested features like tying GenAI output to provided design systems (P2), and having AI provide suggestions during UI design (P5).

Participants also mentioned that most GenAI tools do not keep records of their previous interactions and data, resulting in users having to "repeat everything." (P5) becase GenAI does not "keep conversations in the context", and prevents users from building "complex projects" with GenAI (P13). One participant explained:

> “I need previous research knowledge in the data analysis which the AI doesn’t have. I need the capability to have the record and insights from the [previously used] data and its analysis to involve them [in my current analysis].” (P17)

Our diverse participants also highlighted issues regarding language and cultural nuances. One participant highlighted that GenAI "only works well in English and not in the language that I need to write my contents" (P11), and another noted that GenAI "doesn't know the audience and the proper tone based on the background and the cultures of the audiences from various countries" (P20).

5 DISCUSSION

In this section, we first summarize our results in relation to our research questions, and discuss the implications from our results and draw connections to prior research (subsections 5.1–5.3). Then, we provide recommendations targeting companies, UX practitioners, and GenAI developers (subsection 5.4). Finally, we discuss the limitations in our work and provide directions for future research (subsection 5.5).

5.1 RQ1: How Are Companies Allowing GenAI Use in Their UX Departments and What Policies Are in Place?

According to our results, UX practitioners were largely free to experiment with and use GenAI to their liking. However, the majority of our participants reported a considerable lack of formal policies, initiatives, and communication from their employer in regard to GenAI use. Among them, some participants reported that they were informally told to be "cautious" or "careful", while some reported that this was simply "expected". However, some participants reported that GenAI tools had been blocked in company computers, but even so many of them had not received further guidance. These participants reported taking some maneuvers around the policies, by using GenAI in their personal computers for work that did not involve sensitive data. In a few occasions, participants reported that their company had licensed a private instance of a GenAI tool, or even developed their own tools; in both cases, this allowed them to safely feed company and customer data into the GenAI tools.

Regardless of their employers' views or (lack of) initiatives regarding GenAI use, participants frequently highlighted their individual professionalism and sense of responsibility when using GenAI. Despite the lack of policies or communication from the company, participants stressed that they would not insert sensitive company information into external GenAI tools. While this level of professionalism among UX practitioners is positive and respectable, we argue that the lack of responsibility and initiatives demonstrated by companies in this regard is concerning. It is worth wondering how this might tie into legal issues and the treatment of individual employees if, for example, an employee accidentally shared sensitive information via an external GenAI tool. In other areas of research, the need for new policies is already widely recognized [20, 34]. Furthermore, other large institutions like universities, have already widely adopted GenAI policies that cover multiple stakeholders like staff, faculty, and students [49]. It is surprising, then, that we witnessed such a strong lack of policies, and not only that, but also a lack of communication about GenAI in general.

Participants highlighted that the reasons for some of their employers blocking GenAI tools, or encouraging caution, were largely related to matters of data privacy, confidentiality, and intellectual property. It is likely that large corporations storing vast amounts of sensitive data, and companies in particularly vulnerable industries like banking and financing, are having an especially tough time navigating the recent rise of GenAI. Even though not many of our participants were employed in small companies, they generally seemed to more readily embrace the possibilities that GenAI offered. It should be acknowledged that the companies' concerns are valid. GenAI tools like ChatGPT are vulnerable in many ways; they can be attacked, and they can be used maliciously [28]. At the same time, cybercriminals now have more advanced tools, some AI-enhanced, for launching cyber attaks [28].

5.2 RQ2: How are UX Practitioners and UX Teams integrating GenAI into their Work Practices?

In regards to our RQ2, *we identified a significant lack of team practices and discussions regarding GenAI.* Most participants reported that they made decisions about GenAI use independently of others and that they did not discuss it with their team members or managers. Some even reported that they did not share content with others that they produced with GenAI. Wider adoption of tools (e.g., tools shared or used within the entire UX team) was rare.

We believe this finding is extremely surprising and in some ways concerning. UX and HCI theory and practices have been evolving for decades, and significant evolutions have often been triggered by technological developments [41]. Moreover, UX fields are inherently collaborative where UX practitioners often work closely together [11, 12, 40], and existing research has widely recognized the value of collaboration [70] and co-design [65] in UX.

We are left wondering, then, what might explain this surprising lack of team practices and discussions regarding GenAI. Based on our other findings and prior research, we can speculate on the role of two possible factors. One possible explanation is that UX practitioners might feel uncertain or cautious about how GenAI is perceived by their colleagues and superiors, or feel cautious about being too open about GenAI use so that their employer will not take action against it or see the employee in a bad light. Some of our participants' responses seemed to hint at an almost strategic silence about GenAI. This uncertainty may also link to the lack of company policies and communication, and employees may have been unsure about how their employer feels about GenAI.

Another possible explanation is that we might be witnessing a transformation of the UX fields where AI is partly replacing human collaborators. There is a wealth of research demonstrating effective human-AI collaboration in many UX activities like creation and ideation [13, 36, 56, 67], drawing and sketching [16, 35, 55], and data analysis [38, 39]. Fan et al. [23], for example, demonstrated that some UX evaluators in their study felt like they were working with a "junior colleague" when working with an AI.

Aside from the lack of team practices, UX practitioners reported what they used GenAI for and how they perceived its effects. Generally, there was widespread recognition among UX practitioners that GenAI can make their practices more efficient. This is in line with earlier findings about ML and AI in general [7, 48, 75] as well as GenAI specifically [43, 67].

UX researchers in particular found GenAI useful for their practices and are utilizing GenAI tools at multiple stages of their work. Common practices for practitioners conducting UX research with GenAI included generating drafts for a research plan, summarizing existing research and results, and conducting data analysis, and the UX practitioners saw value in using GenAI for these tasks. This partly contradicts earlier results: Lu et al. [48] reported almost opposite results in that their participants mainly used AI system to work on graphical interface elements but did not find them helpful for activities such as user interviews and user testings. However, Lu et al. [48], conducted their study before the recent GenAI wave; we believe that this demonstrates the power of the new GenAI tools and how they can transform and assists with UX research.

For design work, GenAI use seemed to largely focus on the early stages of design, like brainstorming and creating initial visualizations for communicating ideas. It is not surprising that GenAI was found useful for these activities: prior research supports this and has also proposed AI-enhanced brainstorming and creativity tools and verified their effectiveness [e.g., 13, 32, 67].

Beyond these activities, our interviewees largely perceived GenAI to be lacking for additional design-focused tasks like wireframing, graphic design, and prototyping, highlighting many shortcomings in the current tools. This finding is interesting because existing research has proposed and evaluated a plethora of AI-enhanced tools for design activities with good results, like graphic design [27, 90], wireframing [10, 24], layout optimization [17, 68], and prototyping [50]. Perhaps, then, part of the problem is that such tools are not widely available to UX practitioners, or the practitioners are not aware of them or do not know how to use them. This may link to some earlier findings about UX practitioners being unaware of the possibilities of AI [1]; it is interesting that this might still be the case despite GenAI raising people's awareness so thoroughly. Still, it is clear that despite all these challenges and shortcomings, UX designers still find value in GenAI especially in the early stages of their work, albeit hoping for advancements in the future.

5.3 RQ3: What are the Current Challenges and Needs Regarding the Integration of GenAI into UX Industry Practices?

Participants reported various challenges they faced with GenAI and, in the same vein, requested multiple features and improvements for GenAI that would help them in their UX practices.

Most commonly, participants reported that GenAI can produce inaccurate content, resulting in the content having to be checked. As a result, many stated that rather than trusting the GenAI tools completely, they treated them more as a second opinion, that can occasionally be wrong and must sometimes be corrected or ignored. This in part highlights that UX practitioners must build their own fundamental base skills to be able to assess GenAI outputs. At the same time, we argue that even when GenAI eventually improves and produces more accurate content, people should continue to be in control and not let AI take over; after all, the fundamental objective of AI is to improve human capabilities, not replace them [81]. Concerns about AI "taking over" have been voiced by employees in various fields, also in UX, both in our study as well as prior research [43].

Second, participants reported concerns about others relying on GenAI too much. The reported consequences included reduced efficiency, hurting the UX practitioner's ability for critical thinking, and being unable to identify low-quality output due to not having sufficiently developed their own skills. This concern was prominent among senior UX practitioners, who expressed concern over junior employee's over-dependence on GenAI, and some had already witnessed such cases. This is an interesting finding because in contrast, another study found that junior designers themselves were concerned about skill degradation and job impact [43].

Third, participants expressed a desire to receive more training on GenAI. Many participants pointed to learning to write "better prompts" for GenAI, which they said often required iteration and trial and error before they got the outcome they wanted. Prior research has also found that articulating instructions to the system are a significant part of GenAI-human interaction [67], and especially users with no AI expertise can struggle with generating prompts [88]. In the same vein, participants wished to better understand how AI and tools worked "under the hood" and how they produced their output, believing it would help them use it more efficiently and comprehensively. Indeed, prior research has found that uncertainty surrounding AI's capabilities can be a challenge for designers [19, 85]. Other research has also provided evidence that providing output explanations can improve the user's perceived understanding of the AI [23]. Li et al. [43] also found that UX practitioners wished for improved AI literacy among both senior and junior designers.

Our participants reported several expected benefits from training, like increased efficiency (due to reduced time spent writing and iterating prompts), increased ability to assess output quality, reduced chance of misuse of customer data and other sensitive data, and increased resilience to AI "taking over" the work.

Finally, participants reported things they wish GenAI tools would focus on or functions they would provide. The participants generally called for more focus on UX and UI design, stating that the current tools were not mature enough for adoption. In a similar vein, participants expressed that GenAI tools should be more "human-centric", that is, keep the user's needs in mind that GenAI was being used to design for. Prior research recognizes the need to keep AI assistants designer-centric [18], so it could be argued that one challenge for AI assistants is to consider both the designer's needs and the end user's needs. Other, specific requests included better management of previous work with GenAI, allowing users to refer to earlier conversations and analyses, factoring in the provided design system when generating UIs, predicting the designer's intentions and providing suggestions, more comprehensive language and translation support, and better tools for designing icons.

5.4 Recommendations for Companies, Teams, UX Practitioners, and GenAI Developers

5.4.1 Recommendation #1: Companies need to set up formal policies, communicate with employees, and take responsibility for GenAI use. We urge companies to set up formal policies and practices regarding GenAI use to the benefit of not only the company but also their employees. Our results suggest that companies are relying on the employees' professionalism and goodwill (e.g., to not abuse company data). This opens up potential legal issues for the company but also unfairly shifts the responsibility to individual employees.

It is undoubtedly complex for companies to navigate GenAI tools in regard to data privacy and confidentiality, especially for large corporations and those in particularly sensitive sectors like finance. However, while these policies are being developed, companies should already actively engage in discussions and communication with their UX practitioners, offer updates, and ensure the overall transparency of the process. Lack of communication is likely to foster uncertainty among workers, which is highlighted with AI because it links to fears about job stability and AI replacing human workers [76], even among UX practitioners [43].

Some resources and guidance exist that companies can leverage to develop their own policies. Some universities have begun to set up their own GenAI policies [49]. Researchers have also drafted initial policy considerations for policy makers [47], which touch on many important topics like copyright considerations, AI biases, and potential misuse.

5.4.2 Recommendation #2: Companies should offer GenAI training to UX practitioners. Training was explicitly requested by many participants. In addition, our participants reported several challenges and concerns regarding GenAI use that could be solved or alleviated with training. Based on our findings, company-provided training could focus on the following aspects:

- **Writing GenAI prompts.** Our participants commonly reported spending much time writing and iterating on prompts, some so much so that they questioned whether GenAI was actually worth the time investment. Existing research provides various strategies for improving prompts, such as giving examples of desired outcomes, writing more "code-like" prompts, and including repetition in prompts [88], which could be utilized in training UX practitioners.
- **Fundamental skills and assessment of GenAI output.** Participants reported concerns over some UX practitioners, especially junior employees, relying too much on GenAI without a sufficient ability to assess the quality of the output. Prior research has also identified concerns among UX practitioners about skill degradation [43]. Therefore, training could focus on developing their ability to assess the output quality, but also junior employees' fundamental UX skills.
- **Understanding of AI.** Some participants expressed that they did not really understand AI in general and how specific GenAI tools work, and what their capabilities are, believing that it hindered their ability to use GenAI effectively. Especially, participants highlighted that they could understand and assess GenAI's output better if they understood how the AI came to that conclusion. Guidelines and resources exist [e.g., 4, 58] that are intended to help designers when designing AI-enhanced systems; however, existing research notes that such resources can also help people learn about AI, as well as help develop internal resources [87].
- **Awareness of GenAI tools.** While practically all interviewees used GenAI on some level in their work, some practitioners used it for more surface-level and early work. Especially UX and UI *designers* expressed that they did not think GenAI tools were mature enough to be effective in more involved areas of their work, like wireframing and graphic design. Yet, as already discussed, existing research proposes various tools and method for such activities. At the same time, many design platforms are already offering built-in GenAI features as well as plugins. Therefore, training could focus on raising awareness of various kinds of AI tools tailored for designers that UX practitioners might not be aware of, such as tools for wireframing [10, 24] and graphic design [90], and further train on their use and capabilities.

5.4.3 Recommendation #3: UX teams should discuss, share, and build GenAI-enhanced UX processes and foster collaboration. We urge UX practitioners and their managers to engage in discussions with their team members, to share knowledge and ideas about GenAI and begin building GenAI-enhanced UX practices and processes. Collaborative approaches would ensure alignment with new methodologies and technologies, and encourage innovation and transparency. Sharing knowledge and experiences about GenAI tools can help in identifying best practices, troubleshooting common issues, and exploring new ways to apply these tools.

Shared GenAI practices would undoubtedly make the use of these tools more efficient and productive, as well as foster learning and help UX practitioners with some of the challenges they currently face with GenAI. Some recent work can provide valuable guidance here; Han et al. [29] discuss how individuals can work together to write effective GenAI prompts, and learn from each other in the process. Similarly, shared practices and active discussions and mentoring can play a key role in onboarding and training junior employees and interns. While junior UX practitioners certainly have an individual responsibility to develop their skills and use GenAI responsibly, senior practitioners and managers also have a responsibility towards their junior colleagues.

5.4.4 Recommendation #4: GenAI tools should provide better support to UX designers. Our participants frequently reported that they wished GenAI tools supported their design work better. Participants called for better support for activities like wireframing, graphic design, and prototyping. As already discussed, plenty of AI-enhanced tools for these purposes have been built, but they may exist mainly as research prototypes or may not otherwise be widely available. Therefore, we identify an opportunity to integrate these tools into the more widely used GenAI tools. More broadly, we identify an opportunity for GenAI tools to offer multiple functionalities and modes, which would also support collaboration and practices in UX teams, by enabling team-wide use of the same tools. In another study, participants made a similar suggestion to combine text and image generation capabilities into one interface [67].

5.4.5 *Recommendation #5: GenAI tools should support the principles of explainable AI.*

The practitioners in our study, and other prior research, noted that they are occasionally distrustful of AI tools and their output. While is it strongly recommended that GenAI users indeed do not blindly trust the output and should be capable of assessing its quality, this lead to further issues like hesitancy to utilize seemingly high-quality output due to not knowing how the AI came to that suggestion. Similarly, participants often reported that they wished to have a better understanding of the AI's thought process. These matters link to principles of explainable AI (XAI), such as transparency and accountability [8, 78, 80]. A quick analysis at the currently popular GenAI tools like ChatGPT, DALL-E, and Midjourney reveals that they do not fully support these principles. Therefore, we recommend that the developers of GenAI engage more with explainable AI to support transparency and the users' ability to critically assess the AI's output.

5.5 Limitations and Future Work

Because we are dealing with the rapidly changing landscapes of GenAI and UX, we acknowledge that some of our results are rather a snapshot of the current status in the UX industry. While it is not clear how long some of our results will hold, this opens up opportunities for future research. We also emphasize, as outlined in our discussion and recommendations, that we *want* things to change, and we view our paper as a call-to-action for UX practitioners, teams, and companies. Therefore, it would be valuable to explore UX industry practices in the near future to monitor how these practices are evolving and to identify opportunities for HCI researchers to contribute to building and evaluating these practices.

Furthermore, we chose interviews as an appropriate method because we focused on acquiring qualitative insights into the UX professionals' practices as well as team and company culture. We believe that our results are strong especially because participants also provided information about their colleagues and companies, broadening our results. That said, given the method, we cannot claim generalizability beyond our sample. Rather, now that we have identified critical needs regarding GenAI use in UX, such as lack of company policies and team practices, a broader investigation into these matters using other methods (e.g., with an online survey) is warranted. This would also allow for an investigation into how UX practices differ between countries and cultures.

6 CONCLUSION

In this work, we investigated industry practices regarding GenAI use in the field of user experience, covering UX design and UX research and similar areas, at three levels: practices among individual UX practitioners, practices and discussions in UX teams, and practices and policies in companies with UX departments.

As some of the most significant and surprising results, we identified a significant lack of policies, practices, and discussions regarding GenAI use at both the company level and team level. Instead, individual UX practitioners typically made independent decisions to use GenAI tools in their work, and also showed vigilance for data privacy and confidentiality.

Therefore, we urge companies to adopt GenAI policies and actively communicate with employees as well as offer GenAI-related training. We also urge UX teams and managers to begin developing GenAI-enhanced practices that foster collaboration in the team. We foresee several benefits from adopting such practices, like increased efficiency, shared responsibility over GenAI use, and lower risk for breaches in data privacy, confidentiality, and intellectual property.

Moreover, we highlight how UX researchers in particular have found GenAI useful for their practices and are utilizing GenAI tools at multiple stages of their work, such as writing and creating drafts, designing studies, and analysing data. UX and UI designers, however, typically use GenAI in the early stages for brainstorming and visualization, but find current GenAI tools lacking for advanced design work such as wireframing, graphic design, and prototyping.

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A INTERVIEW QUESTIONS

A.1 Demographic Questions

- How old are you?
- What gender do you identify with?
- What is your country of residence?
- What is your level of education, and field?
- What is your occupation, including your exact job title?
- What is type of your current employment? Are you working for a company full-time or part-time, do you freelance, or something else?
- How many years of experience do you have as a UX professional?

A.2 Main Interview Questions Part 1

- What industry is your company/employer in?
- How big is the company you are working in?
- How big is your team or teams that you typically work with?
- What is your typical role in a UX project?
- In your company, are there any company-wide or team-wide policies around AI tools and their use? What are they?
- Were there any concerns or hesitations within the company or your teams regarding the decision to integrate AI in the workflow?
  - What were the thoughts and attitudes regarding using AI?
  - Did you or do you personally have such concerns or hesitations?
  - Did the thoughts/attitudes/concerns impact the decision-making process at different levels of the company?
- Have you or your team used AI in any part of your UX projects? How?

A.3 Main Interview Questions Part 2A (if the interviewee or their team have used AI)

- Name the tools you use or have used
- In which steps of the process do you integrate AI in your work?
- How many people in your team(s) are using AI in your current projects? For example, are there specific roles that use AI a lot, or some roles that don't?
- Can you walk me through your main steps in your and your team's workflow when you are using AI tools in your projects?
  - How frequently does AI come into play in your current work?
- So Can you walk me through the same workflow in a traditional way without getting an AI assistant/the specific tools? How did you work on projects before AI?
- What were your first experiences like when using AI tools in your work? What challenges did you face, and is there anything you wish you knew or understood at the time?
- To what extent do you trust the AI tools and their outcomes? What kind of a role does AI serve in your decision-making processes? Do you often edit the outcomes or check them for correctness and quality?
- Considering the above questions, is your approach in using AI tools, aligned with the company/team approach? In other words, are the decisions to experiment and adopt AI tools in work, made individually, or internally in teams, or does the company decide and provide the tool(s) for the team?
  - If it is a team or company approach to use the tool, are you obligated to follow the design process with AI tools, or is it just an option?
  - If it is for individual purposes or within teams, do you think the company is against it, or doesn't matter? Are they aware of the use of all AI tools?
  - Are there any employees that hesitate or refuse to use AI tools that you or your company would like to use? If so, what are their reasons?
- What benefits do you think you get out of using AI tools in your work?
- Are you going to use AI tools again in your future projects? Are there any ways in which you or your team or company is looking to change the use of AI tools?

A.4 Main Interview Questions Part 2B (if the interviewee or their team have not used AI)

- Are there any particular reasons for why you and/or your team or company are not using AI tools?
  - Was that a personal decision or obligated by the team or company?
  - Have there been discussions about it at your workplace?
  - What are your coworkers' and team members' attitudes about using AI?

- Have you or your team **tried** using any AI tools? If so, what was the outcome, and did that play into your decision to not use AI tools?
- (if they have experience) What were your first experiences like when using AI tools in your work? What challenges and hesitations? did you face, and is there anything you wish you knew or understood at the time?
- Can you walk me through the design process for a typical project that you have worked or are currently working on?
  - What are the typical challenges or obstacles you face in your UX projects?
- What would need to change so that you and your team would begin to use AI tools in your work?

A.5 Main Interview Questions Part 3 (regardless of prior AI use)

- What in your opinion are the greatest strengths of AI and AI tools?
- What in your opinion are the greatest challenges of AI and AI tools?
- How do you see your work and work practices changing within the next five years?
- Do you have any suggestions for us to focus on in our research?
- Is there anything else you want to add to your session?
- Is there any question that you think I should have asked that I didn't?