MASTER'S THESIS

INFORMATION STUDIES

AI-AUGMENTED UX DESIGN PRACTICES: Investigating how AI is applied as a Designerly Tool in Design Practices

ARTIFICIAL INTELLIGENCE
DESIGNING WITH AI
USER EXPERIENCE DESIGN
HUMAN-AI INTERACTION

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Abstract

Keywords

AI, design with AI, design practice, Human-AI Interaction, User Experience design

Due to the recent deployment of large-scale AI models, various new generative AI models have been released in the fall of 2022 and spring of 2023 with the ability to learn from content and generate content. As there is no standard definition of *Artificial Intelligence (AI)*, AI is mostly referred to as intelligent systems, possibly embedded in larger systems, with capabilities that make AI systems achieve complex goals. The rapid advancement of AI has an impact on human-computer interaction, including the design of information technology. When designing information technology, having a human-centered approach enables User Experience (UX) practitioners to design systems with an emphasis on human beings and their needs. The term UX is used as an umbrella term in system development in which UX practitioners perform activities related to *user research, problem setting, design conceptualization, and testing.*

Through a review of related work, two directions of existing literature were discovered: *1) designing AI systems*, and *2) designing with AI*. In the thesis, the focus is on the latter, as there was a research gap in studies on practices of applying AI to design information technology. Through an explanatory sequential mixed-method study combining quantitative and qualitative approaches, a survey (N=64) served as a preliminary exploration of the phenomena, identification of the best candidates, and informing the qualitative research. The qualitative approach (N=6) consisted of contextual inquiry and semi-structured interviews which enabled further exploration and understanding of the UX practitioners' subjective experiences of applying AI in their work practices. This underlines the pragmatic stance of acquiring knowledge about the practical application of AI in UX-related work practices. To analyze the collected data, inductive thematic analysis was applied due to an interpretivist approach.

Based on a survey, we found that approximately half of the UX practitioners use AI systems across the design process. The findings show that UX practitioners use AI systems as a designerly tool to get inspiration, as a starting point, and for sparring

purposes in stages mainly related to problem setting and design conceptualization. The most common AI application is generative AI which augments the UX practitioners' abilities and supports them in solving trivial and tedious tasks to provide more time to focus on UX tasks with a higher level of importance and abstraction. The findings suggest that the perceived advantages of AI in our study align with related work in other domains.

The findings reveal that the generative AI output is merely used as inspiration rather than being used directly in the design. Due to ethical concerns of trust, biases, and lack of transparency, the output needs to be validated and/or edited before being directly incorporated into the design. In general, Visual generative AI is used to a low degree by UX practitioners, compared to text generative AI, because the overall user experience is not accounted for in the AI output. Based on the UX practitioners' perceived challenges of using AI in the design process, the findings suggest that AI is not able to design autonomously in a human-centered approach because the AI output must be balanced with human creativity, intuition, presence, and empathy. This suggests that AI can support UXPs to perform HCD activities rather than replace them. However, the UXPs' perceived challenges of AI might be false due to a lack of AI literacy, or because the UXPs applied AI systems that did not fit the purpose of their tasks.

A discussion of the findings reveals that AI's efficiency enables an agile and iterative design process while reducing time, budget, and effort resources. However, the discussion of AI's efficiency and automation of certain UX activities suggests a demotion of certain competencies of UX practitioners. In addition, there is a perception among UX practitioners that human-centered design without real users is not human-centered because AI can not account for the contextual and intangible in real-life situations of human beings. Overall, AI can support UX practitioners in line with existing UX practices, methods, and tools despite the perceived advantages and challenges of AI. Based on the findings and discussion, there is a need for further research on AI in relation to its ability to be creative, innovative, and empathic in a human-centered approach to determine if the UXPs' perceived challenges of AI are valid.

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1. Introduction

The increase in computational power and rapid deployment of large-scale *Artificial Intelligence (AI) models* (van der Maas et al., 2021; Sevilla et al., 2022) has caused a release of various new generative AI models in the fall of 2022 and spring of 2023, such as *ChatGPT-3*, and *DALL-E 2* (McKinsey, 2023). As a consequence, AI technology is available for anyone to use in their work practices and everyday lives (de Oliveira Carvalho et al., 2022, p. 132; Dexe et al., 2020; Tsiakas & Murray-Rust, 2022). AI's impact might cause changes for certain roles in various fields because AI systems are able to perform tasks that normally require human intelligence (Rzepka & Berger, 2018; Samoili et al., 2020).

Since its release in November 2022, ChatGPT gained the attention of various communities, especially discussions on how AI might overtake certain jobs or responsibilities (Alshurafat, 2023; Noy & Zhang, 2023; Ward, 2023). In relation, the field of User Experience (UX) design has undergone changes with the emergence of AI technology. AI impact UX practitioners who design information technology on two fronts: 1) *designing the user experience of AI systems* (Bergström & Wärnestål, 2022; Hartikainen et al., 2022; Heier, 2021; Liao et al., 2020; Windl et al., 2022; Yang et al., 2020; Zdanowska & Taylor, 2022), and 2) *using AI systems to design information technology* (Main & Grierson, 2020, p. 7; Windl et al., 2022, p. 1; Yang et al., 2020; Yildirim et al., 2022, p. 10).

The focus of this thesis will be on the latter, in a study of UX practitioners' current experience and application of AI, including how the recent advancement of AI impacts UX work practices. Traditionally, the domain of UX relies on iterative, human-centered design processes with an emphasis on qualitative user research and tests as a basis for designing effective, satisfying, and usable digital products with human beings at the center (ISO 9241-11:2018, 2018). However, the technological leap of AI offers new opportunities and challenges in the process of designing information technology with a human-centered approach. Furthermore, with the emergence of more autonomous decision-making capabilities in AI, the research community underlines ethical concerns such as *fairness*, *transparency*, *trust*, *explainability*, and *privacy* that need to be accounted for (Khan et al., 2022; Long & Magerko, 2020, pp. 6–7; Maslej et al., 2023; de Oliveira Carvalho et al., 2022, p. 136; Robert et al., 2020; Shneiderman, 2020a). Arguably, the advancement of AI will challenge the existing UX work practices that currently rely on UX practitioners to conduct user research, be creative, and solve problems.

1.1 Problem statement

Based on the recent advancement of AI systems in the field of designing information technology, we aim at answering the following problem formulation:

> **Problem formulation**
>
> How are Artificial Intelligence (AI) systems currently being applied by User Experience (UX) practitioners when designing information technology and how will the recent advancement of AI systems transform the UX practices?

The research questions (RQs) aim at guiding our research and answering the problem statement.

RQ1 What characterizes the domains of designing information technology and Artificial Intelligence, and in combination?

RQ2 How are UX practitioners currently designing with AI in their UX work practices?

RQ3 What are the perceived advantages and challenges of UX practitioners' application of AI to the design of information technology?

RQ4 What are the consequences of applying AI, and how might AI impact the domain of UX and related UX practices?

1.1.1 Clarifying the problem statement terms

By *recent advancements* (see § 2.3.1), we refer to development within AI enabled by the increased computing power driving AI development of new techniques and algorithms (Sevilla et al., 2022; van der Maas et al., 2021).

AI systems (see § 2.3.1) refer to the software system designed by humans and driven by data able to achieve complex goals by applying one of the capabilities required for intelligence such as perceiving, interpreting, reasoning, and decision-making. The term encompasses various technologies that can incorporate or leverage the capabilities of AI.

With the term *User Experience* (*UX)*, we refer to the field of designing information technology with a focus on a Human-Centered Design (HCD) approach. UX serves as an umbrella term that encompasses areas such as Human-Computer Interaction (HCI), HCD, User Interface (UI) design, and Interaction design (see § 2.2.1).

With the term *UX practitioners (UXP)*, we refer to the practitioners involved in all stages of the design process, such as user research, problem setting, design conceptualization and development, and user testing (see § 2.2.2).

1.2 Structure of the thesis

In **§ 2. Related Work**, we review existing literature related to the concepts of UX (§ 2.2), AI (§ 2.3), and the role of AI in UX (§ 2.4). The related work chapter seeks to answer RQ1 and RQ2 by presenting related studies on the domains.

In **§ 3. Methodology**, we discuss philosophical stances (§ 3.1.1); research design (§ 3.2); methods' application (§ 3.3); sampling (§ 3.4); approaches to data processing and analysis (§ 3.5); and ethical consideration of our study (§ 3.6).

In **§ 4. Results & Findings**, we analyze the collected data from the quantitative and qualitative approaches enabling us to answer RQ2 by gaining insights into UXPs' usage of AI systems in the design process (§ 4.1; 4.2.1). Furthermore, we seek to gain insights into the perceived advantages and liabilities of using AI to answer RQ3 (§ 4.1.3; 4.2.2, 4.2.3). Finally, we aim at uncovering the UXPs' concerns about applying AI in a human-centered approach, and how it might impact the UX practices which partially answers RQ4 (§ 4.2.4).

In **§ 5. Discussion**, we synthesize and discuss our findings from the quantitative and qualitative approach with the existing literature by discussing the findings that relate to RQ2 and RQ3. Furthermore, we aim at answering RQ4 by discussing the relationship between UXPs and AI systems (§ 5.1); perspectives on AI's advantages and challenges when using AI in designing information technology (§ 5.2); ethical concerns and AI literacy influencing the application of AI (§ 5.3); and the importance of users and empathy in design (§ 5.4). Furthermore, we discuss the limitation of our study from different perspectives (§ 5.5).

1.2.1 Reading Guide

In our thesis, we will introduce various terms that will be abbreviated. This section provides an overview of all the abbreviations. Additionally, we present how references to sections and appendices are done throughout the thesis.

Abbreviations

In the following, a list of abbreviations is provided to guide the reader throughout the thesis.

Abb.	Term	Secti ons
AI	**Artificial Intelligence** *A broad field encompassing multiple definitions and subthemes.*	§2.3.1
ANN	**Artificial Neural Networks** *Subtheme in AI with emphasis on pattern recognition and data analysis*	§2.3.1
HCAI	**Human-Computer Artificial Intelligence** *Term and principles to address the importance of designing human-centered AI systems by accommodating ethical concerns*	§ 2.4.2
HCI	**Human-Computer Interaction** *Design, evaluation, and study of the interactions between human beings and computers*	§ 2.2.1
HCD	**Human-Centered Design** *Design approach with the human in the center, emphasizing the impact on all relevant human beings in the design process*	§ 2.2.1
ML	**Machine learning** *Subtheme in AI with emphasis on learning from input*	§ 2.3.1
NLP	**Natural Language Processing** *Subtheme in AI with emphasis on interpreting & contextualizing text or speech*	§ 2.3.1
SICI	**Semi-structured Interview and Contextual Inquiry** *The combination of qualitative methods that are applied*	§ 3.2.3
Textual GenAI	**Textual Generative Artificial Intelligence** *Generative AI systems that generate text as its output*	§ 2.3.1
UCD	**User-Centered Design** *Design approach with the user in the center, emphasizing the user's needs to create usable, satisfying systems*	§ 2.2.1
UI	**User Interface** *Refers to the design of User Interfaces, focusing on the style, and interactivity of a system*	§ 2.2.1
UX	**User Experience** *Refers to an umbrella term within the design of information technology. The field of User Experience encompasses user interface design and interaction design.*	§ 2.2.1
UXP	**User Experience Practitioner** *A practitioner with UX-related work activities as their primary responsibilities. Encompasses both UX Research- and Design-oriented practitioners.*	§ 2.2.2
Visual GenAI	**Visual Generative Artificial Intelligence** *Generative AI systems that generate visualizations as its output, eg. images*	§ 2.3.1
XAI	**Explainable AI** *Improvement of the explainability, transparency, and interpretability of AI systems*	§ 2.3.2

Table 1: Abbreviations

References

References to sections will be done with the use of: **§**. For instance: "If you want to read about abbreviations and references, go to § 1.2.1".

Appendices will be referred to in plain text, such as "see Appendix [no.]". Additionally, we perform a qualitative analysis by referring to transcripts which can be seen in Appendix 7. Regarding the transcripts, the reference will include the appendix number, 7, the participant number (eg. P4), and the timestamp (eg. 16:22). In combination, the reference to the transcriptions will be as follows: (A7, P4 16:22). If the reference includes multiple participants, semicolons will be applied: (A7, P4 16:22; P5 31:43).

1.3 Motivation for our study

As UXPs ourselves, we have been intrigued to investigate how much potential there is in AI in regard to its application in the UX design process. The release of ChatGPT-3 in November 2022 marked the point in our early research stage and impacted the research objectives to be focused on examining UXPs' practices of applying GenAI. Due to the emerging nature of the study, we have found that there is a research gap in examining the topic of designing with AI as opposed to designing AI systems (§ 2.4). In contrast, our aim was to investigate the impact of AI on the designing process and work practices of UXPs, and overall what is the consequence of applying AI when designing information technology.

Throughout the period of study, we were aware of the hype that GenAI caused in the UXPs' community. The emergence of new large-scale AI models further enables new AI capabilities in existing design tools that impact UX practices. Furthermore, it resulted in discussions of how UXPs secure a human-centered approach to designing information technology in the new era of AI. We believe that by exploring the UXPs' use of AI, we will provide more structure and clarity to certain concepts and further encourage research on the examining impact of the application of AI when designing information technology.

2. Related Work

The following chapter will start with explaining our process of search, selection, and documentation of sources (§ 2.1) necessary for obtaining knowledge on the topics and concepts connected to our study:

§ 2.2 Designing information technology and related work practices

§ 2.3 Understanding of Artificial Intelligence

§ 2.4 Role of AI in UX

2.1 Literature search and selection

A *literature review* is a crucial part of any academic study (Clark et al., 2021; Webster & Watson, 2002), as it establishes the foundation for further investigation and knowledge-seeking (Webster & Watson, 2002, p. 8). The literature review can be viewed as a process of identifying, selecting, organizing, and assessing a wide range of sources. It summarizes a field to support the identification of research questions (Rowley & Slack, 2004, p. 31).

When it comes to topic maturity, Webster & Watson (2002) point out its influence on the outcome of the literature review. While the mature topic requires that the literature review synthesizes and extends the current research, the emerging topic calls for proposing a conceptual model(Torraco, 2005, p. 362; Webster & Watson, 2002, p. 14; Yadav, 2018, p. 363). As a result of the emergence of new AI tools in design and the continuous advancements in the field of AI, the investigated topic is still in its early stages and the findings of our literature review are more conceptual in nature. In addition, there are different types of literature reviews. Grant & Booth (2009) identify fourteen literature review types, *e.g. narrative/literature*, *systematic,* and *scoping review*. During a narrative literature review, researchers collect; summarize; and synthesize a volume of literature to draw certain conclusions on a specific topic. The aim is to get an understanding of the current state of knowledge with the identified areas that can be further researched (Cronin et al., 2008, p. 38; Grant & Booth, 2009). The weakness of this review is that the selection of literature and its criteria are not documented systematically (Cronin et al., 2008; Grant & Booth, 2009) and it can be considered subjective and biased (Grant & Booth, 2009; Munn et al., 2018, p. 5). On the contrary, a systematic literature review is characterized by a very rigorous methodology for reviewing all knowledge of a specific topic to ensure reliable results (Cronin et al., 2008; Grant & Booth, 2009; Munn et al., 2018, p. 2). Part of a systematic review in order to document transparent reporting is the *Preferred Reporting Items for Systematic Review and Meta-Analyses (PRISMA) statement*. Part of the PRISMA methodology is a 27-item checklist listing reporting and recording recommendations (Page et al., 2021).

The scoping review is best suited for reviewing emerging topics requiring processing a robust amount of literature quickly in a structured, replicable way (Munn et al., 2018, pp. 3–5). Furthermore, due to its broad scope, it might be used as a preliminary step for assessing the size and scope of the available literature and informing the systematic review (Grant & Booth, 2009, p. 101; Munn et al., 2018, pp. 4–6).

One of the ways how Cooper proposes to organize the literature review is *conceptual*, meaning the related studies are positioned together, as opposed to chronological or methodological types of organizations (Cooper, 1988, pp. 110–112). The overall goal of the literature review is tied to RQ1, RQ2, and RQ4. The main purpose of the literature review is to get insights on related work in relation to designing information technology and AI; separately and combined (RQ1). The insights from the literature will be used to get insights on current AI practices in UX from academic literature (RQ2) to inform the rest of the study in terms of domain knowledge on UXPs and AI systems. Finally, the literature review aims at providing insights that can be used for discussion of the results and findings (RQ4).

Our literature review process carries characteristics of a narrative literature review where the analysis is conceptually organized. However, to address the weaknesses of the narrative literature review, we have been inspired by the PRISMA checklists, e.g. by specifying inclusion/exclusion criteria, stating RQs we address by literature review or presenting search strategies, to search and select studies that might contribute to the synthesis in a more transparent manner and increase the overall external reliability of our study.

2.1.1 Undertaking the review

We follow Cronin et al.'s (2008) approach to undertaking a narrative literature review distilled into five steps: 1) *Selecting a review topic*; 2) *Searching the literature*; 3) *Gathering, reading, and analyzing the literature*; 4) *Writing the review*; and 5) *Formatting the references* (Cronin et al., 2008, p. 39).

Search

Our literature review documentation style is inspired by the *PRISMA 2020 Checklist* (Page et al., 2021), see Appendix 1.1. To identify the relevant literature we have selected the keywords related to the RQs:

CONCEPTS IN LITERATURE REVIEW		
CONCEPTS	CONCEPT QUESTIONS	KEYWORDS
1. Designing information technology	What does UX field consist of? From which phases does the UX design process consist? How do UXPs decide about their tools? What is are the practices of UX Designer/ UI Designer/ UX/UI Designer/ UX Researcher	IT Design*, System development, Human-Computer Interaction / HCI, User-cent* design / UCD Human-cent* design / HCD, Role of designer, User Experience / UX, User Interface / UI, Interaction design, Usability practice*, job title*, activit*, method*, approach, framework*
2. Artificial Intelligence	How can we define AI? What is AI system? What are AI's capabilities? What is GenAI? How fast is the progress in AI development? What are ethical concerns in AI? How can AI solve ethical concerns? What is human-AI relationship?	Artificial Intelligence, Intelligence AI definition, General / Broad/ Narrow AI Generative AI/ GenAI, Human-AI interaction Ethics, Ethical concerns in AI, Ethical standards, Trust, Transparency Fairness, AI-driven algorithms, Designing fair AI, Explainable AI / XAI Explainability, Human-in-the-loop Human-AI creative collaboration, Human-AI communication, AI development
3. The role of AI in UX	What is the difference between designing with AI and for AI? How do designers already accommodate AI in UX design process? How does AI influence the current UXPs' work practices? What are the challenges of implementing AI into the UX design process?	Artificial Intelligence in design / AI in design AI design tools, AI-enabled tools in design AI interaction design, Human-cent* AI/ HCAI AI design material, AI-enabled systems Designing AI, Designing with AI AI and risk in design, AI impact in UX design

Table 2: Keywords and concepts specification.
Keywords were grouped and used in combinations with boolean operators.

To increase the possible search outcomes we included keywords with similar meanings. We located studies by searching through online databases and scanning the reference lists from the reviewed documents. The primary source of literature has been the online databases of *ACM; Primo; EBSCOhost;* and *ScienceDirect*.

Used tactics were quick & easy at the beginning to get an overview of the field and iterate on our keywords. To further optimize our search, we applied *Boolean logic, limit function,* and *truncation* (Booth et al., 2016, pp. 116–119). In addition, we also utilized *keywords grouping* to search multiple terms from the same keyword group, see Appendix 2.2. Aside from mentioned tactics, we utilized *pearl-growing* to locate related articles on the topic which broaden the initial selection of other articles. Moreover, we also used *citation searching* when following the cited reference to earlier studies (Booth et al., 2016, pp. 115–121). We started the search with just a few keywords to probe the field and then progressively applied limitations and different tactics to reduce the search results to more specific and matching outcomes by *query expansion* (Kekäläinen & Järvelin, 1998, p. 130).

Inclusion and Exclusion criteria

Part of the PRISMA 2020 Checklist is to define inclusion and exclusion criteria enabling us to specify the boundaries based on which we would search and screen the relevant studies (Table 3 and 4).

EXCLUSION CRITERIA
1. Type of source • Exclude secondary papers if there is access to the primary source.
2. New Topics • When there are two studies on the same topic, the priority is the newest publication, if applicable.
3. Level of technological details • Excluding papers with a primary focus on technical aspects of AI.

Table 3: List of exclusion criteria for the studies selection

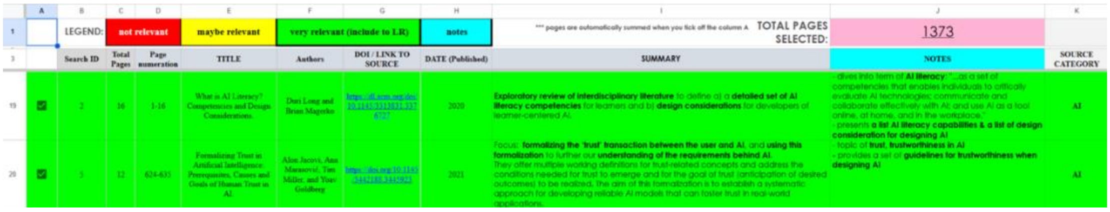
INCLUSION CRITERIA	
1. Research Focus	
Papers should focus on: • Role of AI in designing information technology • AI in general and ethical concerns in the field of AI • Field of HCI and UX • Practices of UXPs' within the UX design process • AI as a design material	Papers should focus on: • AI's impact on the design processes and work practices of UXPs • Challenges in a) designing AI systems, and b) designing with AI • Human-AI collaboration or Human-AI relationship • AI products, tools, or systems related to design
2. Source Type • Primary sources by original authors • Secondary sources e.g. systematic review articles • Conceptual sources, e.g. presenting certain theory or concept regarding one of the areas of interest	
3. Peer-reviewed articles • Academic articles, preferably peer-reviewed	
4. Keyword overview • Contain review keywords in the abstract	
5. Language • English as preferred language	
6. Time-frame • Papers focused on AI application should be published between 2018-2023, if applicable.	

Table 4: List of inclusion criteria for the studies selection

2.1.2 Selection and Documentation

When selecting the relevant literature we utilized a method called *PQRS (preview, question, read, summarize system)* which showed to be useful in keeping consistency and it provided a structure when retrieving the existing literature (Cronin et al., 2008, pp. 40–41). We conducted the selection of the relevant studies in three stages. Firstly, we screened the titles and abstracts against the inclusion/exclusion criteria and documented the search logs in a spreadsheet with the search string and links to relevant papers (see Appendix 2.2). Papers that do not fit the criteria were rejected.

Furthermore, we processed the papers by assessing abstracts and conclusions and extracting information such as the scope of the study for the topic categorization and initial notes about the paper's relevance for the thesis. The search log ID and paper reference was recorded (Figure 1).



	A	B	C	D	E	F	G	H	I	J	K
1		LEGEND:	not relevant		maybe relevant	very relevant (include to LR)		notes	*** pages are automatically summed when you tick off the column A TOTAL PAGES SELECTED:	1373	
3		Search ID	Total Pages	Page numeration	TITLE	Authors	DOI / LINK TO SOURCE	DATE (Published)	SUMMARY	NOTES	SOURCE CATEGORY
19	☑	2	16	1-16	What is AI Literacy? Competencies and Design Considerations	Duri Long and Brian Magerko	https://dl.acm.org/doi/10.1145/3313831.3376727	2020	**Exploratory review of interdisciplinary literature** to define a) a **detailed set of AI literacy competencies** for learners and b) **design considerations** for developers of learner-centered AI.	- dives into term of **AI literacy**: "...as a set of competencies that enables individuals to critically evaluate AI technologies; communicate and collaborate effectively with AI; and use AI as a tool online, at home, and in the workplace." - presents **a list AI literacy capabilities & a list of design consideration for designing AI**	AI
20	☑	5	12	624-635	Formalizing Trust in Artificial Intelligence: Prerequisites, Causes and Goals of Human Trust in AI	Alon Jacovi, Ana Marasović, Tim Miller, and Yoav Goldberg	https://doi.org/10.1145/3442188.3445923	2021	Focus: **formalizing the 'trust' transaction between the user and AI**, and **using this formalization** to further our **understanding of the requirements behind AI**. They offer multiple working definitions for trust-related concepts and address the conditions needed for trust to emerge and for the goal of trust (anticipation of desired outcomes) to be realized. The aim of this formalization is to establish a systematic approach for developing reliable AI models that can foster trust in real-world applications.	- topic of **trust, trustworthiness in AI** - provides a set of **guidelines for trustworthiness when designing AI**	AI

Figure 1: Summary of the reviewed articles in the spreadsheet (Appendix 2.3)

The summary played an important role in the first iteration of the literature review to get an overview of the related work, especially to find affinities between the topics (§ 2.1.3). The whole related work chapter was done in different iterations, and in the latter part of the process, research articles were added throughout the different concepts without being included in the summary.

When the summaries were completed, we proceeded to screen and identify the relevant sections such as the aim, main topics, claims, and results of the paper to be used for structuring the literature overview. Furthermore, we initially categorized each document with keywords and topics to which a study can provide relevant insights and grouped similar articles under unifying headings.

As a part of the process, we presented the studies to each other to discuss their eligibility and relevancy. This enabled us to get acquainted with new terminology and concepts relevant to the specific topic being reviewed by the other researcher which strengthens the study's internal reliability.

Finding affinities between articles

As we chose to conduct the conceptual literature review, it was necessary to cluster all relevant studies, and empirical research under the concepts and outline a relationship between them. From the initial concepts identified in the beginning stages, we have further identified important affinities in each concept by applying an *affinity diagram* which enabled a discussion of the findings, relevance, and connections between the selected articles. An affinity diagram is an interactive, co-creative process of organizing and grouping unstructured data and ideas, defining and clarifying a problem, and/or finding relations in the data to get a joint understanding of the situation (Dahlgaard-Park, 2015, pp. 19–20; Holtzblatt & Beyer, 2017, p. 127). All data is gathered on individual sticky notes to be structured into themes based on their affinities (Holtzblatt & Beyer, 2015, pp. 25–26, 2017, pp. 129–130).

We put the insights from each study on individual sticky notes in the online, collaborative tool *Miro*. The following figure represents the workflow in four phases:

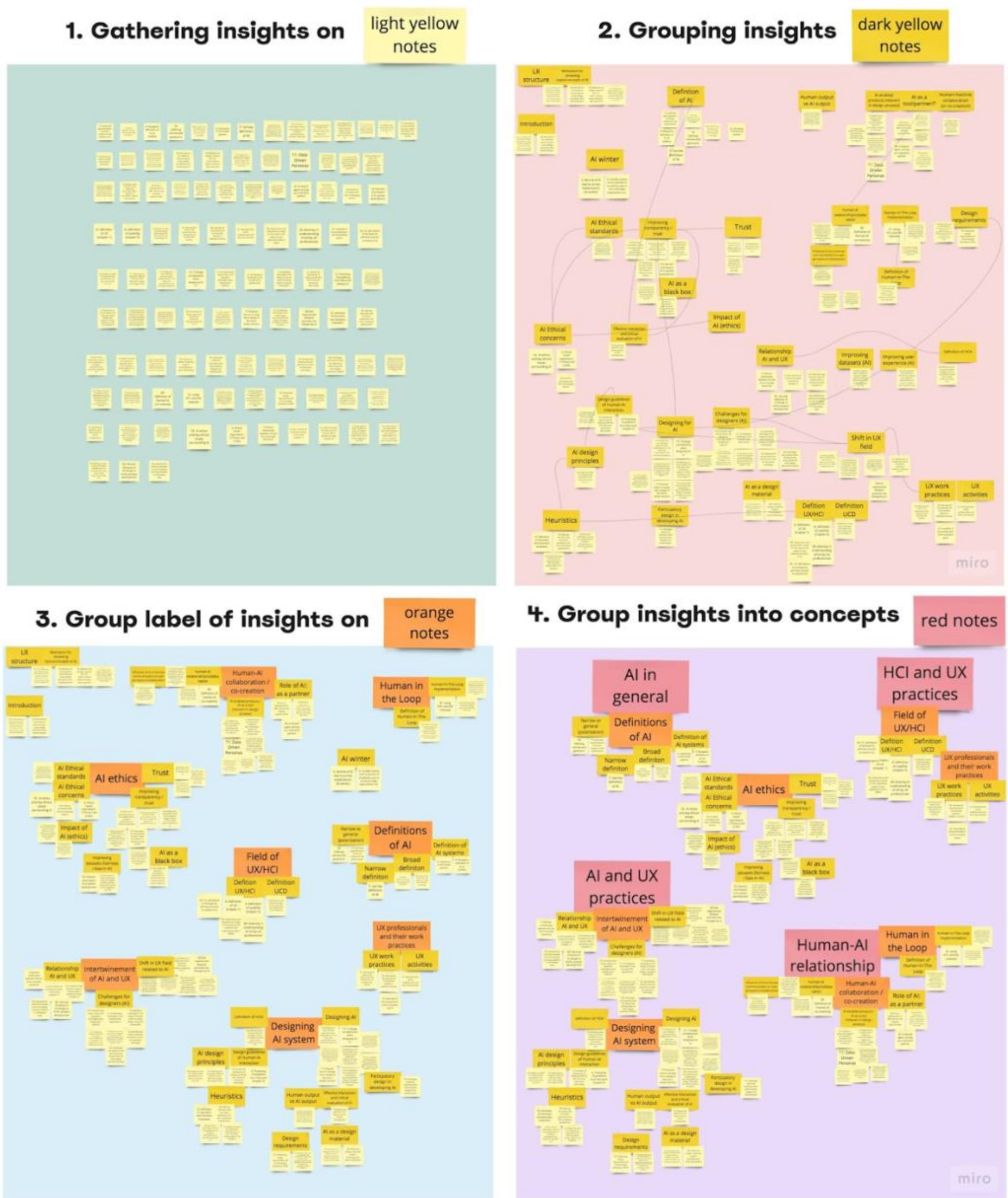


Figure 2: The four phases of our affinity diagram
(the process is further documented in Appendix 1.4)

The brainstorming and conversation during our work with the affinity diagram opened our understanding of the existing literature and we could compare different insights with each other to get a mutual conception of previous findings and how they relate. Furthermore, the affinity diagram process helped in the writing process of the literature review to structure the research articles within the different concepts. The papers have been clustered, and data were structured and synthesized under thematic headings.

2.2 Designing information technology and related work practices

In this part of the literature review, we will present research related to designing information technology with the aim of defining related, intertwined terms (§ 2.1.1). Furthermore, the related work practices within system development will be reviewed to understand how UX practitioners decide on tools, methods, and approaches (§ 2.1.2). With this section, we seek to answer RQ1 in relation to what characterizes the field of UX.

2.2.1 Designing information technology

The field of designing interactive systems has evolved to incorporate numerous acronyms and proposed sub-disciplines that all can be related to designing a system to experience and interact with (Riley, 2019, pp. 191–192; Steane et al., 2020, p. 85). In the following sections, we aim at presenting different terms and design disciplines related to system development that share similar intellectual spaces to position our understanding of the design-related disciplines, frameworks, terms, and methods in the remainder of the thesis.

The term: Design

Before assessing the practice of designing information technology, we will quickly assess the term *design.* Design can be described as a process of research and practice in which designers face *wicked problems* that are ill-formulated, including various stakeholders with conflicting opinions, and confusing in relation to the information and ramifications of the whole system. According to Richard Buchanan (1992), design problems are *indeterminate,* as opposed to determinate, and *"[...] the designer must discover or invent a particular subject out of the problems and issues of specific circumstances"* (Buchanan, 1992, pp. 15–16). This implies that designers are not focusing only on discovering, uncovering, or explaining the indeterminate phenomenon, but also emphasizing the creation and transformation of the situation by providing suggestions for alternative possibilities. The process of transforming an indeterminate problem is defined by John Dewey (1938) as an *inquiry* that is "*the controlled or directed transformation of an indeterminate situation into one that is so determinate in its constituents, distinctions and relations so to convert the elements of the original situation into a unified whole*" (Dewey, 1938a, pp. 104–105). The process of inquiry is engaged by designers who transform the indeterminate situation into knowledge and a set of beliefs to be acted upon. Inquiry is a central term in *pragmatism* with its emphasis on practice. The pragmatic assumptions center around perceiving the world and its capacities through practice and knowledge is produced through practice-oriented actions (Brinkmann & Tanggaard, 2010, p. 245). Based on this, a pragmatic approach within the field of design is a good match because inquiry is about transforming the indeterminate situation that is closely linked with practice into a determinate, unified whole.

In opposition to a pragmatic approach, design can also be viewed from the perspective of *positivism* with a focus on solving problems by applying general methods and principles in a systematic approach. Donald Schön (1983; 1988) compares design from 1) a positivistic point of view referred to as *technical rationality* with 2) the pragmatic approach which is referred to as *reflection-in-action*. In Figure 3, we have compared the two different approaches to design.

DESIGN PERSPECTIVES		
	TECHINCAL RATIONALITY	REFLECTION-IN-ACTION
Philosophy of science	**Positivism**	**Pragmatism**
Problem focus	**Problem solving** Focus on the solution based on causality	**Problem setting** Oriented towards the problem to understand and analyze the problem
Design Approach	**To make the right design** Universal solution	**To design the things right** Focus on what the right things are
Metodology	**General principles** to handle **specific problems.** Systematic, stable methods	**Complex, unstable, unique situations** including **opposite values.** Independent of established methods
Practice	**No specific focus on practice**	**Reflection in practice**

Figure 3: Technical rationality vs Reflection-in-action
(Schön, 1983, pp. 30–69, 1988, pp. 60–75)

Schön (1983) criticizes technical rationality with its positivist approach of objectivity, causality, systematic methods, and knowledge to solve a problem with a universal solution. With problem-solving, through assessing the available means to select the best-suited ends, there is a lack of *problem setting*. Problem setting is a process of defining *"[...] the decision to be made, the ends to be achieved, the means which may be chosen"* (Schön, 1983, p. 40). As opposed to technical rationality with r*eflection-in-action*, the researcher is situated in the context of practice, independent of established theories, techniques, and methods in the construction of a unique case. In opposition to the positivist approach, the designer's inquiry is not limited to causality of the deliberation of means depending on prior established ends because the means and ends are defined interactively in the process of problem setting which is referred to as *naming* and *framing* a problematic situation (Schön, 1988, p. 76). Naming is about defining the problem(s) that will be attended whereas framing is about framing the context in which the designer will attend the problem (Schön, 1983, p. 40). Designing with a pragmatic approach implies an openness to the various problem settings which can be tied to *divergent thinking* which is about being open to the problematic situation, and searching for alternative problem settings and solutions (Schön, 1983, p. 45).

Erik Stolterman (2008) reviewed different ways of defining the fundamental understandings of design. Stolterman concludes that there can be differences between the understandings of design but they all share a *designerly approach* in which design has to be treated as an intellectual human activity. Design deals with the particular and richness of reality in a process to create and form new realities in which design is concrete and situated in practice (Stolterman, 2008, pp. 60–61) which varies from the positivist, scientific approach. Moreover, it is not considered helpful to use predefined tools and methods when encountering a problematic situation in a design process. It is important that the design tools, methods, and techniques can support designers to incorporate them into their own approach in the practice of design. This means that designers can incorporate and adapt to the situation by assessing the suitable kind of tools, methods, and techniques in any specific context (Stolterman, 2008, pp. 60–61). How designers decide on their approach will be further reviewed in § 2.2.2.

HCI

The term, *Human-Computer Interaction* (HCI), origins back to the 1980s and has a relatively short history compared to other more established scientific disciplines. The widespread of personal computers in people's everyday life have required the practitioners within the discipline to focus on various individuals' experiences, values, interactions, and activities in relation to the computer (Bardzell & Bardzell, 2016, p. 22; Dix et al., 2004b, p. 3; Grudin, 1990, pp. 261–262). HCI encompasses many disciplines such as computer science, cognitive science, system design, and human factors engineering (Carroll, 2014; Dix et al., 2004b, p. 4). According to Alan Dix (2018),

> *"Human-Computer Interaction (HCI) is the study of the way in which computer technology influences human work and activities. [...] HCI has an associated design discipline [...] focused on how to design computer technology so that it is as easy and pleasant to use as possible"* (Dix, 2018, p. 1734).

Accordingly, John Caroll & Mary Beth Rosson (2003) describe HCI as "*[...] concerned with understanding how people make use of devices and systems that incorporate or embed* *computation, and how such devices and systems can be more useful and more usable*" (Carroll & Rosson, 2003, p. 431). In the present context, *computer technology* has to be understood more broadly because the scope of research on HCI is expanded. HCI also encompasses various smart devices such as smartphones and tablets (Dix, 2018, p. 1734; Schleicher et al., 2014, p. 339). Additionally, the scope of HCI also includes new technologies such as AI (Hartikainen et al., 2022, p. 1; Lew & Schumacher, 2020a, p. 115; Shneiderman, 2020a, p. 2; Windl et al., 2022, p. 2) which will be presented in § 2.4. Based on the definitions (Dix, 2018, p. 1734; Carroll & Rosson, 2003, p. 431), HCI can be viewed as an academic discipline with studies on activities related to how computer technology impacts people and how it works. On the other hand, HCI can be viewed as the discipline of applied design with a focus on how interventions can be created with technology to make a meaningful difference for individuals using computer technology (Carroll, 2014; Dix, 2018, p. 1735). The associated design disciplines of HCI can be referred to the different design approaches such as *User-Centered Design (UCD)* and *Human-Centered Design (HCD)* with a focus on designing computer technology with the user/the human in the center (Dix, 2018, p. 1734).

User-Centered Design and Human-Centered Design

There has been a paradigm shift from an early focus on the products' technological possibilities to a greater focus on designing for purpose and the users' needs (Bardzell & Bardzell, 2015, p. 80; Gasson, 2003, pp. 29–30; Tosi, 2020, p. 47). The emphasis of design practices on a system's usability, and requirements has changed to focus more on the emotions and experiences of the users during an interaction with the system (Gasson, 2003, p. 30; Tosi, 2020, p. 49). Here, the pragmatic approach to design bodes well, as the user's practices are emphasized and assessed through problem setting. In connection with the emphasis on users, the design philosophies of UCD and HCD both share similarities. UCD is a design philosophy that places the user at the center in all phases of an *iterative* design process. Users are involved throughout the design process to ensure that their needs and expectations are met (Gondomar & Mor, 2020, p. 108; ISO 9241-210:2019, 2019). An iterative design process refers to a process of continuous refinement through trial and error to improve the design in various stages of the design (Goodman et al., 2012a, p. 30). By *International Organization for*

Standardization (*ISO*), HCD is defined as an *"approach to systems design and development that aims to make interactive systems more usable by focusing on the use of the system and applying human factors/ergonomics and usability knowledge and techniques"* (ISO 9241-210:2019, 2019). HCD derives from UCD and their shared emphasis on putting the user at the center of the design process causes practitioners to use the terms interchangeably and synonymously in practice. However, the HCD approach goes beyond only addressing the user with an explicit emphasis on a human approach by including all related stakeholders to consider the impact of the design (ISO 9241-210:2019, 2019; Norman, 2005, p. 16). Based on this, an HCD approach encompasses the aim of UCD but goes beyond creating functional requirements and user needs by emphasizing the entire human experience with social, cultural, and environmental factors.

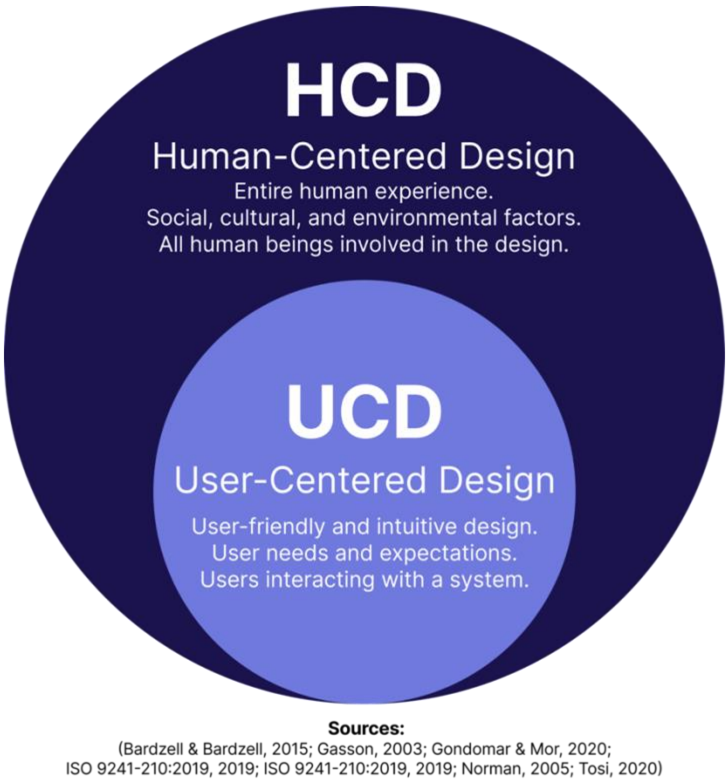


Figure 4: User-Centered Design and Human-Centered Design

The comprehensive HCD approach aligns with human values and emotions in a holistic approach to design. In this thesis, we will use the terms *user* and *human* interchangeably about people who interact with a system (Figure 4).

Usability

Usability is a central term within HCI, and Don Norman (2013) defines usability based on the *ease of use* and *learnability* of a human-made object (Norman, 2013, p. 117). Additionally, the ISO definition of usability includes how individuals, in a specified context of use, can achieve a goal by using a system, product, or service in regard to *effectiveness*, *efficiency,* and *satisfaction* (ISO 9241-11:2018, 2018). Usability is used for evaluating systems which makes the design of user interfaces more practical and tractable while the evaluation brings actionable results for UX practitioners. On the contrary, usability can also be considered insufficient if used too early at the start of a design process where the user interface is underdeveloped (Greenberg & Buxton, 2008, p. 118). Moreover, usability can be evaluated in a situation that is constructed which might not reflect a real scenario or work practice. Usability was especially popular during the 1990s and 2000s but based on the pitfalls, the field of HCI started to include an emphasis on the users and their *experience* and *interactions* with a system which is emphasized with the term *satisfaction* in the definition of usability (Bardzell & Bardzell, 2015, p. 80; Kuutti, 2009, pp. 56–57).

User Experience, User Interface, and Interaction Design

HCI in relation to design can be considered as the forerunner to the terms *user experience design, user interface design,* and *interaction design*. Rather than just focusing on the functionality of systems through usability evaluations, there is a greater emphasis on designing experiences for users interacting with the system in user experience design (Bardzell & Bardzell, 2015, p. 80).

UX, UI, AND INTERACTION DESIGN		
	EXPLANATION	**FOCUS**
User Experience design (UX)	"user's perceptions and responses that result from the use and/or anticipated use of a system, product or service" (ISO 9241-11:2018, 2018).	Focus on the **experience** and **relationship with the system** prior, during, and after using the system (Roto et al., 2011, p. 8).
	"The user experience is the totality of end-users' perceptions as they interact with a product or service. These perceptions include effectiveness (how good is the result?), efficiency (how fast or cheap is it?), emotional satisfaction (how good does it feel?), and the quality of the relationship with the entity that created the product or service (what expectations does it create for subsequent interactions?)" (Kuniavsky, 2010, p. 14).	Focus on the **full experience** and **perceptions of the system's effectiveness** and **efficiency** including the **user's emotional satisfaction** and relation to the product's creator(s).
User Interface design (UI)	User interface (UI) design is the process in which designers creates user interfaces of a system being graphical-, vocal-, and/or gesture-based (Patterson & Erturk, 2015, p. 2).	Focus on the **overall look**, **style**, and **interactivity of the system.** Oftentimes with focus on an **aesthetically experience** (Patterson & Erturk, 2015, p. 2).
	UI can be defined as "[...] the means by which users interact with content to accomplish some goal" (Blair-Early & Zender, 2008, p. 89).	The user's interaction with the system has **a purpose** which is **related to usability** and **user needs** with use of the term **goal**.
Interaction design	"designing interactive products to support people in their everyday and working lives. In particular, it is about creating user experiences that enhance and extend the way people work, communicate and interact" (Preece et al., 2002a, p. 6).	Emphasis on **supporting the user's interaction** with the system, including creation of a user experience, which makes the definition rather broad (Preece et al., 2002a, p. 6).
	Interaction design requires "[...] knowledge of technological possibilities of the platforms and systems in play, skilled aesthetic judgment, and empirically informed empathy with potential users" (Goodman et al., 2011, p. 1061).	Focus on the **technological possibilities**, **visual style**, look, and an **empirical understanding of users.**

Table 5: UX, UI, and Interaction design

Defining User Experience (UX) can be a difficult task since it can refer to almost everything in the user's interaction with the system (Bardzell & Bardzell, 2015, p. 81). UX is one of the focal points for UCD/HCD approaches, and the terms *perceptions,* and *responses* from the ISO 9241-11 definition of UX (see Table 5), refer to the users' experience as *"[...] emotions, beliefs, preferences, perceptions, comfort, behaviours, and accomplishments that occur before, during and after use"* (ISO 9241-11:2018, 2018). The ISO 9241-11 definition of UX emphasizes the interaction with an explicit mention of an interactive system, product, or service, whereas Kuniavsky's (2010) UX definition focuses more on human experience with technology (see Table 5). In Kuniavsky's definition of UX, there is an emphasis on transcending the different aspects of ergonomic, attitudinal, and visual metrics to design an experience related to what the user considers as relevant to an experience. The focus of the designer comes down to understanding what role the system plays in the life of the user based on how the design of the system is perceived (Kuniavsky, 2010, p. 14).

UI is about the overall look, style, and interactivity of a system with an emphasis on aesthetics and accomplishing tasks (Patterson & Erturk, 2015, p. 2). UI design and UX design might be used interchangeably in practice for the sake of simplicity but the difference is the focus of the design. UX can be considered an *umbrella term* (see Figure 5) because it covers a wider range of aspects in designing a user's experience that goes beyond the design of a UI and interaction design (Saffer, 2010, p. 21).

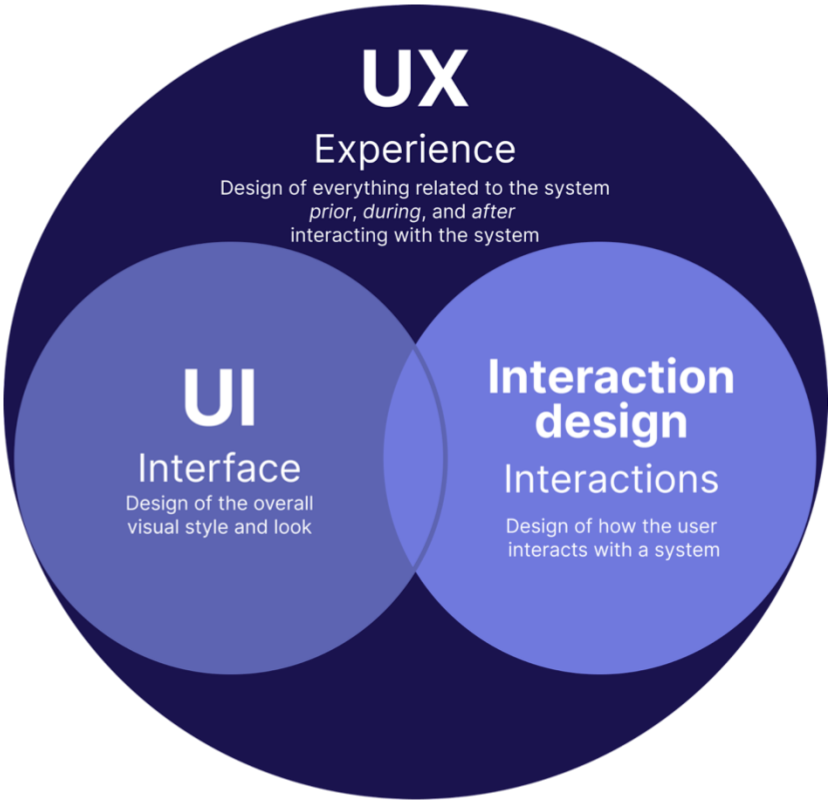


Figure 5: UX as an umbrella term

UX includes all aspects of a system in a higher level of design, whereas UI can be considered an element of UX because the UI plays a vital role in the user experience related to emotional satisfaction (Patterson & Erturk, 2015, p. 2). Like UI design, interaction design can be viewed as a component within the umbrella term UX design with its focus on the user's interaction with the system. With interaction design, as defined by Preece et al. (2002) (see Table 5), there is a clear emphasis on supporting the user's interaction with the system, including the creation of a user experience, which makes the definition rather broad (Preece et al., 2002a, p. 6). Based on Goodman et al.'s (2011) definition in Table 5, interaction design includes multiple facets: technological abilities, visual style and look, and an understanding of users on a deeper level which is a vital part of UX. The scope of interaction design is related to the HCD approach with its inclusion of the empirical foundation of empathizing with potential users of the system.

In this thesis, we will use the umbrella term UX to encompass all activities related to the design of information technology with a HCD approach including interaction design and UI design. Throughout, we will clearly refer to the various terms for a specification if needed.

2.2.2 UX practitioners and their activities

The field of UX spans various roles and job titles. A non-academic research (survey, N=693) done by the Nielsen Norman Group (Rosala & Krause, 2019) on *UX practitioners (UXPs),* reveals that their 693 respondents shared 134 unique job titles related to UX. Respondents were sampled based on their activities relating to the field of UX. The distribution of roles related to the UX-landscape was categorized into the following four groups: 1) *Designers,* 2) *Researchers,* 3) *Non Specialized UX* (eg. consultants), and 4) *Content specialists.* The most common prefix in the job titles is UX, and other prefixes were also popular such as product, digital, UI, human factors, and usability (Rosala & Krause, 2019, pp. 16–19). In this stage of the thesis, the term *UX practitioner* (see Figure 6) will refer to all four categories unless stated specifically later in the project.

Overall, UX practices can be divided into four categories: 1. *Research* (user data collection to inform the design), 2. *Interaction design* (focus on interactions and information architecture), 3. *Creative design* (emphasis on content and aesthetics), and 4. *Front-end development* (coding the actual system) (Patterson & Erturk, 2015, pp. 2–3). In the thesis, we will focus on UX practices related to *UX Research*, while interaction design and creative design will be referred to as *UX Design*. For the remainder of the thesis, we will exclude Front-End Development in our understanding of UX practices but bear in mind the importance of the collaboration between members of a software development team which also includes stakeholders such as programmers. Figure 6 visualizes the division of UX practices in relation to UXPs:

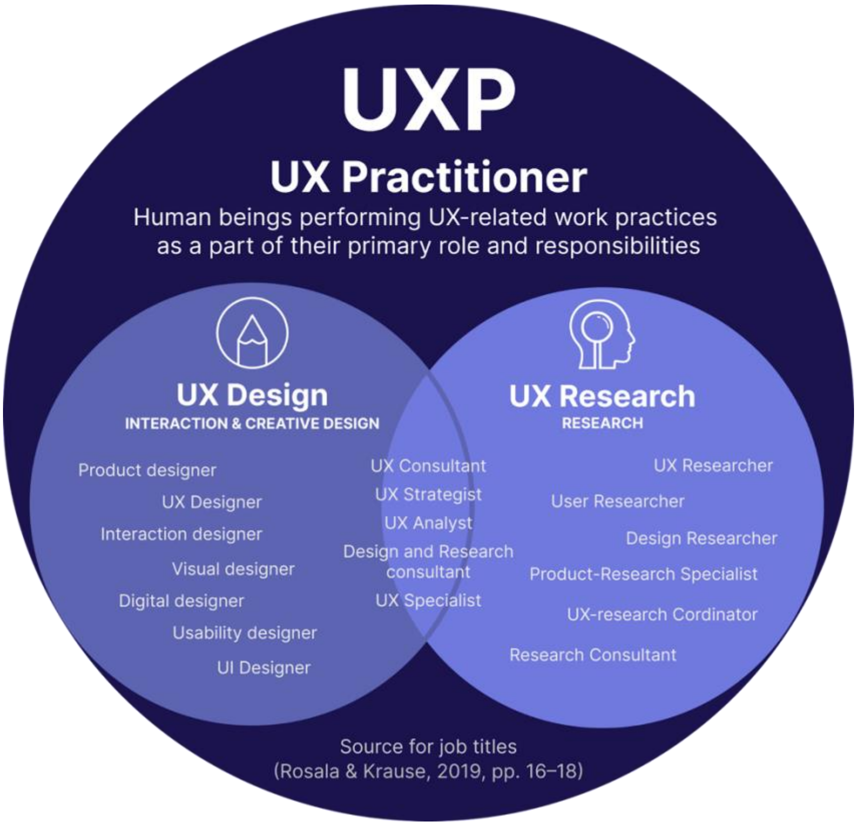


Figure 6: Visualization of UXPs in relation to UX practices and job titles

UX Research

UX researchers perform activities such as *interviews, surveys, user tests, field studies,* and *card sorting* but as stated earlier, work practices can overlap to also include design related activities such as *writing user stories* (Rosala & Krause, 2019, p. 25). Martinelli et al. (2022) present six groups of UX research practices based on a systematic literature review: 1) *Research planning*, 2) *Collecting data with users*, 3) *Data analysis,* 4)

Design with research, 5) *Information organization and communication about users,* and 6) *Research training* (Martinelli et al., 2022, p. 5).

Research planning is about making a strategy for user research, eg. defining research objectives, defining roles and responsibilities within the team, and identifying the market and users, including recruitment strategies (Martinelli et al., 2022, p. 5). *Collecting data with users* relates to generating data through methods such as *surveys, focus groups, interviews, card sorting, user evaluations*, and *user tests* (Gray, 2016, p. 4049; Martinelli et al., 2022, p. 5). The collected data is processed through data analysis in which user data qualitatively and/or quantitatively are analyzed to discover important information and generate valuable insights with the aim of supporting the decision-making (Martinelli et al., 2022, p. 5) such as evaluating the usability of low-to-high fidelity prototypes/products, and defining personas (Gray, 2016, p. 4048). Furthermore, user research calls for an emotional connection by listening and *empathizing* with the users which includes relating to the user(s) in a situational context to understand why certain aspects and experiences are more meaningful than others (Köppen & Meinel, 2015, p. 18; Kouprie & Visser, 2009, p. 438).

Information organization and communication about users refers to activities of sharing knowledge about the user research and design within the software development team and related stakeholders to bring teams, users, and features closer together (Martinelli et al., 2022, p. 5) which is also referred to as *representation* (Gray, 2016, p. 4049). *Research training* is about educating and maintaining UX research skills eminent to solidify a culture of including users for research and evaluation (Martinelli et al., 2022, p. 5). To adopt UX approaches in a system development team, there has to be a certain amount of communication and leadership to enforce the culture of UX competencies between the individuals and groups in the team. Meanwhile, UX practices must also be promoted to stakeholders and management to adopt the flow of UX competencies (Gray, 2016, p. 4048; Gray et al., 2015, p. 3293). Activities in *design with research* focus on generating initial design proposals and/or developing prototypes that support user research actions, such as sketching and user participation (Martinelli et al., 2022, p. 5) which is closely related to the focus of UX design.

UX Design

Activities for UX Designers tend to rely on designing *wireframes, sketching, prototypes, user journeys, UI design, design systems,* and *style guides* but UX Designers can also carry out qualitative usability tests and other UX research-related activities (Rosala & Krause, 2019, p. 25). According to Stolterman (2008), UX designers are inclined to apply precise and simple techniques and/or tools when deemed necessary in the design process. The applied design framework must be iterative and support reflective decision-making without prescribing and forcing certain methods to be applied (Stolterman, 2008, p. 63). A synthesis of the existing UX Design frameworks will be presented in § 2.2.2 Design approaches and frameworks. UXPs are inclined to use divergent thinking in the design process with an intriguing, reflecting, and interpreting mind related to how the methods, tools, techniques, and concepts can be applied (Schön, 1983, p. 45; Stolterman, 2008, p. 63). Finally, the design process has to be supported by philosophical and theoretical ideas on a higher level, such as reflective practice, HCD, and a focus on UX to avoid prescribing methods and outcomes (Stolterman, 2008, p. 63). These insights on UXPs are in line with the pragmatic approach to design with a focus on users and their practices in an open, iterative approach without prescribing methods, techniques, or tools.

How UXPs decide on methods, tools, and techniques

The purpose of the following section is to understand UXPs' rationale for picking their available methods, tools, and techniques. The design process can be quite complex in which numerous activities and challenges have to be addressed with a virtually infinite range of different tools, methods, and techniques (Stolterman & Pierce, 2012, p. 126). These can be referred to as a large collection of *designerly tools* that are traditionally useful by designers, clearly defined, and with a precise purpose to be applied by designers without removing the freedom from the designer to navigate. Designerly tools aim at supporting and scaffolding design activities that are adopted and valued by UXPs (Gray, 2016, p. 4046; Stolterman, 2008, p. 56; Stolterman et al., 2009, p. 1). Designers often draw upon different designerly tools from various fields related to interaction design which makes designers more open to new methods (Stolterman & Pierce, 2012, p. 126). Overall, designerly tools can be categorized into four main categories: 1) *Physical,* eg. pen, paper, and whiteboard; 2) *Software,* eg. websites, and digital software; 3) *Theoretical,* eg. heuristics, mind map, and usability; 4) *Others*, eg. team communication, memory (Stolterman et al., 2009, p. 8). Generally, designerly tools can support the designer in *thinking,* such as brainstorming on a whiteboard, and/or support a design *outcome,* such as sketching a UI in a software tool. However, the reality seems more complex, for instance, sketching doesn't only supply an outcome because it also supports the designers' thinking in a creative process (Stolterman et al., 2009, pp. 9–10).

When UXPs decide on designerly tools for a specific situation in the design process, it can be described through the *Tools-In-Use-Model* as presented by Stolterman et al. (2009). The model describes the dynamic and reciprocal relationships between the concepts of *purpose, activities,* and *tools* in the design process. The decision of a tool is based on a linear understanding of first defining the purpose of a given action, followed by the appropriate activity as perceived by the designer in relation to the purpose. Finally, the designer will pick a tool based on the former purpose and activity (Stolterman et al., 2009, p. 5). The rationale for choosing a tool can also rely on making the *process faster and/or more efficient*; the *tool's ease of use*; *the freedom and flexibility of the tool*; *the tool's availability and accessibility*; and *how it supports an individual vs a team approach* (Stolterman & Pierce, 2012, p. 27). But the reality can be more complex, and findings show that UXPs don't necessarily follow the tools-in-use model or rationale for choosing a tool due to their experience, lack of resources, time constraints, habits, familiarity with certain tools, and external pressure from the organization which sees them diverge from what can be perceived as the correct way of doing things in theory (Stolterman et al., 2009, p. 10; Stolterman & Pierce, 2012, p. 27). To decide on a tool primarily based on how fast and efficient it is, is not always considered the optimal approach due to many of these tools having a prescriptive nature which lacks the ability to explore the design thoroughly (Stolterman & Pierce, 2012, p. 27) and emphasizes the problem solving over problem setting. A study also shows that designers choose tools based on branding and their professional identity to solidify their identification within a particular design community to gain respect or status (Stolterman & Pierce, 2012, p. 28). Furthermore, UXPs use tools diversely and creatively without necessarily performing the standard way of utilizing a certain tool and method. This gives an indication of UXPs as deciding on their tools and approach based on the situation which is grounded in an overall judgment based on the perceived benefits of using a specific approach (Stolterman et al., 2009, p. 7; Stolterman & Pierce, 2012, p. 27). This is closely related to design as a pragmatic, rational, and situational process where designerly tools are picked based on how to reach the purpose without following a prescribed design approach (Gray, 2016, p. 4051). Moreover, introducing new methods based on HCI research can be problematic due to the theoretical complexity and not accommodating the practical limitations of UXPs in terms of time, budget, and resources (Stolterman, 2008, p. 55).

Design approaches and frameworks

Preece et al. (2002) identify four basic activities of design 1) *Identifying user needs and establishing requirements*, 2) *Developing alternative designs to meet the needs requirements*, 3) *Building interactive versions*, and 4) *Evaluating the interactive system* (Preece et al., 2002b, p. 168). Additionally, in a systematic review of design process models, Howard et al. (2008) present six general stages in a design process: 1. *Establishing needs,* 2. *Analysis of task,* 3. *Conceptual design,* 4. *Embodiment design,* 5. *Detailed design,* and 6. *Implementation* (Howard et al., 2008, p. 163) that are also identified in design process models for organizations working with system development (Iversen et al., 2018, p. 3068). The role of a design process model is to guide the design process and communicate the design rationale to multiple members of the team as well as external stakeholders (Iversen et al., 2018, p. 3065).

According to Dix et al. (2004), design is not only about the system but also about understanding and choosing how the system will affect the work practices of the involved stakeholders (Dix et al., 2004a, p. 192) which is related to an HCD approach. According to Preece et al. (2002), design activities are often generic and reside in other design disciplines too (Preece et al., 2002b, p. 168). Throughout our research on design processes, we have identified multiple design frameworks which present different phases of a UX research and design process. Each framework describes an approach to design and their primary goal is to guide the design process. We synthesized the design process models and frameworks (see Appendix 3 for review) that were found during our research process into Figure 7:

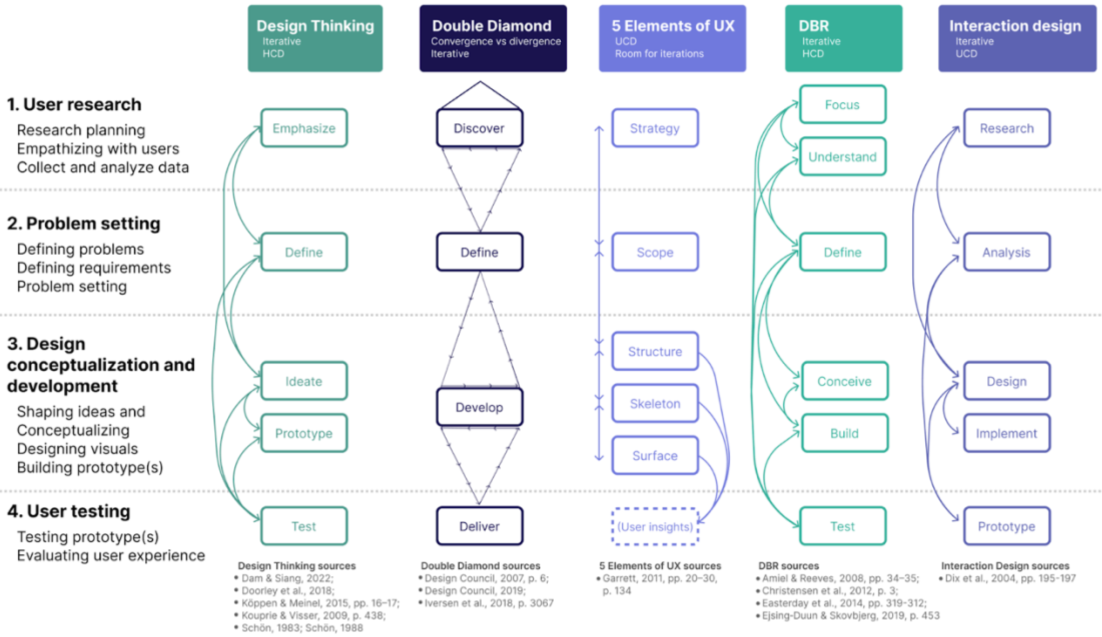


Figure 7: Comparing design frameworks

(see Appendix 3 for a review of design approaches and frameworks)

Based on our review of the shared similarities of design frameworks, we categorized four main phases of designing information technology: 1) *User research*; 2) *Problem setting*; 3) *Design conceptualization and development*; and 4) *User testing*. All UX design frameworks in Figure 7 acknowledge an iterative approach. Especially the frameworks of Design Thinking, UCD, Design-Based Research (DBR), and Interaction Design emphasize a non-linear approach to design providing room for problem setting and solving. Reviewing the different design frameworks helps us understand the general principles of UX design and research which can be used as a reference to where AI is, or might be, applied in relation to the UXPs' work activities.

Designers are facing wicked problems in complex contexts of various intertwined physical, digital, and biological spheres which can be referred to as the fourth industrial age: "[...] *the emergence and fusion of new forms of automation, nanotechnology, robotics and biotechnology, which together are disrupting whole industries along with the nature and scope of design work*" (Steane et al., 2020, p. 86). The new technology, including AI, might impact established UXP's practice, role, and identity which results in a need for evolving the design skills in which new opportunities for better design and research might emerge (Steane et al., 2020, p. 86). Furthermore, AI brings a lot of new context to user experience and it is suggested that the UXP should determine the intentionality when designing information technologies that incorporate AI (Kore, 2022a, p. 109). To understand AI's impact on designing information technology (see § 2.4), we need to understand what AI is in general which will be the subject of review in § 2.3.

2.3 Understanding Artificial Intelligence

The field of AI is broad and has been influenced by various fields, including computer science, linguistics, cybernetics, psychology, economics, philosophy, mathematics, and similar fields, etc. (Kore, 2022b, pp. 12–13). In the following section, we will start outlining the definition of intelligence and what consequence it has on the definition of AI, then continue with characterizing AI as *general*, *broad*, or *narrow AI*. Furthermore, we will present what an AI system is, what generative AI is, and how exponential the progress in AI is. By doing this, we seek to answer RQ1.

2.3.1 Defining AI

AI as a research discipline was coined at *Dartmouth College* when a small group of scientists gathered for the *Research Project on Artificial Intelligence* in 1956 (Moor, 2006). Throughout the literature review process, we found out there is no standard definition of AI. However, it can be useful to consider AI as *"[...] a computer program that takes a dataset as input and applies one of a wide variety of algorithms to compute correlations and relationships in that data"* (Agarwal & Regalado, 2020). Due to the absence of a common AI definition and taxonomy, there are appearing tendencies to demand a process for establishing its operational definition on the political level (AI HLEG, 2019b; Samoili et al., 2020). The aim is to avoid misunderstanding and increase shared common knowledge which is essential for fruitful discussion on topics such as AI policies, and AI ethics guidelines (AI HLEG, 2019b, p. 1). In Table 6, we provide an overview of definitions of AI with explanation:

AI DEFINITIONS		
	DEFINITION	**EXPLANATION**
Example of Informal definition	*"[...] a computer program that takes a dataset as input and applies one of a wide variety of algorithms to compute correlations and relationships in that data"* (Agarwal & Regalado, 2020).	Lingua Franca: Handbook provides a straightforward definition of AI as a part of the guide to designing human-centered AI (Agarwal & Regalado, 2020).
Operational definition as a part of establishing definition for policymaking process	*"Artificial intelligence (AI) systems are software (and possibly also hardware) systems designed by humans that, given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information, derived from this data and deciding the best action(s) to take to achieve the given goal. AI systems can either use symbolic rules or learn a numeric model, and they can also adapt their behavior by analyzing how the environment is affected by their previous actions"* (Samoili et al., 2020, p. 4).	The authors conducted a qualitative analysis of 55 core documents regarding AI definitions which included: 1) 29 AI policy and institutional documents; 2) 23 research publications; and 3) 3 market reports, published between 1955 and 2019 (Samoili et al., 2020, p. 4). They considered the definition proposed by the High-Level Expert Group on Artificial Intelligence (AI HLEG), an independent expert group established by the European Commission, as the most suitable to work on, because it integrates aspects of perception, interpretation, adaptation to behavior, understanding, and decision-making (Samoili et al., 2020, p. 4).

Table 6: Overview of AI definition (Agarwal & Regalado, 2020; Samoili et al., 2020)

Determining the nature of *intelligence* is central when defining AI (Legg & Hutter, 2007; Schank, 1980; van der Maas et al., 2021). However, the difficulties in defining and measuring intelligence led to interpretational issues inherited by AI (Kore, 2022b; Lew & Schumacher, 2020a; Samoili et al., 2020). Originally, the phrase *artificial intelligence* was used for the first time in 1955 in a proposal for a summer research project to discuss the specific aspects of the artificial intelligence problem. In the proposal, it was stated that computers can be made to perform intelligent tasks based on the surmise that "*[...] Every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it*" (McCarthy et al., 1955, p. 2).

As a result, different AI researchers studied the question of when a system is considered intelligent (Schank, 1980; Legg & Hutter, 2007; Russel & Norvig, 2010; Van der Masset al., 2021). While Schank concluded that intelligence is all about making generalizations from totally new situations for future needs, which was a weakness of AI at that time (Schank, 1980, p. 12), Legg & Hutter (2007) proposed an informal working definition of intelligence as measuring *“[...] an agent’s ability to achieve goals in a wide range of environments”* (Legg & Hutter, 2007, p. 9). This definition follows Schank’s broader perception of intelligence, as the goal is not just simply to perform a task well but to adapt and learn how to cope with various situations, problems, and environments. And as they point out, similarly to Schank, this flexibility presents the key characteristic and difference between humans and many AI systems (Legg & Hutter, 2007, p. 17). Van der Masset al. (2021) confirmed Schank’s observation that intelligence is about generalization which is still a weakness of AI systems. Yet, the new techniques in AI, e.g. transfer learning, cause a significant difference between the older AI systems and the current ones. The main difference is that the modern AI system can learn through *deep learning* and *reinforcement learning* which are the key techniques used in AI. They believe that progress achieved in the field of AI will enforce a redefinition of intelligence and how to measure it (van der Maas et al., 2021, pp. 5–7). In reflection on Legg & Hutter's definition of AI, van der Maas et al. (2021) also admitted that while AI is capable of solving problems and achieving goals, it is not as successful when confronted with completely new situations for which it has not been prepared and trained (van der Maas et al., 2021, p. 5).

When defining AI based on ability, researchers differ between the terms *general AI, broad AI,* and *narrow AI* (Goertzel & Wang, 2007; Hochreiter, 2022; Kore, 2022b). Goertzel & Wang (2007) described *Artificial General Intelligence (AGI)* as a term adopted to refer to the specific research field. The AGI emphasizes *“[...] the “general” nature of desired capabilities of the systems [...] aims at “intelligence as a whole”* (Goertzel & Wang, 2007, p. 1). The result of such a scope is that desired AGI systems are meant to be similar to the capabilities of the human mind which is a vision shared with the first generation of AI researchers (Goertzel & Wang, 2007, pp. 2–3). As a way to address and overcome the current challenges and limitations of deep learning, Hochreiter (2022) defines a new layer of AI - *broad AI*. *”A broad AI is a sophisticated* *and adaptive system, which successfully performs any cognitive task by virtue of its sensory perception, previous experience, and learned skills"* (Hochreiter, 2022, p. 56).

However, most of the current AI systems belong to *narrow AI*, such as *speech-to-text*, *machine translation*, *object detection*, *face recognition*, and *web search* (Kore, 2022b, p. 19). Narrow AI refers to the development of AI products that are specialized to perform specific tasks extremely well, such as *translation*, *search*, *detection*, and *recognition* (Kore, 2022b, p. 18). The distinction between broad and narrow AI is due to the properties broad AI possesses, for instance, *knowledge transfer and interaction*, *adaptability and robustness*, *abstraction and reasoning*, and *efficiency* (Hochreiter, 2022, p. 56).

AI can be classified into five main subdomains, including 1) *Machine Learning (ML);* 2) *Natural Language Processing (NLP)*; 3) *Computer Vision (CV);* 4) *Artificial Neural Networks (ANN);* and 5) *AI robotics* (Williams et al., 2021), see Figure 8. But based on the emphasis on GenAI in our thesis, we will only focus on ML, NLP, and ANN.

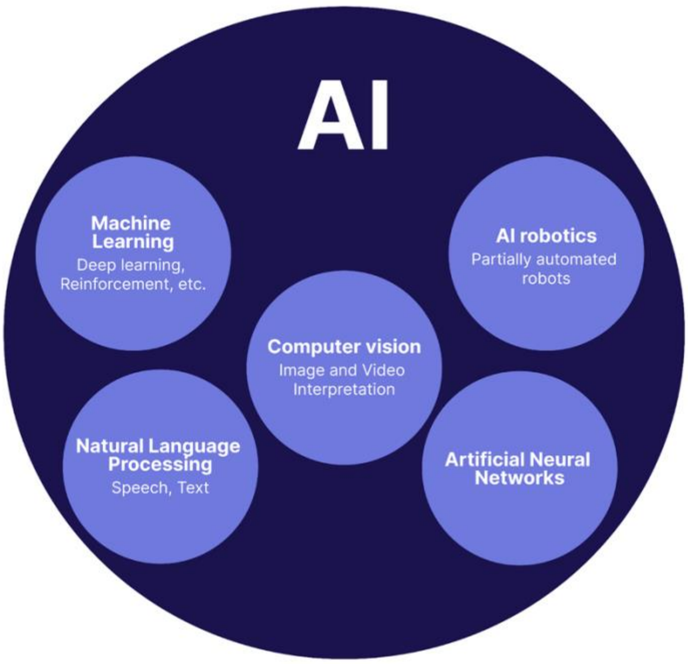


Figure 8: Simplified view of AI sub-domains (Williams et al., 2021, p. 2)

AI system

Literature provides different perspectives on AI systems depending on how much AI's capabilities are part of the product/service. Table 7 shows the variety of viewpoints on AI systems:

DEFINITION OF AI SYSTEMS		
	VIEWPOINT	**FOCUS**
Umbrella Term: AI system	An AI system refers to a deployable software system driven by data, incorporating one or more ML models, and is equipped with a user interface for input collection and output presentation. Its purpose is to support end-users in specific task execution (Deshpande & Sharp, 2022, p. 228).	As AI encompasses a range of technologies beyond ML, the AI system serves as an umbrella term (Deshpande & Sharp, 2022, p. 228).
Operational definition of AI incorporating specification of AI systems	"Artificial intelligence (AI) systems are software (and possibly also hardware) systems designed by humans that, given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information, derived from this data and deciding the best action(s) to take to achieve the given goal. AI systems can either use symbolic rules or learn a numeric model, and they can also adapt their behavior by analyzing how the environment is affected by their previous actions" (Samoili et al., 2020, p. 4).	The authors operationalize the definition of AI and AI systems by using a concrete taxonomy and keywords characterizing the subdomains of AI (Samoili et al., 2020 p. 6). The current AI systems are goal-directed in which the goal, and the way how to achieve it, are specified by a human being (AI HLEG, 2019b, p. 7).
AI-enabled systems	AI-enabled systems possess one or more of the capabilities that require intelligence (Rzepka & Berger, 2018, p. 9).	AI-enhanced systems: AI has been applied as a way to improve the system's performance (Rzepka & Berger, 2018, p.1). AI-based system: AI has been applied as a way to develop a new system (Rzepka & Berger, 2018, p.1).
AI-infused systems	AI-infused systems "[...] that have features harnessing AI capabilities that are directly exposed to the end user" (Amershi et al., 2019, p. 1).	Developers are enabled to integrate a variety of AI capabilities into UI (Amershi et al., 2019, p. 1).

Table 7: Definition of AI systems (Rzepka & Berger, 2018; Samoili et al., 2020)

An AI system refers to a *deployable software system driven by data*, incorporating one or more ML models, and is equipped with a user interface for input collection and output presentation. Its purpose is to support end-users in specific task execution. As AI encompasses a range of technologies beyond ML, the *AI system* serves as an umbrella term (Deshpande & Sharp, 2022, p. 228). Usually, an AI system is embedded as a component (software or hardware) in a larger system (AI HLEG, 2019b, p. 2). AI technology has gotten widespread and many products used on a daily basis already contain certain functionality which is enabled by AI (Amershi et al., 2019; de Oliveira Carvalho et al., 2022). AI has been applied either as a way to improve the system's performance or to develop a new system. While the former system is referred to as an AI-enhanced system, the latter is known as an AI-based system, both belonging under the umbrella term *AI-enabled system* (Rzepka & Berger, 2018, p.1). In contrast, Amershi et al. (2019) present a new term *AI-infused* systems "[...] that have features harnessing AI capabilities that are directly exposed to the end user" (Amershi et al., 2019, p. 1). The most extensive definition of AI systems is offered by the operational definition of AI by Samoili et al. (2020) (see Table 7). This definition follows the idea that certain capabilities, such as information processing (collecting and interpreting), decision-making (reasoning, learning), perceiving, and achieving certain goals, require intelligence (Samoili et al., 2020, p. 4). And therefore AI-enabled systems must have at least one of these capabilities to be considered intelligent (Rzepka & Berger, 2018, p. 9). Furthermore, the operational definition underlines that the current AI systems are goal-directed in which the goal, and the way how to achieve it, are specified by a human being. Nevertheless, some AI systems are given more freedom to make a decision on how to achieve a goal (AI HLEG, 2019b, p. 7) which is possible due to the way AI systems are built (Komischke, 2021; Kore, 2022b, p. 21).

In general, there are two kinds of AI-supported activities: 1) *decision-making,* and 2) *artifact creation*. The former was developed with the purpose to make the decision-making process of people more accurate and faster within different domains, while the latter is meant to assist humans in tasks involving artifact creation (Weisz et al., 2022, pp. 3–4). In the following, we will introduce GenAI which supports both decision-making and artifact creation.

Generative AI (GenAI)

The current advances in AI and techniques derive from the development of *artificial neural networks (ANNs)* which is a computational model originally inspired by biological neural networks (van der Maas et al., 2021). The true potential of ANNs was made possible with increased computing power in the 2010s which enabled the creation of much more complex and layered architectures, which we now call *deep learning* (Sevilla et al., 2022; van der Maas et al., 2021, p. 2). While the most suited context of ANNs is in modeling perceptual processes, such as speech and object recognition, ANNs become increasingly integrated into other AI techniques such as *reinforcement learning* and *natural language processing (NLP)* as a preprocessing step in the scale-up process reinforcement learning models. Reinforcement learning techniques excel in learning adaptive behavior and the systems can outperform humans in a specific range of tasks (van der Maas et al., 2021, p. 3). While NLP models focus on machine translation, speech-to-text, AI assistants (eg. Siri), and generating original text and speech (for example GPT-3 model) (van der Maas et al., 2021, p. 2), computer vision models are trained to learn from images and videos and among their capabilities belong ability to detect and recognize faces, object detection, image generation, and visual reasoning (Maslej et al.. 2023, p. 81). When referring to *Generative AI* (GenAI), we refer to AI systems able to generate content/artifacts as an output rather than just analyzing the existing data and generating decisions (J. Sun et al., 2022, p. 212; van der Maas et al., 2021; Weisz et al., 2022). The produced artifacts can differ in terms of variety and complexity (J. Sun et al., 2022). Some create visual output such as images, avatars, or videos, for instance generating photorealistic face images of non-existent people (eg. Fotor) or creating images from text description (eg. DALL-E) (van der Maas et al., 2021, p. 3). Others are text-generative and can generate code, summarize articles, or write articles. OpenAI's *GPT-3 model* is a prime example of GenAI development that is able to create human-like language output across domains. In contrast to the GPT-3 model, GenAI models specify their output for certain domains, e.g. *GitHub CoPilot* assists developers with suggestions for code completion (J. Sun et al., 2022, p. 212). Huan et al. (2022) divided the GenAI landscape into 7 categories and provided examples of model layers (Table 8).

GENERATIVE AI LANDSCAPE	
OUTPUT CATEGORY	GENERATIVE AI MODELS
1. Text	OpenAI ChatGPT-3, DeepMind Gopher, Facebook OPT, Hugging Face Bloom, Cohere, Anthropic, AI2, PaLM
2. Code	OpenAI ChatGPT-3, Tabrine, Stability.ai, AlphaCode, Copilot, CodeGen
3. Image	OpenAI Dall-E 2, Stable Diffusion, Craiyon, Meta Make-A-Scene, Google Images
4. Speech	OpenAI Whisper
5. Video	Microsoft X-CLIP, Meta Make-A-Video
6. 3D	DreamFusion, NVIDIA GET3D, MDM
7. Others	GaTo, CICERO

Table 8: Generative AI Landscape with examples
(Huang et al., 2022; Maslej et al., 2023, pp. 74–80)

From its launch in November 2022 till February, ChatGPT reached 100 million monthly active users, earning the title of the overall fastest-growing consumer application (K. Hu, 2023). Due to its expanding reach, there are already early research studies regarding GenAI and its effects. While some explore the impact of ChatGPT within a specific group of professionals, e.g. within accounting (Alshurafat, 2023) or those engaged in writing tasks (Noy & Zhang, 2023), others explore the potential of GenAI in teaching and education (Fauzi et al., 2023; Kung et al., 2023; M. Alshater, 2022; Peres et al., 2023).

While it is true that GenAI showcases remarkable advancements in question-answering and the generation of text, images, and code that were unimaginable just a decade ago, they are also susceptible to generating false information, exhibiting biases, and can be manipulated to serve malicious purposes that further underlines the demand for the complex ethical considerations involved in their implementation (Maslej et al., 2023, p. 2).

Progress in AI

The advances in computing power in terms of speed and capacity are driving AI development of new techniques and algorithms (van der Maas et al., 2021). To predict progress in AI, specifically in the field of ML, Sevilla et al. (2022) investigated the trends of ML models and their compute demands between 1952 and 2022. Based on their findings, they divided the history of computing in connection to ML into three periods: 1) *Pre- Deep Learning Era,* 2) t*he Deep Learning Era,* and 3) *the Large Scale Era* (Sevilla et al., 2022, p. 1). In Figure 9, it is visible how the first 50 years are characterized by slow growth until around 2010 when the slope changed. Since then the progress has accelerated and not stopped yet (Sevilla et al., 2022, p. 3):

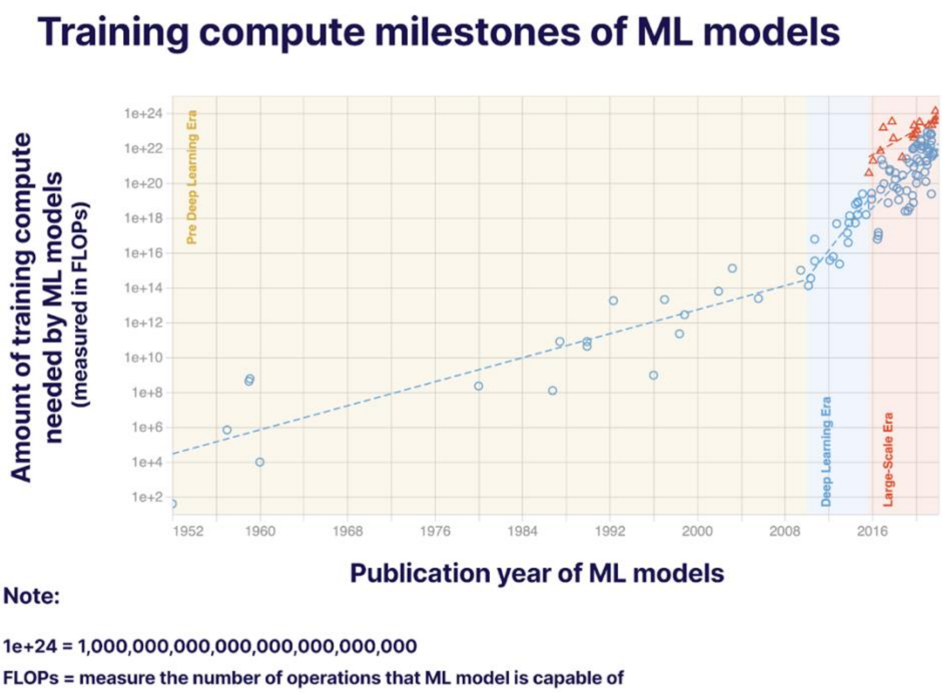


Figure 9: The graph showcasing 121 milestones ML models published between 1952 and 2022. (Sevilla et al., 2022, p. 4) **© 2022 IEEE**

Around 2015-2016, a new trend of large-scale ML models emerged with 10 to 100-fold larger requirements in training compute (Sevilla et al., 2022, p. 1). Figure 10 zooms on how much the training compute each of the large-scale models needs.

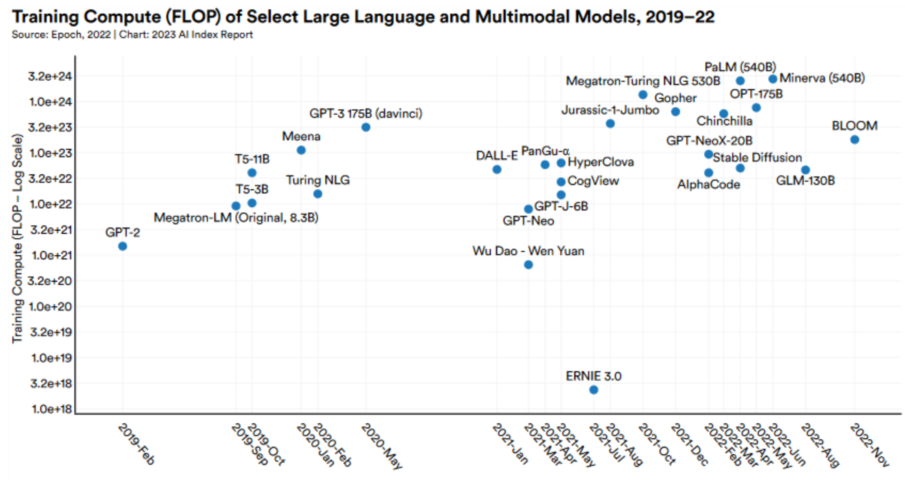


Figure 10: Trends in training compute for selected large-scale models (Maslej et al., 2023, p. 61)

In 2023, the trend of large-scale models is still continuing and is assumed that it will as it is largely carried by the tech giants that have resources and motivation to train them and keep AI hype (Sevilla et al., 2022, p. 5). However, there were already periods of over-optimism when findings and investment into AI significantly declined. These are referred to as *AI winters* that happened in the past, e.g. the 1970s and 1980s. The main reason for AI winters was the collision between overhyped promises about AI capabilities and the disappointments when these promises were under-delivered (Lew & Schumacher, 2020a, p. 29; Wallach et al., 2020, pp. 146–147).

Due to challenges in interpreting and measuring intelligence, a lack of a standardized definition for AI has arisen. However, there is an increased demand among policymakers to create an operationalized definition of AI to enforce the creation of ethical and safe AI systems. In the context of this thesis, the term *AI system* is used to encompass various technologies that can incorporate or leverage the capabilities of AI. Moreover in our thesis, the term *AI* predominantly refers to what is known as GenAI due to the AI systems being generative to support both decision-making and artifact creation. The literature review conducted in this study does not explore the technical aspects of AI and how the computational methods work in detail. Instead, our focus has been to explore what the progress in AI has been that led to existing GenAI. In the thesis, GenAI will be divided into two categories: 1) *text GenAI* where AI generates textual output; and 2) *visual GenAI* where AI generates visual output such as images.

2.3.2 AI Ethics

In this section, we will further explore two polarized perspectives on AI, concerns, and the challenges of the rapid development of AI. Furthermore, we will outline the impact of AI ethics and how *Explainable Artificial Intelligence (XAI)* shifts the focus on improving the current practices in AI. In addition, we will look into the role of trust in AI systems and how trust and trustworthiness can be addressed. In the end, we will map the landscape of initiatives aiming to standardize ethics in the AI sector. The topic of AI Ethics contains a lot of nuances and complexities. The following section aims at presenting the ethical aspects related to our research focus.

AI Ethical concerns and challenges

According to Luusua & Ylipulli (2020), there are two polarized positions on how to look at AI. On one side of the spectrum, there is *the philosophical approach to AI* represented by Boström & Yudkowsky (2014) who perceive AI as a technology that already mimics human intelligence, although it operates only within specific domains currently. Furthermore, they envision that future AI systems can possess superhuman intelligence and abilities due to recent rapid AI development, which puts new demands on ethical aspects of AI (Bostrom & Yudkowsky, 2018, p. 68). They refer to general AI and stress the human vulnerability related to advances in AI capabilities (Bostrom & Yudkowsky, 2018, pp. 58–59).

On the opposite side, there is *the engineering approach to AI*, disagreeing with the claims that AGI is fundamentally dangerous (Luusua & Ylipulli, 2020, p. 1235). Researchers with an engineering approach to AI believe that the claims are made based on misconceptions and misunderstanding about AGI and intelligence in general (Goertzel & Wang, 2007, p. 8). Misconception can be illustrated when the terms AI, machine learning (ML), or robotics are used interchangeably, although there are different AI subdomains (Komischke, 2021; Kore, 2022b; Long & Magerko, 2020).

Despite some researchers highlighting a risk that comes with developing systems that have autonomous decision-making capabilities (Bostrom & Yudkowsky, 2018; Khan et al., 2022), there is an undeniable increased daily usage of AI-enabled products in different contexts (de Oliveira Carvalho et al., 2022, p. 132; Dexe et al., 2020; Tsiakas & Murray-Rust, 2022). However, there has been a rise in the number of reported AI incidents and controversies, e.g. deepfake videos of public figures (Maslej et al., 2023, p. 133) which further underlines the need to ensure that human-AI interaction would be safe (Liao & Sundar, 2022; Meske & Bunde, 2020; Shneiderman, 2020a; Tsiakas & Murray-Rust, 2022). As a result, AI Ethics is raised into prominence and Samoili et al. (2020) even consider AI Ethics as one of the AI subdomains.

When discussing how AI should be used, there are emerging ethical concerns surrounding it such as *privacy, accountability, bias/fairness, misinformation, ethical decision-making, diversity, and transparency* (Khan et al., 2022; Long & Magerko, 2020, pp. 6–7; Maslej et al., 2023; Robert et al., 2020; Shneiderman, 2020a), *human control, explainability, and non-discrimination* (AI HLEG, 2019a; de Oliveira Carvalho et al., 2022, p. 136). According to Turilli & Floridi (2009), *transparency* is not an ethical principle by itself, but just a pro-ethical condition for other principles.

In a systematic review conducted by Khan et al. (2022), they identified 27 primary academic articles addressing AI ethics principles. Only 17 (63%) discussed challenging factors of AI ethics (Khan et al., 2022, p. 389). Among the most commonly cited AI ethical principles were *transparency, privacy, accountability, and fairness* (Khan et al., 2022, p. 383). Regarding the challenges hindering the applicability of ethics in the field of AI, they reported 15 factors and the most cited were *a lack of ethical knowledge* and *vague principles* (Khan et al., 2022, p. 389). In addition to these findings, they propose a maturity model (Figure 11) to assess an organization's ethical capability when developing AI systems (Khan et al., 2022, p. 390).

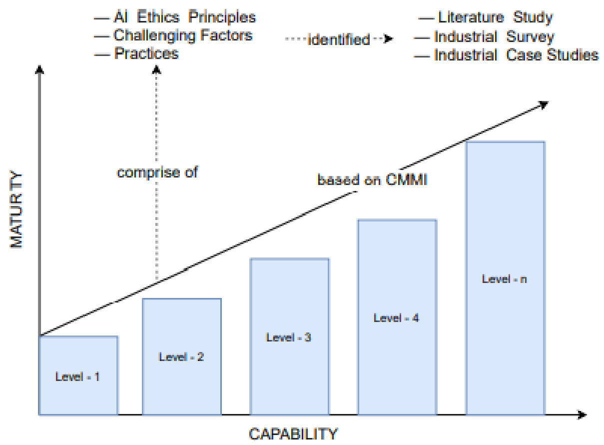


Figure 11: The proposed maturity model of AI ethics (Khan et al., 2022, p. 390)

Black box, biases, fairness, and respect

In connection to AI ethics, it is important to mention the term *black boxes* is a term of interest. It describes situations when it is impossible to understand how the dataset is obtained, what data are missing, and what the underlying rationale is applied to build the algorithm (AI HLEG, 2019a; Lew & Schumacher, 2020a, pp. 72–73; Long & Magerko, 2020; Meske & Bunde, 2020). For instance, Stable Difussion's training datasets consist of images without the creator's consent (Maslej et al., 2023, p. 152). In addition, some algorithms hide crucial assumptions, *"[...] input information, and parameters in their black box models that are not directly observable"* (de Oliveira Carvalho et al., 2022, p. 131). In contrast to the black box, a *responsible AI system* is *"[...] an AI system which enables the use of AI technologies aligned with user expectations and prevalent societal laws, rules, and regulations"* (Deshpande & Sharp, 2022, p. 229).

The issue with datasets used for training AI models is an underrepresentation of certain groups resulting that AI systems' decisions and outcomes are being biased by the attributes, preferences, and usage patterns of the overrepresented user group in the dataset (Sambasivan & Holbrook, 2018). As a consequence, misrepresentation can introduce and strengthen dangerous biases, e.g. recidivism prediction (Seymour et al., 2022, p. 641), biases against female applicants in AI-powered recruitment engines (Robert et al., 2020), or reflecting common social stereotypes in visual GenAI (Maslej et al., 2023, p. 152). It needs to be underlined that the cause of biases relates to humans as also to algorithms. While humans are responsible for the selection of the data and algorithm, algorithms account for their inclination to means and modes when drawing conclusions (Salminen et al., 2020, p. 94). Biases either encoded into AI systems or learned from human behavior lead AI systems to actions or decisions which are unfair (Robert et al., 2020). However, obtaining and curating a dataset that will more accurately and appropriately represent the context is not an easy task (Lew & Schumacher, 2020a; Robert et al., 2020, p. 553; Salminen et al., 2020). The problem with fairness is also a *lack of fairness differentiation (distributive, procedural,* and *interactional)* (Robert et al., 2020, pp. 553–554).

As the concept of fairness in AI is getting more exposure, there is more research on fairness and related respect. For instance, Seymour & Kleek (2022) highlight the importance of asking questions at the beginning of designing the AI system, and they emphasize how people should be dealt with, represented, and classified in the datasets. By doing so, there is a way of challenging the positivist approach in AI (Seymour et al., 2022, p. 650).

Explainable Artificial Intelligence

To avoid black box models, there is a need for a transparent, well-organized, and conducted research setup. The main objective is to avoid training AI algorithms on the dataset which are biased and fundamentally incorrect. That can be achieved by having control over the sample from which the dataset is created (Lew & Schumacher, 2020a, pp. 134–136). Furthermore, people have difficulties understanding and evaluating algorithms, therefore, the accountability of algorithms needs to explain algorithmic decision-making processes (Liao et al., 2020; Meske & Bunde, 2020; Robert et al., 2020; Salminen et al., 2020, p. 90).

To address these issues, a new field of AI called *Explainable Artificial Intelligence* (*XAI*) has emerged intending to study ways how to improve the explainability, transparency, and interpretability of AI algorithms (de Oliveira Carvalho et al., 2022, p. 131; Meske & Bunde, 2020; Tsiakas & Murray-Rust, 2022). *Explainability* is one of the important aspects of ethical principles of AI, as it is a starting point in assessing the adequacy of other ethical principles, e.g. accountability, fairness, reliability, privacy, and safety (de Oliveira Carvalho et al., 2022, p. 132). An AI system can be described as *interpretable* if its *"[...] operations are understandable to humans, either through inspection of the system or some explanation produced during its operation"* (de Oliveira Carvalho et al., 2022, p. 131). In addition, XAI also aims that explainability and interpretability would not hinder the performance of AI systems (Meske & Bunde, 2020, p. 57).

Trust

A key component of human-AI interactions that XAI is attempting to address is *trust* (Gurney et al., 2022; Jacovi et al., 2021; Meske & Bunde, 2020). One of the reasons why people use AI is to decrease the uncertainty regarding a specific goal and make the decision-making process easier, for instance in situations that might have fatal consequences: medical diagnostics or autonomous driving (Gurney et al., 2022; Meske & Bunde, 2020, p. 55). Although AI outperforms humans with the speed and accuracy of their computing capabilities, it is not error-free (Gurney et al., 2022, pp. 22–23). It is shown that behavioral measure predicts trust in AI better, meaning that the ability to explain the reasoning behind the decision affected human compliance (Gurney et al., 2022, pp. 30–31). In addition, it is emphasized that trust and trustworthiness are terms detached one from another: users can trust an AI model which is not trustworthy and a trustworthy AI model might not gain the trust of the user. If trust is not sourced in trustworthiness, it is not ethically desirable (Jacovi et al., 2021, p. 633).

Some authors believe that the way how to increase trust and trustworthiness in AI systems is to improve communication (de Oliveira Carvalho et al., 2022; Liao & Sundar, 2022), while others focus on the explanation interface of AI systems (Meske & Bunde, 2020). In terms of improving communication, the structured conversation enabling a reflection on ethical principles can help users to get an understanding of how the AI system works (de Oliveira Carvalho et al., 2022, pp. 145–146). Furthermore, studying the connection between trust and trustworthiness in connection to the information processing and making trust judgments shows that increasing trust in a trustworthy AI system can be achieved *"[...] if trustworthiness cues in the transparency affordance are both truthfully communicated and appropriately assessed by the user"*(Liao & Sundar, 2022, p. 1261). In terms of the explanation interface of AI systems, results show that the local explanations performs better than having a global explanation for the whole AI system (Meske & Bunde, 2020, p. 65).

AI Ethical standards

There are different stakeholders engaged in the discussion and development of AI Ethics guidelines, principles, and policies to address the impacts of AI systems. The relevant stakeholders for responsible AI systems can be divided into 1) *individual stakeholders* such as users, developers, HCI researchers, and AI experts; 2) *organizational stakeholders* including research institutes, private companies, and professional bodies; and 3) *national/international stakeholders* involved in adopting laws, rules, and regulations (Deshpande & Sharp, 2022, p. 233).

Within the EU, the European Commission's vision of AI is to be trustworthy and human-centric. The European strategy on AI is based on two documents developed by *High-Level Expert Group on Artificial Intelligence,* an independent expert group established by the European Commission. The first is called *Ethics Guidelines for Trustworthy AI* and establishes the foundation of ethical concerns and best practices when developing, deploying, and using AI technologies (AI HLEG, 2019a). The second document is *Policy and Investment Recommendations for Trustworthy AI* aimed to address the ethical concerns and prevent and minimize harmful impacts of discriminatory and fraudulent practices or privacy and data breaches (Hickman & Petrin, 2021, p. 593). Due to their general nature and lack of enforcement, it is difficult to translate them into practice. Despite that they present a positive step forward, there has been a demand for more effective and enforceable legislative means to govern organizations to apply a framework for achieving Trustworthy AI (Hickman & Petrin, 2021, p. 621). In 2021 a soft law approach has been switched to a legislative approach when the European Commission proposed a new regulatory framework for AI called *Artificial Intelligence Act*. The purpose of the act is to ensure a safe and lawful AI system respecting fundamental human rights (European Commission, 2023).

Among efforts outside of the EU, there is the Committee on Artificial Intelligence (CAI) of the Council of Europe working on *the convention on AI* (Council of Europe, 2023), the *Ethically Aligned Design guidelines* by IEEE (Chatila & Havens, 2019), and *ISO/IEC JTC 1/SC 42* as an outcome of the joint ISO/IEC international standard committee (ISO, 2022).

The rapid development of AI and its incorporation into many daily products have introduced challenges and ethical concerns regarding the development of AI systems. Therefore, the focus of academia has shifted from technical excellence to developing AI systems that are reliable, trustworthy, ethical, and safe. Among the issues that need to be addressed is the insight into unfairness caused by biased datasets and misinterpretations of certain groups resulting in discrimination and misrepresentation. The growing need for explainability, transparency, and trust in AI outputs has led to the emergence of numerous guidelines from different stakeholders. There is a growing policymaker interest and community consensus for more robust legislative measures that can effectively prevent the misuse of AI systems. The aim is to establish enforceable mechanisms that promote trustworthy AI and ensure greater accountability in its use.

2.3.3 Human-AI relationship

While the access to AI for everyone with the internet is relatively new, the perspectives of the complementary relationship between computers and humans origins back to the 1960s (Lew & Schumacher, 2020b, p. 39). Licklider (1960) presented the perspective of *Man-Computer Symbiosis* in which he highlights that human beings be in charge of strategic groundwork such as setting goals, creating hypotheses, and evaluating, whereas computers will do routine work to prepare for insights and decision-making (Licklider, 1960, p. 4). It is emphasized how computers and people can augment and extend each other's capabilities to achieve greater results in tandem (Licklider, 1960, p. 4) which is similar to what Dellermann et al. (2019) refer to as *hybrid intelligent systems*: *"the ability to accomplish complex goals by combining human and artificial intelligence to collectively achieve superior results than* *each of the could have done in separation and continuously improve by learning from each other"* (Dellermann et al., 2019, p. 5). The difference between the two perspectives seems to be the emphasis on how the two entities, human and computer, work together: the Man-Computer symbiosis has a greater emphasis on how the computer augments the abilities of people, whereas the perspective on hybrid intelligent system tends to focus on how both actors work together in tandem to elevate the outcome.

AI as a tool or partner and Human-AI co-creativity

Within the relationship between human beings and AI, some designers view AI as a *tool* to solve tasks by offering new stimuli and creative opportunities to the designers (Kim et al., 2021, p. 250; Rezwana & Maher, 2022a, p. 9), while AI also is perceived as a *partner* to spare and collaborate with (Kim et al., 2021, p. 257; Qian & Qian, 2020, p. 70; Rezwana & Maher, 2022a, p. 9). The distinction between tool and partner is divided by the level of communication and interaction between the entities. For AI to be viewed as a partner and support *Human-AI co-creativity*, the AI system needs to be able to provide a status, feedback, critique, opinions (Rezwana & Maher, 2022a, p. 9), query strategy, interpretability, and/or suggestions (Dellermann et al., 2019, p. 9), as opposed to being perceived as just a tool for application (Rezwana & Maher, 2022b, p. 38). *Co-creativity* refers to a creative process in which multiple entities, human(s) and/or computer(s), contribute to a creative process (Candy & Edmonds, 2002, p. 135) and with the advancing technology of AI, the AI system can serve more as an equal to human beings in the collaborative environment of the creative processes (Davis, 2013, p. 10). In close proximity to the hybrid intelligent systems, and AI as a partner, the subfield of Human-AI co-creativity is about human beings and AI in a creative collaboration process to create content, ideas, and performances in tandem (Davis, 2013, p. 9; Rezwana & Maher, 2022b, p. 38).

The human-AI relationship can also be determined by the *human-to-AI interaction* in which a human needs to provide input, teach, and train the AI in relation to the outcome of the output and interactions (Dellermann et al., 2019, p. 8). To ensure a good relationship between AI and human beings, while avoiding an AI winter, there needs to be a clear division of the contributions shared between AI and people, because "each will be more successful if there is an understanding about who does what, when, and how" (Lew & Schumacher, 2020b, p. 51), see § 2.4.3.

Human in the loop

The growth of AI results in increasing doubts regarding validity and reliability (Herrmann, 2022, p. 46; So, 2020, p. 137) which the *human-in-the-loop* concept can accommodate by introducing a human as an integral part when AI is involved (So, 2020, p. 137). In the concept of human-in-the-loop, humans play an important role in providing training, input, feedback, and making the final judgments, whereas the AI system assists and augments their capabilities (see § 2.4.3). Combining human expertise and intuition with AI's strengths of efficiency, the human-in-the-loop concept might result in more reliable and informed outcomes (Dellermann et al., 2019, p. 2; So, 2020, p. 136; Tsiakas & Murray-Rust, 2022, pp. 588–589).

Integrating AI in work practices

In the context of integrating AI in future work practices, Tsiakas & Murray-Rust (2022) propose the potential benefits of combining human-in-the-loop and XAI in the interactions with AI:

INTEGRATING AI IN WORK PRACTICES	
EXPLAINABLE AI (XAI)	HUMAN-IN-THE-LOOP
Strengthen the users' perception and trust in the underlying data and models utilized for decision-making.	Enable users to actively engage in the decision-making process by providing feedback to the AI system and its decision.
Offer insights into the impact of both AI and human decisions within the workplace.	Facilitate user negotiations with AI models and decisions by granting them the ability to actively interact and influence the system.
Foster a shared understanding and strengthen awareness among human-AI teams in the workplace.	Promote exchange of feedback between human-AI teams, fostering shared autonomy and collaboration.

Table 9: Combining human-in-the-loop and XAI in future work of human-AI interactions (Tsiakas & Murray-Rust, 2022, p. 593).

By combining aspects from XAI (see Table 9 and § 2.3.2) and human-in-the-loop (Table 9), the users challenge, negotiate and inform decisions based on AI's justification of its output. Meanwhile, the AI system needs to be informed and trained with data by matching the AI model to real needs (Tsiakas & Murray-Rust, 2022, p. 593). Based on this, integrating AI in work practices in organizations must be done by ensuring fair, reliable, and trustworthy AI systems (§ 2.3.2), to augment human performances as opposed to replacing human beings with autonomous, automatic, and non-transparent AI systems (Tsiakas & Murray-Rust, 2022, p. 588).

A similar perspective is provided by Herrmann (2022), to describe the relationship between human beings and AI, while successfully enabling human beings to use AI in advancing their capabilities. Herrmann (2022) proposes ten modes of AI interactions:

INTERACTION MODES	
	EXPLANATION
1. Explanation and possibilities	AI providing transparency of its output enable users to understand the AI output, and explore how to use the system.
2. Testing and error detection	Users can validate AI output and systems, and detect errors.
3. Re-training	The AI system can be re-trained with improved data sets by users to align the AI outcome with the expectations of the users and facilitate continuous learning.
4. Data and method variation	Users can switch between data sets and methods to improve the accuracy based on domain-specific knowledge.
5. Flexible data input filtering	Users can filter data, omit inputs, and observe intermediate results to guide the data input inserted in the AI system.
6. Identification and comparison	Users can identify and compare similar cases to solve a task, understand the AI output, and support the decision-making.
7. Refinement	The AI output can be refined, specified, and tailored for output including the contextual factors by users.
8. Intervention	User can guide and correct the AI outputs based on their expertise to address ethical considerations such as biases.
9. Vetoing	Users are allowed to reject or ignore AI decisions and findings.
10. Critiquing	AI provide critical feedback to human experts to improve their work, avoid possible mistakes, and consider alternative solutions.

Table 10: AI interactions for advancing human-AI capabilities (Herrmann, 2022, pp. 39–46)

By embedding the insights from Table 10 in the organizational context, the ten modes of interactions lay a foundation for enabling human beings to successfully employ AI to advance the human-AI capabilities (Herrmann, 2022, p. 47).

In conclusion, the Man-Computer symbiosis, the perspective of human-AI co-creativity, the distinction between perceiving AI as a tool or partner, the concept of hybrid intelligent systems, and the human-in-the-loop concept highlight the significance of the communication and interaction between human beings and AI in which their capabilities can be augmented in tandem. On one hand, the Man-Computer symbiosis, AI as a tool, and human-in-the-loop concept highlight the importance of the human agency of validating, training and providing feedback to the AI to augment the capabilities of humans. In this viewpoint, there is an aim to ensure fair, reliable, and trustworthy AI systems that augment human performance rather than replacing humans with autonomous and non-transparent AI systems. On the other hand, the perspective of a hybrid intelligent system, human-AI co-creativity, and AI as a partner emphasizes the equality between human and AI to a higher degree in a collaborative process. By understanding and implementing modes of AI interactions, workplaces can successfully leverage AI to advance human-AI capabilities. Overall, integrating AI into work practices requires humans to challenge, negotiate, and inform decisions based on AI's justifications.

2.4 The Role of AI in UX

In the following section, we aim to provide an overview of the role of AI in UX. We characterize the relationship between AI and UX including the transformative impact of AI on the field of UX. Through the review of the academic literature, we have identified two distinct perspectives on the design of AI systems: 1) *Designing for AI* and 2) *Designing with AI*. When defining designing for AI, we will explore the challenges caused by AI and the proposed solutions to tackle them. Regarding designing with AI, which represents our research focus, we will define *AI as a design material* and present how *AI-enabled products* might support creativity and collaboration.

2.4.1 Relationship between AI and UX

The rapid advancement of AI has introduced both challenges and opportunities to the field of design when creating user experiences (Wallach et al., 2020, p. 146; Wu & Zhang, 2020, p. 167). While AI can be considered an initiator of new experiences, UX secures designing the best human-AI interactions. Some would define their relationship as *"mutually beneficial"* (Wallach et al., 2020, p. 162), others would say that both fields share *"common DNA"* (Lew & Schumacher, 2020a, p. 114). Despite the differences in defining the relationship, the common denominator is that at the current state, AI and UX are vital for each other in pursuit to create products with a great user experience (Hartikainen et al., 2022; Lew & Schumacher, 2020a).

As a part of mitigating negative aspects of AI, such as biased datasets or lack of transparency (§ 2.3.2), there is a shift in how to approach designing AI systems (Li & Etchemendy, 2021; Windl et al., 2022, p. 1). This resulted in the increased importance of *Human-centered AI (HCAI)* that emphasizes *"amplifying, augmenting, and enhancing human performance"* (Shneiderman, 2020b) while building systems that are *"reliable, safe, and trustworthy"* (Shneiderman, 2020a, p. 2) which is also related to ensuring better integration of AI in work practices (see § 2.3.3). As a result, the desired qualities of AI systems become to effectively meet human needs, facilitate activities, and uphold human values (Agarwal & Regalado, 2020; Shneiderman, 2020a, p. 2). The transition, from solely measuring algorithm performance to assessing human performance and satisfaction, underlines the shift towards HCAI, emphasizing the importance of designing AI with a human focus (Hartikainen et al., 2022, p. 1; Lew & Schumacher, 2020a, p. 115; Shneiderman, 2020a, p. 2; Windl et al., 2022, p. 2). In contrast to academia, the practice shows that topics such as *ethics, transparency*, and *explainability* and how to effectively address them in the AI development process are less emphasized than *technical excellence* which is valued higher (Hartikainen et al., 2022, p. 8). It is suggested that the task of how to effectively work with AI is for the HCI research community to enable UXPs to design AI solutions that have a human in the center (Windl et al., 2022, p. 1) and can support collaboration within interdisciplinary teams (Zdanowska & Taylor, 2022, p. 11). Hartikainen et al. (2022) point out that the amount of data gathered by AI algorithms can serve as a valuable source of information for UXPs in the process of solving problems in a new collaborative way (Hartikainen et al., 2022, p. 2). Therefore, UX Design should not be understood as a mere set of methods and practices helping to develop AI systems, but rather as a resource that can have a wider influence on teamwork, development life-cycle, and the organizational structure itself (Zdanowska & Taylor, 2022, p. 13).

As mentioned earlier, we have identified two independent research focuses when investigating the topic of designing AI systems: *designing for AI* and *designing with AI*. While the former focus on conditions related to designing AI systems has received considerable attention from researchers, the latter focus on designing with AI has received relatively less exploration in the existing literature to the best of our knowledge. Due to its lower coverage, we consider *designing with AI* a research gap within the academic literature. In the study, our focus is primarily on designing with AI rather than designing for AI (see section Designing with AI).

2.4.2 Designing for AI

There have been several empirical studies investigating the practices and challenges of UXP when working on designing AI systems (Bergström & Wärnestål, 2022; Hartikainen et al., 2022; Heier, 2021; Liao et al., 2020; Windl et al., 2022; Yang et al., 2020; Zdanowska & Taylor, 2022). Researchers identified two main attributes of AI causing issues in human-AI interaction design: *uncertainty surrounding AI's capabilities* (Bergström & Wärnestål, 2022; Heier, 2021, p. 212; Long & Magerko, 2020; Yang et al., 2020, p. 9) and *AI's output complexity* (Bergström & Wärnestål, 2022, p. 1; Heier, 2021, p. 3; Yang et al., 2020, p. 6; Zdanowska & Taylor, 2022, p. 12). While the former presents a difficulty for the UXPs' ideation phase when assessing the feasibility of their design ideas, the latter point out to the design complexity of the AI system's interactions to fully capture and simulate all possible scenarios (Yang et al., 2020, pp. 6–7). According to studies of UXPs, the most commonly identified challenges in designing AI systems can be divided and categorized based on their relation to the design stages (Table 11-14).

CHALLENGES IN USER RESEARCH	
PERCEIVED CHALLENGES BY UXPS	DESCRIPTION
Challenges caused by digitally less mature clients	Clients that are not digitally mature require more guided communication and clarification about AI capabilities (Bergström & Wärnestål, 2022, p. 14). In addition, despite their lack of AI literacy, clients are still insisting to drive the decision-making process and even specify users' requirements (Hartikainen et al., 2022, p. 8).
Challenges in collaboration and project organization	Lack of end-user/human viewpoint is also caused by developers specifying users- needs based on their reasoning (Hartikainen et al., 2022, p. 9).
Challenges in designing ethical AI systems	It was due to the lack of support for ethical concerns, e.g. fairness, accountability, and transparency from the side of their companies but also a lack of practical tools (Bergström & Wärnestål, 2022, pp. 14–15; Zdanowska & Taylor, 2022, p. 9).
Challenges in organizations	Some UXPs express that the due to the unclarity of their role within the team and project when designing for AI, they feel unsure of what competencies to develop and what set of skillset is expected from them to possess (Bergström & Wärnestål, 2022, p. 11).

Table 11: Overview of challenges in the stage of *User research* when designing AI system

CHALLENGES IN PROBLEM SETTING	
PERCEIVED CHALLENGES BY UXPS	DESCRIPTION
Challenges in understanding AI capabilities due to lack of AI literacy	UXPs lack competencies in data science, ML, and in a general understanding of AI capabilities which makes it difficult for them to estimate what the AI system can do and how reliably which is crucial in problem defining stage (Bergström & Wärnestål, 2022; Heier, 2021, p. 212; Long & Magerko, 2020; Yang et al., 2020, p. 9).

Table 12: Overview of challenges in the stage of *Problem setting* when designing AI system

CHALLENGES IN USER TESTING	
PERCEIVED CHALLENGES BY UXPS	DESCRIPTION
Challenges in iterative prototyping and testing	Dynamic nature and complexity of AI are challenging for iterative testing and prototyping (Hartikainen et al., 2022, p. 9; Heier, 2021, p. 212; Yang et al., 2020, p. 9)

Table 13: Overview of challenges in the stage of *User testing* when designing AI system

CHALLENGES IN DESIGN CONCEPTUALIZATION	
PERCEIVED CHALLENGES BY UXPS	**DESCRIPTION**
Challenges in collaboration	The lack of AI literacy creates a dependency and need for efficient ways how to communicate between the designer and others, e.g. machine engineers (Bergström & Wärnestål, 2022; Yang et al., 2020, p. 9). One study reports that a significant factor driving collaboration among interdisciplinary teams is the lack of knowledge in designing for AI/ML (Zdanowska & Taylor, 2022, p. 11).
Challenges in envisioning novel and technically feasible designs with clearly articulated design criteria	Due to the lack of tools and methods when working with AI, UXPs have difficulties in defining user needs and requirements and also ideating, e.g. sketching or prototyping with large datasets (Bergström & Wärnestål, 2022, p. 1; Heier, 2021, p. 3; Yang et al., 2020, p. 9; Zdanowska & Taylor, 2022, p. 12). In the process of designing for AI, prototyping requires to be high-fidelity and is not only about revealing usability problems but most importantly about understanding that the design is feasible and is aligned with users' mental models(Zdanowska & Taylor, 2022, p. 12).

Table 14: Overview of challenges in the stage of *Design conceptualization and development* when designing AI system

As a way to approach the challenges and support UXPs, different tools, and aids were developed: *Human-centered AI guidelines* (Agarwal & Regalado, 2020; Amershi et al., 2019; Google PAIR, 2021); *design principles for gamification of AI systems* (Wiethof et al., 2022); *design heuristics for AI* (Jin et al., 2021); *modes of AI interactions* (Herrmann, 2022); *XAI question bank* (Liao et al., 2020); *MATCH model* (Liao & Sundar, 2022); *AI design considerations* (Long & Magerko, 2020); and *framework to analyze and the complexity of AI systems* (Yang et al., 2020).

These tools further underline the importance of the human-centered perspective in the process of designing AI systems (Agarwal & Regalado, 2020; Heier, 2021, p. 208; Shneiderman, 2020a, p. 2). Despite of range of new tools, techniques, and methods, there is still a need for developing more actionable approaches how to facilitate the process of designing AI systems (Agarwal & Regalado, 2020; Heier, 2021; Zdanowska & Taylor, 2022, p. 12). Among such areas which need more attention are prototyping (Heier, 2021, p. 212) and AI literacy (Heier, 2021, p. 213; Long & Magerko, 2020).

2.4.3 Designing with AI

The advancements in AI have opened up opportunities in the field of HCI and UX, where AI has the potential to enhance user experience and enable interactions that were previously impossible. As a result, there is a hopeful outlook on effectively envisioning new applications of AI (Bakaev, Speicher, et al., 2022; Bergström & Wärnestål, 2022; Hartikainen et al., 2022, p. 2; Holmquist, 2017; Knemeyer & Follett, 2019; Windl et al., 2022; Yang et al., 2020, p. 1; Yildirim et al., 2022, p. 1). With the introduction of the concept of *AI as a design material,* AI can be viewed as a collection of technical capabilities that practitioners can harness to design and craft innovative features, products, and services (Main & Grierson, 2020, p. 7; Windl et al., 2022, p. 1; Yang et al., 2020; Yildirim et al., 2022, p. 10). The idea is based on viewing design as an introspective process where designers actively engage in a dialogue with materials, allowing them to envision and bring forth concepts that are yet to materialize (Schön, 1992a, p. 132). It has been shown that UXPs exposed to the amount of data and level of abstractions that designing for AI represents, exhibited greater proficiency and ease in their utilization of AI. In addition, these designers engaged in reflective dialogues with AI and effectively utilized their data science knowledge as a means to obtain insights into the possibilities offered by AI (Yildirim et al., 2022, p. 10). However, to use AI as a design material successfully, UXPs need to know the capabilities and limitations of AI (Holmquist, 2017, p. 31; Long & Magerko, 2020; Wu & Zhang, 2020; Yang et al., 2020).
Long & Magerko (2020) define *AI literacy* as a necessary skillset *"to critically evaluate AI technologies; communicate and collaborate effectively with AI; and use AI as a tool online, at home, and in the workplace"* (Long & Magerko, 2020, p. 2). They provide a list of competencies and design considerations which the HCI community needs to take into consideration when interacting with AI in their practices, among which is *AI Ethics, AI's strengths and weakness, and Explainability* which is related to § 2.3.2.

UXPs who adopt AI as a design material early will be better prepared for the shift AI is causing in the domain of UX (Holmquist, 2017, p. 33; Wu & Zhang, 2020, p. 175). While some warn that computational power, perceptual intelligence, and cognitive capabilities of AI have the potential to transform or even replace various conventional design tasks, particularly those that rely heavily on data analysis and standardization (Wu & Zhang, 2020, p. 167), others underline the potential of AI to empower UX capabilities (Bergström & Wärnestål, 2022, p. 7) where AI would optimize performance and repetitive tasks and augment existing abilities (Knemeyer & Follett, 2019, p. 71; Yildirim et al., 2022, p. 4). Another way how AI can create value for UXPs is through processing information about users, and the context; making sense of it; and acting upon the knowledge. The ability to transform external facts into *machine intelligence,* allows AI to acquire social norms and common-sense knowledge from human interactions (Yang et al., 2018, p. 8).

As a consequence of the operationalization of AI in HCI to harness AI's capabilities in the UX design process, there have been several studies presenting various AI-enabled products incorporating AI into design practice (Bakaev, Heil, et al., 2022; Bakaev, Speicher, et al., 2022; Y. Hu et al., 2020; Karahasanović et al., 2021; Main & Grierson, 2020; Malsattar et al., 2019; X. Sun et al., 2022):

EXAMPLES OF AI-ENABLED PRODUCTS

DESIGN STAGES	AI-ENABLED TOOLS	DESCRIPTION
User research	AI personas	It support tool designed for the development of systems involving both human and AI agents (Karahasanović et al., 2021, p. 229).
Problem setting	No research found	
Design conceptualization and development	EasySketchDesign	It helps UXPs in conceptual product design to find reference pictures based on the drawing (Y. Hu et al., 2020, p. 312).
Design conceptualization and development	Writing Buddy	It is intended to act as a digital collaborative writing partner assisting with story writing (Samuel et al., 2016, pp. 388–394).
Design conceptualization and development	ObjectResponder	It enables to swiftly prototype and conceptualize interaction ideas for context-aware intelligent systems deployed in real-world environments (Malsattar et al., 2019, p. 1087).
Design conceptualization and development	Give Me a Hand	It is a hand posture drawing tool creating 3D models of hands (X. Sun et al., 2022, p. 495).
User testing	WUI Measurement Integration Platform	It predicts the usability per aesthetics, complexity, and orderliness impression scales for web UIs (Bakaev, Heil, et al., 2022, p. 219).

Table 15: Examples of AI-enabled products and their capabilities which can enhance UXPs in the UX design process

The studies presented in Table 15 point out several subthemes which need to be addressed to understand the UXPs' attitudes toward AI and also provides valuable insights into the future enhancement of such systems to better support UXPs throughout the design process.

The first subtheme, *the sense of ownership*, highlights that despite collaborating on the task with AI, UXPs still experience a sense of creative ownership over the outcome while acknowledging the collaborative role played by AI in the process (Main & Grierson, 2020, p. 8; Samuel et al., 2016, p. 394).

In the second subtheme, *empathy and collaboration*, having an AI persona in the design process showed to helped UXPs to gain familiarity and empathy with the technology and also enabled them to facilitate better communication and collaboration among themselves, AI specialists, and domain experts within the team (Karahasanović et al., 2021, p. 236).

Within the third subtheme, *creativity and innovation*, some suggest that due to the exposure to the AI's perspective through the AI-enabled design tools, their understanding of the context alters allowing them to embrace new possibilities, challenge traditional notions of context, and generate novel ideas (Malsattar et al., 2019, p. 1087). AI can support UXPs in the discovery phase with the diversification of sources of inspiration, such as mood boards, inspiration research, and materials research (Main & Grierson, 2020, p. 7), or then later in the usability validation and evaluation phase (Bakaev, Speicher, et al., 2022, p. 412). AI design tools support UXPs to speed up the process (Bakaev, Speicher, et al., 2022, p. 412; Y. Hu et al., 2020, p. 318). While the creative process has been improved, tools require further development to fully support the creative process (Y. Hu et al., 2020, p. 318; X. Sun et al., 2022, pp. 509–510).

The fourth subtheme, *the shift in designers' perception of AI*, argues that AI should not be viewed solely as a design material but as an active design partner which would allow UXPs to design with AI (Main & Grierson, 2020, p. 7; Malsattar et al., 2019, p.

1087). This subtheme is related to the perspectives on hybrid intelligent systems, human-AI co-creativity, and AI as a partner (see § 2.3.3).

Due to increasing demand for AI systems that have a human at the core and provide a great user experience, HCAI has raised to prominence. Part of this development means that transparency, trustworthiness, explainability, and ethics when developing AI systems got into the focus of HCI. There is a difference between designing for AI where the focus is on designing systems that incorporates AI in them and designing with AI, the perspective to view AI as a design material supporting UXPs in the design process. In terms of designing for AI, UXPs face different challenges from which AI literacy and lack of tools and methods which helps them to envision their concepts are prevalent. Concerning designing with AI shows that the UX field has started to take advantage of AI's capabilities in the form of AI design tools aimed at supporting UXPs in their practices. As a consequence of applying AI in the design process, the field of UX has started to examine how ownership, empathy, creativity, and collaboration are influenced by this shift.

3. Methodology

In this chapter, we outline our research strategy and design of this study. In addition, we explain how we gain knowledge and what philosophical assumptions we make during the process. Furthermore, we specify methods and procedures for data collection, analysis, and interpretation.

3.1 Research strategy

The methods and theories applied by social researchers influence the research focus including how the results and findings are interpreted. Therefore, the researcher needs to reflect on their ontological and epistemological approaches, the relationship between research and theory, and the data gathering approach (Bryman, 2016a, pp. 16–17).

3.1.1 Philosophy of Science

Throughout the study, researchers need to be aware of the philosophical assumptions in the process of gaining knowledge (Creswell & Plano Clark, 2018a, p. 38). There are two key ways to think about research philosophy: 1) *ontology* and 2) *epistemology*. Ontology is involved in examining the fundamental nature of reality, which in turn prompts researchers to question their assumptions about how the world operates and their dedication to specific perspectives and views which further leads to a discussion of *objectivism* and *subjectivism* position of the social actors (Saunders et al., 2012, pp. 129–131). Epistemology is concerned with the study of knowledge, including what is considered valid or acceptable knowledge within a particular field of study(Saunders et al., 2012, p. 132).

In the following, we will present four research paradigms related to social sciences as defined by Mackenzie & Knipe (2006). Meanwhile, we explore how the research paradigms might be applied in our study which eventually will inform our decision on an overall philosophical direction for our study. A *positivistic* stance could provide an objective study and understanding of empirical observations (Mackenzie & Knipe, 2006). For instance, through positivist experiments, we are able to measure and find empirical evidence of the efficiency and/or productivity of UXPs' application of AI. If we consider a *constructivist/interpretivist* approach, we are able to emphasize the study of subjective experience with the aim of uncovering the world of human experiences that are constructed by the research subjects (Mackenzie & Knipe, 2006). An interpretivist approach opens up an exploration of the UXPs' perceptions, emotions, and intentions to understand their experience when applying AI to perform UX activities, emphasizing their views on the phenomenon being studied. With the application of the *transformative* paradigm, the research addresses issues related to social injustice, conflicts, and political agendas (Mackenzie & Knipe, 2006). With a transformative stance, we can study the conflicts between UXP-organization, UX-AI, etc., that might arise in the era of integrating AI in work practices. For instance, we could explore the discrimination of UXPs if the organization wants to make the UXPs more efficient by enforcing AI to be used. Finally, the *pragmatic* paradigm is problem-centered and emphasizes practice situated in its real-world context and consequences of actions (Mackenzie & Knipe, 2006). A pragmatic approach would allow us to enter the work practices of UXPs to understand their AI usage in relation to other UX work practices. Eventually, a pragmatic study could inform suggestions to change UX practices.

Based on the research questions, the research objective of this study is to understand how UXPs apply AI in their work practices to gain insights into how AI impacts the field of UX. With the new, emerging AI systems that are easily accessible, there is a research gap in exploring *how* AI is applied in the current UXPs' work practices and accordingly, *what* opportunities and challenges that UXPs are experiencing. To study the phenomenon of using AI for designing in the UX domain, we opt for an interpretivist approach to understanding the UXPs' subjective experience of applying AI. Meanwhile, by combining interpretivism with pragmatism, we emphasize the importance of studying practice in its real-world context in which the meaning is linked with actions. In the following sections, we will present pragmatism and interpretivism which open up a discussion of the consequences of combining them.

Pragmatism: Knowing is in our actions

Pragmatism considers the research question as the most important determining factor for epistemology and ontology (Creswell & Plano Clark, 2018a, p. 36; Saunders et al., 2012, p. 149). Pragmatism is fundamentally a philosophy of *action*, which asserts that human beings are active participants who only make sense of their experience and understanding of the world in relation to their practical engagement with it (Brinkmann, 2006, p. 31; Schön, 1992b, p. 121). In regard to the ontological stance in pragmatism, the core *"[...] is actions and change; humans acting in the world that is in a constant state of becoming"* (Goldkuhl, 2012, p. 139). In terms of epistemology, the focus is on *"[...] action and change and the interplay between knowledge and action"* (Goldkuhl, 2012, p. 136). According to Donald Schön (1983), knowing is in the action which is referred to as reflection-in-action. Schön implies that our knowing is implicit and tacit in our patterns of action related to our interaction with materials in the situation (Schön, 1983, p. 49). Actions play a crucial role in modifying and transforming reality, which can be achieved through knowledge and intentionality. As a result, actions are integral to cognitive development and gaining a deeper understanding of our experiences (Goldkuhl, 2012, p. 139; Schön, 1983, pp. 49–50).

In pragmatism, there is a focus on addressing issues in the real world. This process is described by John Dewey (1938) with the term *inquiry* as *"[...] the controlled or directed transformation of an indeterminate situation into one that is so determinate in its constituent distinctions and relations as to convert the elements of the original situation into a unified whole"* (Dewey, 1938b, pp. 104–105). In our study, we do not engage in the inquiry perspective by emphasizing the practical consequences in future experiences by transforming an indeterminate situation into a unified whole situation. Rather, we focus on pragmatism and its ontological stance on the significance of practice in gaining knowledge, in our case, about how UXPs apply AI tools in their workflow when engaged in UX activities. We utilize pragmatic ontological views that the world and its properties are perceived through practice (Brinkmann, 2006, p. 31; Ejsing-Duun & Skovbjerg, 2019, p. 447). The forms of knowledge in pragmatism can differ from explanation, understanding, to prescriptive, normative, or prospective (Goldkuhl, 2012, p. 140). In our study, the pragmatic approach allows UXPs to demonstrate their knowledge about AI tools and showcase their work practices, while they further enable us to observe their workflows, uncover patterns and habits, and explain UXPs' application of AI during UX-related activities (see § 3.2.3).

Interpretivism: Understanding human experience

Interpretivism is a research paradigm with the intention of understanding human experience with an underlying assumption that reality is socially constructed (Mackenzie & Knipe, 2006, p. 196). From an ontological stance,

> *"[...] the interpretive research is to understand how members of a social group, through their participation in social processes, enact their particular realities and endow them with meaning, and to show how these meanings, beliefs and intentions of the members help to constitute their actions"* (Goldkuhl, 2012, p. 138).

The aim of the researcher is understanding the actors' view of reality. The researcher relies upon the participant's perspective in the situational context of the study (Goldkuhl, 2012, p. 138; Mackenzie & Knipe, 2006, p. 196). From the epistemological stance, there are essential two principles: 1) t*he hermeneutic circle,* and 2) *principle of contextualization*. While the former refers to creating the understanding as alternating between the whole and its individual parts, the latter emphasizes the importance of getting to understand the context which preceded the currently investigated situation (Goldkuhl, 2012, p. 138). During data generation, the researchers and subjects are co-creators of the meaning (Goldkuhl, 2012, pp. 138–139) in which the researcher's impact on the situation is explicitly recognized (Mackenzie & Knipe, 2006, p. 196).

As a key concept of interpretivism is to uncover, analyze and understand the existing subjective meanings (Goldkuhl, 2012, p. 138), we use the interpretivist paradigm in a part of the study where we examine UXPs' thoughts and impressions of utilizing AI tools in during UX activities and their feelings about AI, and how reliable AI might be in an HCD approach (§ 3.3.3). Part of our pursuit to understand the context of UXPs who use AI is also by understanding the background which led to it. This was done through the literature review (§ 2.2) and quantitative data gathering (§ 3.2.3) which allows us to contextualize and understand the context of UXPs who use AI tools in UX activities.

Consequences of combining pragmatism and interpretivism

The combination of two paradigms can provide a complimentary, comprehensive, and nuanced understanding of UXPs' interpretation, feelings, and application of AI. However, we need to carefully consider the balance of integrating the different methods that will be applied from each perspective to ensure the coherence between the applied methods and the findings. Furthermore, the combination of relying on subjective meaning-making (interpretivism) while also studying context-dependency work practices (pragmatism), the external validity might be weakened due to the lack of generalizability across the field of AI application by other UXPs with other subjective meanings and contexts.

Nevertheless, by adopting an interpretivist position, we are able to explore the subjective perspectives and interpretations of UXPs' attitudes, beliefs, and values that shape their use and perception of using AI in the field of UX. Whereas interpretivism relies on people to explain and recall a process from outside of the situation and context of practice, pragmatism can uncover habitual, reasoning, and invisible details of people performing activities. With this combination, we are able to take into account both the subjective and practical aspects of the UXPs' use of AI which provide us with different data sources and perspectives about the investigated problem. In addition, when taking an interpretivist approach, we as researchers and UXPs ourselves need to be aware of potential biases we might bring to the study from our own practice. We need to remain open and challenge our own assumptions when interpreting data.

3.2 Research design and data collection methods

This section contains an outline of the research strategy for conducting the study. The section will provide an overview of quantitative and qualitative approaches which will inform our decisions of the research design in the remainder of the thesis.

3.2.1 Research strategies

While Bryman (2016) refers to a research design as a way to provide structure for data gathering and analysis (Bryman, 2016b, p. 46), by the research strategy he refers to the overall direction of the study (Bryman, 2016a, p. 35). The literature distinguishes three approaches/strategies to research: 1) *qualitative*, 2) *quantitative,* and 3) *mixed methods* (Bryman, 2016e; Creswell & Creswell, 2018a). While qualitative research focuses on investigating and *"[...] understanding the meaning individuals or groups ascribe to a social or human problem"*(Creswell & Creswell, 2018a, p. 41), quantitative research is characterized as an approach that aims to test theoretical hypotheses by examining the interplay between variables (Creswell & Creswell, 2018a, p. 41). The third approach, mixed method research, is described as *"[...] an approach to an inquiry involving collecting both quantitative and qualitative data, integrating the two forms of data"* (Creswell & Creswell, 2018a, p. 41). The combination of research methods provides additional insight and data that are mutually beneficial (Bryman, 2016e, p. 628; Creswell & Plano Clark, 2018a, p. 43), and leads to a more comprehensive understanding of a particular problem (Creswell & Creswell, 2018b, p. 294).

Doing research on the use of AI as an emerging technology, we do not know to what extent UXPs use AI for designing. To get an insight into whether UXPs even apply AI, can be studied through quantitative data to get a broad overview. Furthermore, we also aim at understanding how AI is applied (RQ2), and the opportunities and challenges as perceived by the UXPs (RQ3). Due to our interpretivist and pragmatic stances, qualitative data is best suited to get close to practices by understanding the depth, richness, complexity, and context of the practical usage of, and experiences with, AI for designing. The combination of quantitative and qualitative data in a mixed methods approach can provide insights that support the results and findings.

However, the complexity of mixed methods also requires more extensive data gathering and more time for analysis and interpretation (Creswell & Creswell, 2018b, p. 298). There are different classifications and taxonomy of mixed methods designs, however, the classification system based on Creswell & Plano Clark (2018) divides the mixed methods strategies into three core types: 1) *Convergent mixed methods design*, 2) *Explanatory Sequential Mixed Methods Design* and 3) *Exploratory Sequential Mixed Methods Design* (Creswell & Plano Clark, 2018b, p. 69).

Throughout *convergent mixed methods design*, qualitative and quantitative data are collected simultaneously, analyzed separately, and finally integrated and compared against each other to further confirm or reject insights from one or another (Creswell & Creswell, 2018b). On the contrary, during *explanatory sequential design* quantitative data are collected in the first place, analyzed, and based on the results are used to plan a qualitative design approach. The overall objective is to use qualitative insights to explain in detail specific parts of the quantitative data insights (Creswell & Creswell, 2018b, p. 304). In comparison to explanatory, *exploratory research design* starts with qualitative collection analysis first, based on which an instrument is being developed, and in the third quantitative phase it is administered to the sample of the population to be tested (Creswell & Creswell, 2018b, p. 306). All these three mixed methods design types are divided based on two components: *sequence* and *emphasis*. While sequence refers to the order in which the methods are used, emphasis points to the priority that a researcher gives to the methods (DeCarlo, 2018, p. 189).

Due to our aim at understanding the practice and experience of the UXPs, the qualitative data will be emphasized in the thesis. However, to get an insight into the domain and explore whether AI is even applied for designing, quantitative research can provide an overview to guide and inform the qualitative data-gathering process. Based on these reflections, we opt for an explanatory sequential design.

As mixed methods research consists of combining qualitative and quantitative methods which are seen as representations of the different epistemologies, there is a need to integrate and reconcile different perspectives which they bring with them(Timans et al., 2019, pp. 208–209). The authors suggest that researchers applying mixed methods research should be transparent and reflective about the epistemological and ontological assumptions (Creswell & Plano Clark, 2018b, p. 43; Timans et al., 2019, pp. 210–212). As each phase of the mixed methods research requires a change in the underlying philosophical assumptions, it is necessary to identify the particular perspective that informs our mixed methods research (Creswell & Plano Clark, 2018b, p. 43).

When characterizing the nature of the relationship between research and theory, the mixed methods approach allows combining *inductive* and *deductive* logical reasoning. The relationship between theory and research is inductive when the theory is the outcome of the research, meaning that the researcher generalizes based on the findings and observations (Bryman, 2016a, p. 26). This is typical for qualitative research and it enables the researcher to create new ideas (DeCarlo, 2018, p. 190). With a deductive stance, theory guides the inquiry, meaning that the researcher, based on the acquired knowledge from a certain domain, deducts the hypothesis which is further inquired into the research to motivate the entire data-gathering process (Bryman, 2016a, p. 24). Deductive reasoning is typical for quantitative research enabling the researchers to test new ideas (DeCarlo, 2018, p. 190).
In our mixed method study, we combine deductive and inductive strategies in a *sequential explanatory mixed method design* (§ 3.3).

3.2.2 Quantitative approach

First part of the sequential explanatory mixed method design requires conducting quantitative research. Our aim is to gather insights about the proportion of use of AI by UXPs' in their work practices as well as their opinion regarding the integration of AI tools in the UX design process. There are different quantitative research methods, such as *experiments, systematic observations*, different types of *surveys* (e.g. *semantic* *differential scale*, *longitudinal survey*), and *text mining* of posts on Social Media followed by *sentimental or cluster analysis* to extract the emotional stance. As we look for a method that combines on one hand collecting insights and also supporting the recruitment of participants for the qualitative research part, we consider an online survey as the most suitable for achieving the described aim. In the following, we will discuss a survey's suitability.

According to Bryman (2016), a *self-completion questionnaire* (also referred to as a *survey* in the thesis) is a quantitative user research method consisting of a set of questions that respondents complete without the help of the researcher (Bryman, 2016d, p. 232). A survey enables respondents to characterize themselves, their opinions, behavior, preferences, and attitudes in a structured way (Goodman et al., 2012b, p. 327). Generally, online surveys are seen as a cost- and time-efficient method (Bryman, 2016e, p. 233), however, the absence of researchers to address respondents' potential questions or potential misconceptions might have an impact on response rate and accuracy (Fricker & Schonlau, 2002). The online survey participation rate is linked to their announced length (Fan & Yan, 2010; Galesic & Bosnjak, 2009). In addition, the item responses have a tendency to lower in quality over the course of the survey (Galesic & Bosnjak, 2009, p. 358). Moreover, the response rate tends to be influenced not only by the length of the survey but also by the order of the questions, survey format, invitation design, or contact delivery modes (Fan & Yan, 2010, p. 137). On the other hand, among the survey's advantages is its flexibility allowing respondents to answer at their own preferred time (Kurzhals, 2021, p. 178).

When designing the survey, the researchers can use various types of questions, such as *multiple-choice questions, single-select questions, short open-ended questions, Likert scale questions*, or *dichotomous questions* (Goodman et al., 2012). The choice of the questions and their order dictate the pace, focus and progressively uncover insights about the participants (Goodman et al., 2012, p. 341). For instance, opting for multiple-choice questions gives participants the possibility to generate answers which are mutually exclusive, specific, and exhaustive (Goodman et al., 2012, p. 334). In contrast, Likert scale questions are a series of statements accompanied by a selection of five to seven options ranging answers from negative to positive and prompt participants to select the one which fits the best their attitudes to the specific topic (Goodman et al., 2012, p. 339).

In terms of targeting and engaging with specific audiences, social media play an increased role in allowing easier access (Stokes et al., 2019). From external validity, researchers need to take into account that social media as participant recruitment platforms might cause selection biases or have unrepresentative samples (Stokes et al., 2019, p. 103).
The survey serves as a mean to understand the context of UXPs' who use AI, what is the proportion of UXPs who use AI, what are their perceived challenges and impressions of AI. By doing so, we apply interpretivist approach in our study which helps us further answer RQ2 and RQ3.

3.2.3 Qualitative approach

Second part of the sequential explanatory mixed method design requires conducting qualitative research. There are different qualitative research methods such as a *qualitative interview, focus group, ethnography, contextual inquiry,* and *observations*.
In terms of qualitative interview, it can be conducted in a *structured, semi-structured*, and *unstructured* manner. A semi-structured interview is a qualitative, flexible data collection method in which the researcher ask open-ended questions to encourage the participant to share their personal insights and experience in details (Brinkmann & Tanggaard, 2010, pp. 37–38; Bryman, 2016h, pp. 468–469). The structured interview is mainly used in quantitative studies with a focus on maximizing the reliability and validity of the measurements of key concepts due to clearly specified research questions and purpose with a focus on generating answers to be streamlined for coding and processing analysis. On the contrary, semi-structured and unstructured interview are oftentimes used in qualitative studies with an open-ended research agenda and room for adjusting to the participants' perspectives and points of view (Bryman, 2016g, pp. 466–467). Another interview approach is *focus groups* which involve a group of similar individuals to discuss open-ended questions related to a specific topic in a session led by a facilitator. The aim of a focus group is to gain insights into the interactions between the participants and their construction of

attitudes, opinions, and experiences related to the topic(s) presented (Bryman, 2016h, p. 501). Meanwhile, a *contextual inquiry* is a process of observing and asking questions while the participants are performing related work activities in their natural work environment to better understand their practices and application of different artifacts, their motivations and strategies, and how their activities contribute to their overall work life (Holtzblatt & Beyer, 2015, pp. 13–14). This type of ethnographic field data-gathering method allows participants to articulate tacit knowledge that relies on their unconscious and habitual work practices (Holtzblatt & Beyer, 2015, p. 11).

To understand the subjective experiences of UXPs, we opt for a semi-structured interview because it allows for open-ended questions while also having a structure to compare the data across multiple participants. Additionally, we combine *semi-structured interviews* with *contextual inquiry* to study UXPs' work practices in a situation as close as possible to the natural context of their work practice. In the following, we will discuss the reasons why we applied a combination of the semi-structured interview based on our interpretivist positioning and contextual inquiry due to a pragmatic worldview of the coherence between theory and practice.

Combination of semi-structured interview and contextual inquiry

The semi-structured interview is supported by an *interview guide* to help the researcher in asking questions when it seems natural and fitting in an open-ended conversation with the participant. The interview guide strengthens the study's internal reliability because of a more consistent data collection to be compared in the analysis while also leaving room for an open-ended, explorative approach to pursue the participants' perspectives (Brinkmann & Tanggaard, 2010, p. 38; Bryman, 2016g, p. 469; Kvale, 1996, p. 129). As opposed to the unstructured, the semi-structured interview ensures that the majority of the interview questions are connected with the research questions and the majority of the questions are available in all the interviews. Meanwhile, in contrast to the structured interview, the semi-structured interview accommodates open-ended questions to follow up on the participants' insights. With aspects from the semi-structured interview, as opposed to focus groups, we focus on exploring individual experiences and perspectives in a specific context rather than emphasizing a group consensus and their general attitudes toward AI.

According to Brinkman & Tanggaard (2010, p. 30), an interview can never be neutral and fully unbiased because the interview is an active interaction between two or more people that leads to answers that are socially exchanged and based on the situational context. This insight also corresponds to our interpretivist stance. Additionally, the conversation and outcome of an interview will always be constructed through the conversational interaction with the participant and the researcher will not be able to fully understand the intended meaning and experiences of the participant but the goal is to get as close as possible to the experiences (Brinkmann & Tanggaard, 2010, pp. 30–31). On the other hand, the conversation and questions in contextual inquiry can be very open-ended and it is considered good practice to prepare a list of questions prior to the session (English & Rampoldi-Hnilo, 2004, p. 1484; Holtzblatt & Beyer, 2015, p. 13) which will be supported by the methodological approach of a semi-structured interview with an interview guide (see Appendix 6.1.2). Approaches from contextual inquiry can be applied to accommodate the lack of getting close to practice to gain a deeper understanding of the UXP's experience, practices, and challenges in relation to applying AI in their UX activities. Whereas classic interviews and focus groups rely on participants to explain and recall processes from outside of the situational context, contextual inquiry can uncover habitual, reasoning, and invisible details of the UXP's use of AI in the context of UX-related activities. While contextual inquiry emphasizes observation and inquiry of participants performing work activities in the actual observation session, there is also room for *retrospective accounts* which is a detailed walkthrough of a specific use or event in a recent period of time to understand work practices outside the interview (Holtzblatt & Beyer, 2015, p. 13). The limitations of contextual inquiry can be access to the natural work environment in which other people outside the inquiry might be affected by the presence of researchers and recording equipment, resources of time and money to travel, and fitting the schedules of all involved actors (Kaplan, 2022).

Remote contextual inquiry

As presented by Holtzblatt & Blatter (2015), a contextual inquiry is based on the researcher being present on-site. But the rise of technological devices and online meeting software on the internet opens up the possibilities for conducting contextual inquiry remotely if the work activities are primarily computer-based and desk-based without moving frequently out of the researcher's sight. The participant and researcher(s) can interact through online meeting software by sharing audio and video (Donnelly et al., 2021; English & Rampoldi-Hnilo, 2004; Kaplan, 2022). The participant shares their screen through a video-call platform, allowing researchers to follow and capture the participant performing activities while asking questions which also provides an opportunity to observe and record the work practices of the computer environment from the participant's point of view (English & Rampoldi-Hnilo, 2004, p. 1484; Kaplan, 2022). The imitations of doing remote contextual inquiry are the lack of observing the natural environment and on-site artifacts that are less observable remotely unless it is brought to attention by the participant or the researcher (Donnelly et al., 2021, p. 236; English & Rampoldi-Hnilo, 2004, p. 1487; Kaplan, 2022). Furthermore in remote contextual inquiry, it is important to ensure reliable internet connection, access to a platform with video-call, screen-sharing, and screen-recording capabilities, and adequate webcam and audio quality for all involved actors (Kaplan, 2022).

3.3 Method application

In this section, we provide an account of the chosen mixed method design employment in this study. Alongside that, we elicit how chosen methods of survey, semi-structured interview, and contextual inquiry were utilized to enable us to answer the objective of this study in the most suitable way.

3.3.1 Application of a Mixed Methods Design

In § 3.2.1, we establish our research design as *explanatory sequential*. We employ the survey to acquire quantitative insights on the domain of UXP and their adoption of AI. In addition, we use the data to categorize the UXP into two groups: *1) UXPs with AI experience* and *2) UXPs without AI experience*. While the quantitative data from the survey will serve as a foundation for shaping qualitative questions to inquire about UXP's practices, utilization of AI tools, and in general their attitude towards AI, the qualitative data collection aims to further expand the knowledge by investigating specifics of UXPs' use of AI in their work practices in the form of contextual inquiry and semi-structured interviews (§ 3.3.2).

Our explanatory sequential design can be further characterized as the *case-selection variant.* The case-selection variant emphasizes qualitative data exploration in comparison to the traditional *follow-up explanation variant* where the importance is on the qualitative data assisting in the explanation of the quantitative data. The most significant consequence of the quantitative data is in their preliminary input for the problem examination and identification of the best candidates for the qualitative research part (Creswell & Plano Clark, 2018b, p. 90). Therefore, the quantitative data about the participants' characteristics provide guidance through purposive sampling to select those participants who might help us explain the survey insights and further understand the context of UXPs' application of AI tools in the design process (§ 3.4.1). After conducting quantitative and qualitative data collection, we proceed with a separate analysis of the survey and contextual inquiries combined with semi-structured interviews. Finally, we combine the results and discuss them in connection with the conducted literature review.

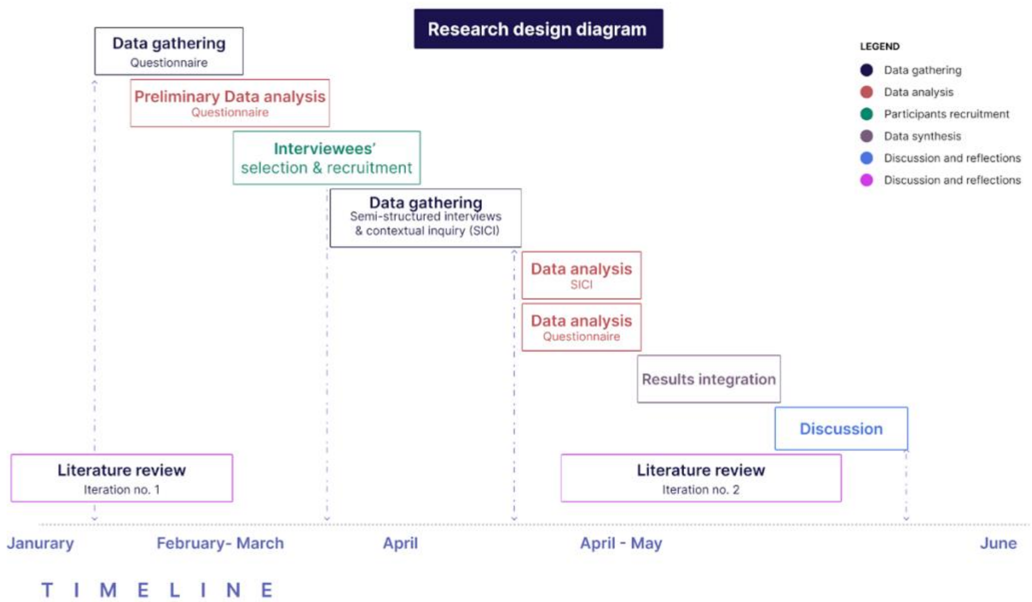


Figure 12: Research design diagram inspired by(Creswell & Plano Clark, 2018b)

3.3.2 Application of survey

To advance our knowledge about our audience on a larger scale, we chose to deploy an online survey distributed through social networks as the most suitable way of accessing our target audience. When reporting information about the questionnaire, we are inspired by the guidelines provided by Grimshaw (2014).

Through the survey, we have gathered insights about UXPs' practices, and the challenges they face during any stage of the design process. In addition, we have collected UXPs' attitudes, experiences, and thoughts about using AI tools in the design process. The survey consisted of five sections: *1) professional background; 2) work practices and activities; 3) AI as a part of the design process; 4) utilizing AI tools;* and *5) a prompt* to sign up for the follow-up interview (see Appendix 4.1).

SURVEY IN RELATION TO RQS	
RQS	SURVEY THEMES
RQ2 How are UX practitioners currently designing with AI in their UX work practices?	**1. Professional background** eg. What is your role in the company? **2. Work practices and activities** eg. Which UX/UI responsibilities do you perform in your role on a regular basis?
RQ3 What are the perceived advantages and challenges of UX practitioners' application of AI to the design of information technology?	**3. AI as a part of the design process** Have you heard of any AI tools that could be used in any part of design process? **4. Utilizing AI tools** In which part of your job do you utilize AI tools?

Table 16: Survey questions' relation to the RQs.

Throughout the survey, we included *characteristic*, *attitudinal*, and *behavioral* questions to cover the landscape we investigated which is presented in the following sections.

In the first theme, *Professional background*, we incorporate characteristic questions to get more understanding of the respondents' role, seniority, and educational background.

Meanwhile, the second theme, *Work practices and activities*, consists of behavioral questions to further understand respondents' responsibilities, which challenges they face in the UX design process, and also to probe which design framework they use. The intention with the framework has initially been connected with the project scope where we aimed to focus on a certain stage of the UX design process and design the AI tool which would assist UXP in their work practices and eliminate the challenges. However, the problem formulation has been refined and the designing of the AI tools has been delimited.

The third section, *AI as a part of the design process*, shifts the respondents' attention to the AI aspect and used attitudinal questions to explore their thoughts and impressions of utilizing AI tools during the design process. We also probe which AI tools they have heard of which could be used in the UX design process. If they answer positively to the question if they have any experience in utilizing AI tools in any part of the design process, they would continue further to section four. Otherwise, they would be redirected to section five.

In the fourth section, *Utilizing AI tools*, we investigate which AI tools they have used and how by utilizing behavioral questions. Furthermore, we ask in which part of their UX activities they have used them. We also investigate their perceived advantages of using AI in the design process and if they experienced any challenges while using AI for UX activities.

The last section, *Contact information*, allows respondents to decide if they want to participate in the contextual inquiry and semi-structured interview. If they decided to do so, they would be asked to leave an email for us to contact them, as the survey has been set as anonymous by default due to GDPR. As a consequence of that, we have not offered any incentives to the survey's participants, as we would not be able to identify all the participants. Not providing reimbursement might have an impact on the response rate.

Regarding the format of the questions, we apply *multiple choice questions*, *single select questions*, *short open-ended questions*, *Likert scale questions*, and *dichotomous questions*. Based on insights from Rosala & Krause (2019), if applicable, some multiple-choice questions also include *Other option* to provide respondents the freedom to specify their answers if any of the provided options do not fit their context, e.g. in the case of job titles, educational background, and UX/UI responsibilities. Only those UXPs who answered the dichotomous question positively (as having previous experience with utilizing AI tools), would proceed to section four, otherwise, they would be navigated to section five. Likert scale questions are the most suited when exploring the respondent's attitude towards AI, specifically their insights on the relationship between UXPs' and AI. As people have tendencies to have biases towards the left, *order effect*, and also have the inclination to agree with statements, *acquiescence* (Brace, 2008, pp. 74–75), we have placed the *Strongly disagree* on the left side while *Strongly agree* on the right side of the scale. Short open-ended questions play a role to further follow-up to the previous question to expand respondents' thinking process or behavior. All open questions are optional, so the respondent could decide to skip them if they feel not to answer them.

Pilot test of survey

To assess the quality of the survey, we conducted a *pilot test*. Preliminary analysis of answers from pilot tests provides valuable information about the validity and reliability of the questionnaire. While *content validity* refers to the survey structure and effectiveness of questions to answer the research questions, reliability deals with the clarity of the questions ensuring that respondents understand the questions and feel confident and comfortable answering them (Saunders et al., 2012c, pp. 451–452). Although some authors suggest that testing with 5-10 users is sufficient (Goodman et al., 2012; Liu, 2019), others recommend testing with 10% of the intended sample (Jarrett & Krug, 2021, p. 357). Despite our efforts, we managed to pilot-test with 6 respondents which represents 10% of our minimal intended sample size for a survey. Based on the received feedback, we have made some alterations. To increase the content validity, we addressed the format and description of the questions to capture the possible range of UXPs' attitudes, behaviors, challenges, etc., and ensure that respondents understand the questions (see Appendix 4.3). Our aim in changing the survey was also to decrease the time spent on filling out the survey. In this matter, we have been successful as the average time of deployed survey decreased to 8 minutes and 5 seconds while still containing the primary areas of our research interest.

3.3.3 Application of qualitative data gathering methods

In the remainder of the thesis, we will refer to the qualitative data gathering session as *SICI* (**S**emi-structured **I**nterview, **C**ontextual **I**nquiry). We conducted either on-site SICI or remote SICI based on the participant's preference in each session. The restricted population of UXPs with AI experience led us to be flexible and accept the limitations of remote SICI. Although we identify the remote limitations of missing out on immersing ourselves in the lives of UXPs and the importance of other on-site artifacts in their natural work environment, we argue that, due to our focus is on the UXP's practices using AI on a computer device, the application of remote SICI still provides a deep understanding of UXP's work practices regarding designing with AI. The limitations can be accommodated by conducting remote pilot studies and being vigilant in noticing the impact of the surrounding artifacts that might complement the work practices in the situation (Kaplan, 2022). We conducted two pilot studies to test the remote set-up and refine the interview guide to support follow-up questions regarding their application of AI (see Appendix 6.2). We describe the sampling of participants for the SICI in § 3.4.2.

Before conducting each session, we assigned the roles of *facilitator* and *observer*. The facilitator was guiding the whole session by introducing, observing, and asking questions. The observer was passive and made sure to record the session, write field notes, and store the recording and consent form. Each interview consisted of an introduction to the session which includes the study's purpose, a definition of AI tools to align the understanding, information about data protection with GDPR, assuring anonymous status including the company's, and ensuring the consent form is understood and signed (also sent in advance). The introduction and consent form can be located in Appendix 6.1.1 and 6.1.3.

The questions in contextual inquiry can be guided by 1) an introduction to the participant's role and situation, 2) followed by the participant carrying out work activities while the researcher observes and asks questions that lead to a conversation and discussion about the activities, and 3) finally the session will be concluded to clarify certain observations and (Holtzblatt & Beyer, 2015, p. 13). We applied the three phases as proposed by Holtzblatt & Beyer (2015) but we added an extra focus and set of questions before the concluding session of the interview guide to better understand UXP's AI literacy and feelings towards AI in a HCD approach. The first three themes of the contextual inquiry in our data collection are related to our RQs which are visualized in the following table:

INTERVIEW GUIDE IN RELATION TO RQS	
RQS	INTERVIEW GUIDE THEMES
RQ2 How are UX practitioners currently designing with AI in their UX work practices?	**1. Introduction to their UX role** eg. Can you briefly explain your role?
RQ3 What are the perceived advantages and challenges of UX practitioners' application of AI to the design of information technology?	**2. UX work practices with AI** eg. Please show us how you apply AI to [their UX activity]
RQ4 What are the consequences of applying AI, and how might AI impact the domain of UX and related UX practices?	**3. AI Literacy, AI feeling, & AI in HCD** eg. In a HCD approach, how do you feel about AI?

Table 17: Interview guide questions' relation to the RQs (Appendix 6.1.2).

The first theme, *Introduction to their UX role,* is about priming the situation and understanding their role and responsibilities as UX practitioners. The introductory part assures that the participant feels comfortable in the situation while also providing context for the facilitator to ask questions related to the participant's UX role and responsibilities in the remainder of the contextual inquiry.

The second theme, *UX work practices with AI,* constitutes the observational and inquiring part of the contextual inquiry in which the participant performs their work activities related to applying AI. Although contextual inquiry oftentimes is controlled by the participant performing rather random work tasks, there is room for steering and guiding the conversation toward the focus of the study as long as they are performing their own, natural work activities (Holtzblatt & Beyer, 2015, p. 13). Due to our focus on AI and the limitations of our participants' availability, we decided to focus our contextual inquiry primarily on work activities related to their application of AI. Meanwhile, we did not exclude other work practices, methods, or tools if they were applied in the situation.

The third theme, *AI Literacy, AI feeling, and AI in an HCD approach,* relates to our inclusion of a semi-structured interview in which we focus on the UXPs' evaluation of AI in the domain of UX, their feelings about AI, and how reliable AI might be in an HCD approach. This part of the session draws on aspects from the semi-structured interview with open-ended questions about the participant's professional and personal attitude towards AI's pros and cons in the UX practices.

During the contextual inquiry, it is important to take field notes to follow-up on the activities during the interview, but it is also important to document the observations that might not be captured on the recordings (English & Rampoldi-Hnilo, 2004, p. 1484; Lazar et al., 2017a, p. 211). Our field notes can be located in Appendix 8 which supports our memory in analyzing the interviews.

3.4 Sampling

In the sampling sections, we briefly present different sampling strategies to inform our sampling strategies in the quantitative data gathering (§ 3.4.1) and qualitative data gathering (§ 3.4.2). Part of the research design is selecting a sampling strategy that specifies the procedure based on providing a representative sample of participants for the study (Bryman, 2016d, p. 187; Creswell & Creswell, 2018b). Overall, sampling techniques can be categorized into two groups: 1) *probability/representative sampling* and 2) *non-probability sampling* (Bryman, 2016d, p. 184; Saunders et al., 2012b, p. 261).

There are four non-probability sampling techniques groups: 1) *Quota*, 2) *Purposive* 3) *Volunteer* (self-selection, snowball), and 4) *Haphazard* (Saunders et al., 2012b, p. 284). The most suited sampling technique for a market research dealing with a large population is *quota* where the population is divided into specific categories and the selection of the participants is completely non-random (Bryman, 2016d, p. 205). In contrast, *purposive sampling* is used for small populations when the researchers' objective is to find and select the most informative sources (Saunders et al., 2012b, p. 287). Volunteer sampling uses two different techniques: 1) *snowball sampling* and 2) *self-selection sampling*. The former is used in situations when the participants are difficult to find and the researchers ask the already identified participants to help them to identify the further case, while the latter allows the members of the population to react to the published research and decide if they want to participate or not. The last non-probability sampling technique is called *haphazard sampling* and its most common form is convenience sampling. It follows no principles when selecting participants as its main advantage is that it allows to include participants who are easily obtainable. That, however, leads to samples that are prone to biases that are difficult to control (Saunders et al., 2012b, pp. 289–291).

In terms of the sampling, having a representative sample is one of the important factors of probability sampling (Saunders et al., 2012b, p. 267), because it secures the known probability of selecting each case from the population and it also enables *"[...] to make statistical inferences about the characteristics of the population"* (Saunders et al., 2012b, pp. 261–262). In contrast to probability sampling, the non-probability samples allow generalization only about *“[...] the population from which that sample was taken, however, it is not done on the statistical foundation”* (Saunders et al., 2012b, pp. 261–262). In qualitative research, non-probability sampling is mostly employed and used in exploratory studies or studies which focus on an in-depth understanding of the research topic (DeCarlo, 2018; Saunders et al., 2012b). The sample size depends on the RQs, objectives that need to be found out, and available resources. When using semi-structured interviews, the data collection needs to run until the researchers reach *data saturation*. The minimum probability sample size of the homogeneous population for semi-structured interviews is between 4-12 (Saunders et al., 2012b, p. 283).

3.4.1 Sampling: Survey

As there are 134 different job titles reported within the UX field (Rosala & Krause, 2019), § 2.2.2, it was necessary to address the UXPs by including *UI (UX/UI Practitioner)* when addressing our targeted audience for the survey.

In our survey design, we have applied a combination of non-probability sampling techniques, specifically *self-selection, snowball,* and *purposive sampling*. The *self-selection sampling* was a consequence of publicly announcing our research and the survey on LinkedIn, Facebook, and the Copenhagen Fintech Slack Channel. The benefit of self-selection sampling is that it allows UXPs to decide if they want to participate or not. As part of posting on Social Media, we also prompted our network to share it with UXPs in their network which can be categorized as *snowball sampling*. However, the bias of such sampling cases might lead to a *homogenous sample* (Saunders et al., 2012b, p. 289). To the best of our knowledge, the snowball sampling method did not affect our reach significantly due to the response rate in the following period of time. Furthermore, we tried to reach out to large UX communities on Social Media to increase the response rate but sharing surveys in the majority of these groups is not allowed due to their policies.

To increase the response rate, we applied *purposive sampling* as it allowed us to contact cases that, to the best of our knowledge, suited our targeted audience and by that meet our research objectives (Saunders et al., 2012b, p. 287). An example of this approach is contacting *Information Studies Alumni* from Aalborg University in Copenhagen.

As a part of the sampling process, we attempted to estimate the population of UXPs in Denmark. To our knowledge, there is no exact representation of UX professionals in Denmark. One source of information could be trade unions, such as *IDA,* or community groups and forums, including *CPHUX* or *UX Danmark*. Their numbers, however, reflect only their membership base or the number of potentially interested to join such an organization. Another source that we made use of is *LinkedIn* searching and filtering functionality. However, we need to point out that this tool has a few drawbacks too. Firstly, not every UXP might have a LinkedIn profile. Secondly, there are numerous variations for job titles in the UX field (Rosala & Krause, 2019). And thirdly, not all UXPs have profiles that would specify their UX skills or include keywords that would make their profile easier to recognize by the search engine. However, to make our estimation more concrete, we limited our sample frame to the group of UXPs residing in Copenhagen. Our searches were limited to the Copenhagen *Metropolitan Area* and *Capital Region Area*. Based on Advanced Search on LinkedIn, we estimated the sample frame of UXPs residing in the Copenhagen Metropolitan Area to be around 1300 people (see appendix 4.5). Opting for non-probability sampling was due to the fact that we did not have accurate and complete information about the sample frame which would represent a population of UXPs in Denmark (later on limited to the Copenhagen Metropolitan Area).

While there is no straightforward rule or definitive answer to determine the sample size in social research, the considerations regarding the sample size are affected by the *research objectives*, *characteristics of the population*, *time,* and *cost* (Bryman, 2016d, p. 183). The research objective of RQ2 is to focus on UXPs and their application of AI. The purpose of the survey is an open exploration of UXPs to generate insights that could inform our qualitative data gathering while also providing a preliminary view of how widespread the use of AI is in the field of UX. Furthermore, the sample size was also determined by the access to UXPs and time. The survey reached 64 participants in total (≈5% of UXPs in Copenhagen Metropolitan Area, N=1300) which is not sufficient to generalize the findings across the entire population of UXPs. However, it can serve as a preliminary view into UXPs and how they might use AI.

Participant's background from survey

The following figures show the background of the respondents that answered our survey. The proportion of different UXPs who responded to the survey is summed up as follows:

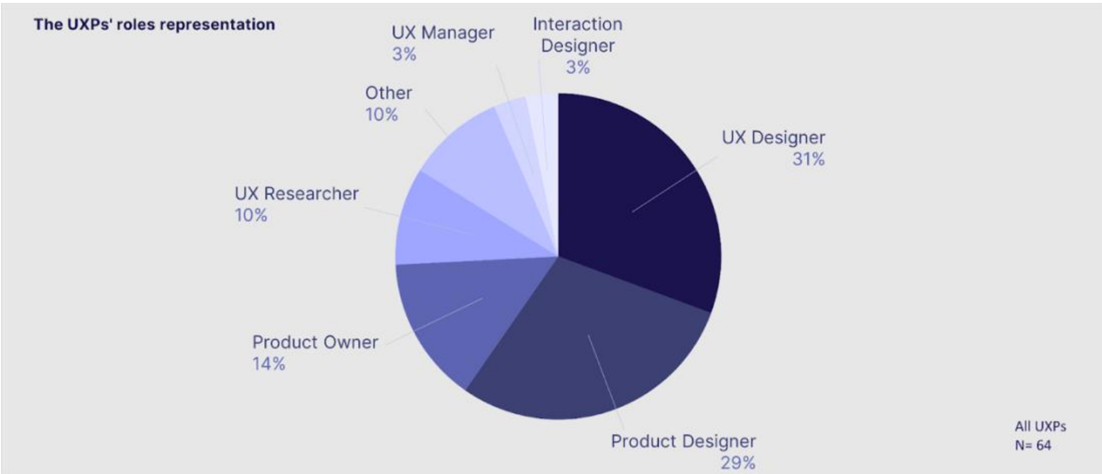


Figure 13: The survey respondents' roles (N=64).

The most prevalent role was *UX Designer*, accounting for 31% of respondents, followed by *Product Designer* with 29 % representation, while the least represented are *UX Managers* and *Interaction Designers* with only reaching 3% each.

In terms of experience, 28% of respondents have between 3-4 years of experience. While 32% of respondents have less than 2 years of experience, 39% of participants have over 5 years of experience. To highlight the seniority of our respondents' pool, 11% of participants have above 9 years of experience:

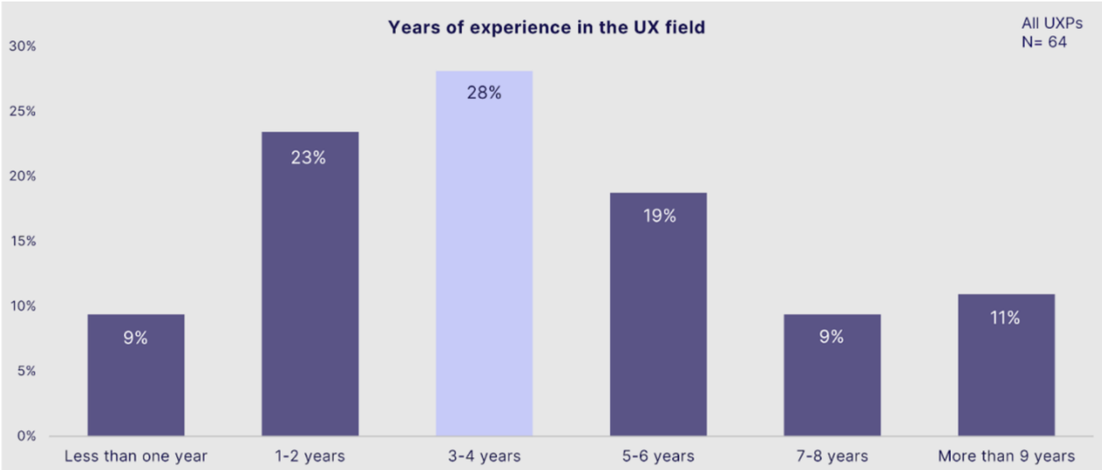


Figure 14: Overview of survey respondents' years of experience (N=64).

Regarding education, due to our sampling targeting AAU's Information Studies Alumni, the data shows that 40% of respondents are accounted for those with an *Information Science* background, followed by *Design- related education* background with 23% and *HCI* with 19% of representation:

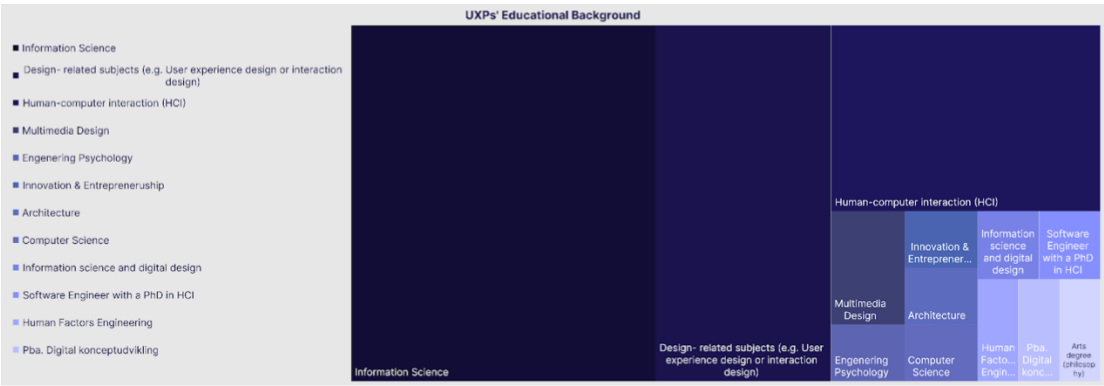


Figure 15: Overview of survey respondents' education background (N=64).

With reference to the reported UX/UI responsibilities performed by UXPs in their role, the respondents identified the most common responsibility to be *User research* (27%), followed by *Interaction design* with 24% and *Information Architecture* with 19%. The least represented was *Content Strategy* with 11%:

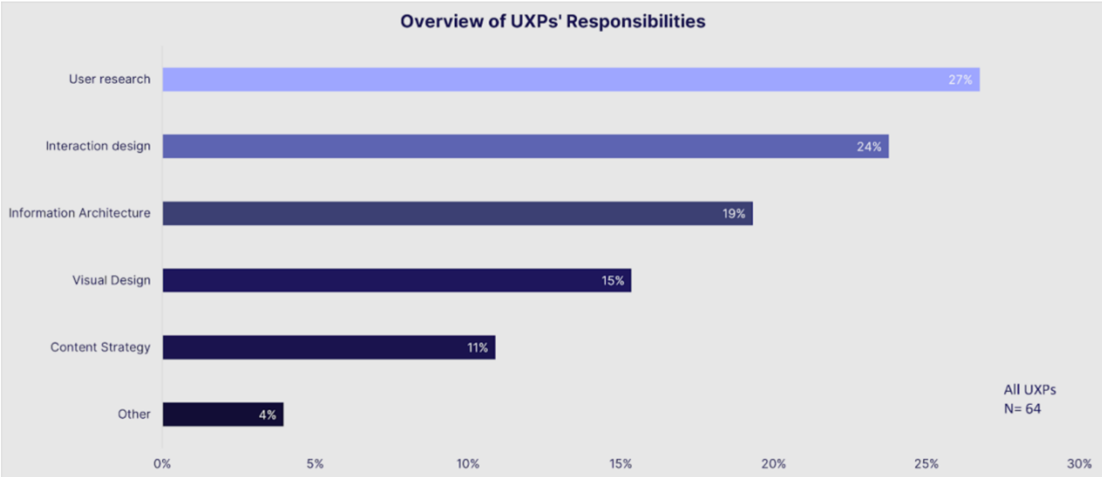


Figure 16: Overview of survey respondents' UX/UI related responsibilities (N=64).

Out of 64 respondents, 52% respondents reported their use of AI in the design process:

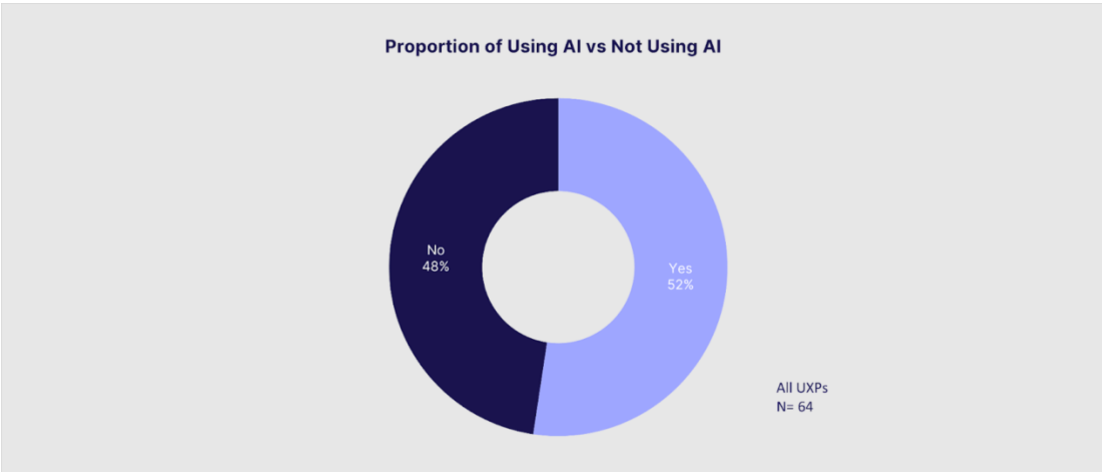


Figure 17: Proportion of UXPs with experience in using AI to design with (N=64).

3.4.2 Sampling: Semi-structured interview & Contextual Inquiry (SICI)

During recruitment for the SICI, we applied the combination of *purposive sampling* and *volunteer sampling*. The primary technique was *generic purposive sampling* which is oftentimes employed in mixed methods studies in which the survey act as a foundation for selecting interviewees (Bryman, 2016f, p. 422). The benefit of this technique is that the selection reflects the important criteria to preserve the quality of the study (Bryman, 2016f, p. 423). The survey's final section allowed respondents to leave their contact information for a follow-up SICI (see Appendix 4.1.5). Subsequently, we divided respondents into two groups based on their experience with applying AI tools. Due to our focus on exploring the practices of AI-experienced UXPs, we only contacted UXPs with AI experience for UX activities. Additionally to the best of our ability, we sampled the UXPs based on their experience and application of AI. Furthermore, we also sampled UXPs based on their perceived practices and experiences with certain AI tools, eg. approaching UXPs that seemingly used GenAI in a different way than the majority of our sample who used it for UX copywriting (Appendix 5). One interview participant was selected through *snowball sampling* as it was recommended by one of the survey respondents. We created a list of 12 potential candidates for the SICI, see Appendix 6.3. From 12 candidates, 6 UXPs decided to participate in the SICI.

Participants' background from the SICI

To provide an insight into our six participants from the SICI, we summarized their professional background with a specification of their current UX role, experience, and type of applied AI tools (Table 18).

PARTICIPANTS IN SICI SESSIONS				
PARTICIPANTS	ROLE	EXPERIENCE LEVEL & RESPONSIBILITIES	AI TOOLS	ORGANIZATIONAL CONTEXT
P1 Participant 1	Design Lead in startup, UX/UI Student Assistant.	3-4 years • Product Design • Visual Design • UX Copywriting • Marketing Copywriting.	Chat GPT, Wordtune, Nichess, Midjourney, & Figma AI plugin Non-AI: Figma	Startup in connection to video ad creation.
P2 Participant 2	UX Designer Part-time in corporation.	2 years • UX research • Prototyping (past) • Data Management.	ChatGPT Non-AI: • Figma.	Renewable energy company- responsible for data platforms.
P3 Participant 3	Senior UX Designer in Silicon Valley (remote work).	5-6 years • UX research • Ideation • Product Design • Prototyping • Problem solving.	ChatGPT Non-AI: • Figma.	Development of a financial tool for cloud cost analytics
P4 Participant 4	UX Director in a design agency.	15 years • Management • Ideation • UI & Interaction Design • Customer relations • UX Strategy.	ChatGPT, Stable Diffusion, DiffusionBee Non-AI: • Figma • Webflow.	Working in design agency means each project is different.
P5 Participant 5	Chief Experience Officer (CXO) in a startup.	10+ years • UX Research & Design • Customer relations • Testing • Teaching UX Design • Marketing copywriting	ChatGPT (twice a month) Non-AI: • Figma	Developing a platform for unmoderated, remote user testing
P6 Participant 6	Senior Product Designer	7-8 years • UX Research • UX Design • UX copywriting	ChatGPT Non-AI: • Figma	Making applications for compliance managers

Table 18: Overview of participants in SICI

Based on Table 18, it can be argued that we have secured a heterogeneous group in our qualitative data gathering. Concerning seniority, we managed to interview two senior designers with over ten years of experience, two designers who have between five to eight years of experience, and two student designers who can be classified as junior designers with two to four years of experience. Regarding the workplaces, four designers work in early- to late-stage startups, one designer works for a multinational company, and one for an established Danish national company. In addition, two of the participants work fully remotely. In terms of their AI tools adoptions, there is a different level of trust and usage (§ 4.2.3).

3.5 Data processing and analysis

In this section, we will outline the approach to the data processing, examining, and understanding of quantitative (§ 3.5.1) and qualitative data (§ 3.5.2).

3.5.1 Analysis approach: Survey

To analyze the gathered data from the survey, we performed quantitative and qualitative analyses. Without processing and analyzing, the raw quantitative data do not hold much meaning (Saunders et al., 2012b, p. 472). Our aim was to use various visualization methods to effectively communicate the insights about UXPs' use of AI, their perceived challenges, and advantages of using AI in their UX design process in connection to the RQ2 and RQ3.

The type of collected quantitative data and the nature of the sample determine what type of analysis can be conducted (Bryman, 2016c, p. 330; Saunders et al., 2012b, p. 472). From the statistical point of inquiry, there are *descriptive* and *inferential statistics*. While inferential is concerned with inferring some characteristics about the whole population from the sample, the descriptive aims at describing, and summarizing a specific sample of data (observations and measurements) without that intention (Howell, 2010, p. 5; Turner & Houle, 2019, p. 300). One of the descriptive analysis approaches is *exploratory data analysis* which examines the data in detail to understand it and argue the choice of visualizing techniques to explore, present and describe the data in connection to RQs (Howell, 2010, p. 5; Saunders et al., 2012c, p. 487).

In connection with our philosophical approaches, we combine deductive and inductive approaches when interpreting data from survey. While deductive interpretation (top-down) is based on the concepts/themes theories that emerged from the literature review to create survey themes, inductive analysis is beneficial when interpreting open-ended questions for the themes identification. As stated in § 3.4.1, an inferential analysis would be possible only if we applied probability sampling where a sample size is accurate and large enough to provide a representative sample of the population (Saunders et al., 2012a). As a consequence, the results are not used for generalization for the whole population of UXPs residing in Copenhagen. And therefore while analyzing the data from the survey, we do focus on exploring, describing, and summarizing characteristics of the UXP sampling. To do so, we use descriptive statistics to analyze data from a non-probability sample. However, in terms of analyzing open questions and 'Other' options which represent qualitative data, we identified main categories/themes by utilizing *content analysis*. A content analysis aims at identifying patterns across data with an emphasis on the content, context, and meaning of data (Elo & Kyngäs, 2008, p. 108). Content analysis is oftentimes used for quantitative purposes of counting the number of appearances in larger datasets (Braun & Clarke, 2006, p. 98).

Exploring and presenting data

To be able to conduct the survey analysis, we needed to determine the types of collected data. Saunders et al. (2012) divide quantitative data into two groups: 1) *categorical* and 2) *numerical*. While categorical data are measured on a nominal scale and are assigned categories, numerical data represent some sort of measurement and are measured numerically (Howell, 2010, p. 6; Saunders et al., 2012c, p. 475). Numerical data can be further distinguished as *continuous* and *discrete* or alternative as *ratio* and *interval* data. While discrete variables have a limited number of values, they are allowed to take any value (Howell, 2010; Saunders et al., 2012c, pp. 476–477). The difference between ratio and interval data is in the ratio data has a specified *fixed zero point* (Bryman, 2016b, p. 335). Categorical data can be divided into *nominal* which can not be ranked, while *ordinal* variables can be ranked and present a more precise form of categorical data, typically used for the Likert scale (Bryman, 2016b, p. 335; Saunders et al., 2012c, p. 475).

Selecting the most effective visualization to communicate the findings depends on the data type and communication purposes (Healy, K., 2018; Kirk, 2012, p. 120). Kirk (2012) classifies visualization methods in terms of their communication function into 5 types: 1) *Comparing categories*, 2) *Assessing hierarchies and part-to-whole relationships*,

3) *Showing changes over time,* 4) *Plotting connections and relationships b*etween multivariate datasets, and 5) *Mapping geo-spatial data* (Kirk, 2012, p. 120).

In our study, we use visualization methods for comparing categories and assessing the part-to-whole relationship. A *bar chart* is an effective diagram to compare categorical or numerical variables to showcase the length/height of columns, while a *histogram* showcases distributions through the frequency of occurrences for interval/ratio variables (Kirk, 2012, p. 123-125; Saunders et al., 2012c, p. 488; Wilke, 2019). *Ordered bar charts* are used, eg. for Figure 19. Regarding presenting part-to-whole relationship, we use a *pie chart,* e.g. to present participants' backgrounds (Kirk, 2012, p. 132). To demonstrate the sequencing of sentimental ordinal data from Liker scales, we opt for a *stacked bar chart* as it allows us to capture and compare different responses for the statement, e.g. Figure 21 (Kirk, 2012, p. 132; Saunders et a., 2012c, p. 501). Furthermore, to offer an additional layer of representation of clustered units based on their values for categorical nominal data or ratio data, we employ a tree map (Kirk, 2012, p. 134-135). Regarding the open questions, we have conducted the content analysis and based on the identified themes further visualized them by utilizing stacked bar charts positioned next to each another to communicate the disparity (see Figure 21).

All survey data can be seen in Appendix 5. When interpreting data, we are cautious not to generalize for the whole population. To assess the validity of the findings, the results will be further compared with the results from the qualitative data in § 5.

3.5.2 Analysis approach to SICI

To analyze the collected data from SICI, we conduct a *qualitative analysis*. The purpose of qualitative analysis is to transform unstructured data into detailed, comprehensive descriptions of the complex situation being studied (Lazar et al., 2017b, p. 300). The goal of our qualitative analysis is to understand how the UXPs apply AI in their current work practices and how AI affects the UX practices which are related to RQ2, RQ3, and RQ4.

Rich qualitative data can be analyzed by applying a variety of methods, such as *discourse analysis, conceptual analysis, thematic analysis, content analysis,* and *grounded theory*. A discourse analysis aims at understanding the structure of discourses within language to identify cues of how the phenomena are viewed, perceived, and framed (Lazar et al., 2017a, p. 221). Conceptual analysis is a systematic, deductive approach with codes based on concepts, themes, and/or theories (Jabareen, 2009). In close proximity, thematic analysis is a method for *"[...] identifying, analysing and reporting patterns (themes) within data"* (Braun & Clarke, 2006, p. 79). As opposed to conceptual analysis, thematic analysis can be conducted both *inductively* (bottom-up) and *deductively* (top-down) (Braun & Clarke, 2006, p. 83). Closely related to a thematic analysis, a content analysis aims at identifying patterns across data. Content analysis is oftentimes viewed as similar to thematic analysis due to the flexibility (inductive and/or deductive approach) and identification of patterns across rich datasets. The difference is that content analysis is oftentimes used for quantitative purposes of counting numbers of appearances in larger datasets (Braun & Clarke, 2006, p. 98). Thematic analysis can be related to grounded theory in which patterns are identified in the data with the purpose of generating a useful, plausible theory of the phenomena. Thematic analysis and grounded theory can be combined but in its purest form, thematic analysis does not aim at developing theory which is the main purpose of grounded theory (Braun & Clarke, 2006, pp. 80–81).

Due to our combined philosophical approach of pragmatism and interpretivism, we have opted for an inductive thematic analysis approach. We aim at exploring and understanding the subjective meanings and experiences of UXPs. The flexible, inductive analysis affords an open approach to allow themes and insights to emerge based on the research subjects' own meaning which aligns with our interpretivist stance. However, as a researcher performing inductive thematic analysis, it is important to acknowledge the theoretical positions, values, and biases that will emerge in the process of selecting, editing, and interpreting the data (Braun & Clarke, 2006, p. 80). Researcher bias and subjectivity might implicate the study's *intern reliability,* but by establishing *inter-coder reliability,* we accommodate the subjective nature of the interpretations in the analysis. Furthermore, inductive thematic analysis allows for a detailed and nuanced understanding of UXPs' perspectives and experiences in the context of working with AI whereas a deductive approach relies on applying pre-existing theories or concepts.

The qualitative analysis process

To conduct our inductive thematic analysis, we are inspired by six, recursive phases to a structured thematic analysis as presented by Braun & Clarke (2006): 1) *Familiarizing with data*, 2) *Generating initial codes*, 3) *Search for themes*, 4) *Reviewing themes*, 5) *Defining and naming themes*, and 6) *Producing the report* (Braun & Clarke, 2006, p. 87). In the following sections, we will briefly document and present how we processed the qualitative data based on the six phases of thematic analysis.

Getting *familiarized with data* is about transcribing, (re)reading the data, and noting initial ideas for analysis (Braun & Clarke, 2006, p. 87). The qualitative data from the SICI consist of field notes and screen and audio recordings. To familiarize ourselves with the data, the field notes are revisited, recordings are viewed, and the audio is transcribed. A transcription makes the auditive data more tangible and applicable for analysis (Braun & Clarke, 2006, p. 87; Brinkmann & Tanggaard, 2010, p. 43) and can be considered a key element of data analysis where ideas for analysis are created (Braun & Clarke, 2006, pp. 87–88). The transcriptions are located in subsections 1-6 in Appendix 7. Transcriptions support the study's internal reliability because it strengthens the consistency and stability of data across the researchers and readers over time. The transcriptions were done through an online data insight tool, *Dovetail*, which offers transcription alongside audio and screen recording which strengthens a multimodal analysis. Due to possible mistakes made by Dovetail, and the lack of familiarizing ourselves with the data by not performing the actual transcription manually, we put extra emphasis on rereading the transcriptions and correcting mistakes. In addition, just before reading the transcripts, watching the screen recordings, and listening to the audio, we revisited the field notes to immerse ourselves as much as possible in the situational context that was described.

The second phase of thematic analysis, *generating initial codes*, consists of noting and coding features of interest in a systematic approach across the dataset. A *code* refers to a feature of the data that the researchers find interesting in relation to the phenomenon. Coding is a process of organizing data into meaningful groups that eventually will be the basis of the themes in the next phase (Braun & Clarke, 2006, p. 88). The codes consist of a combination of *in vivo coding* (Bryman, 2016, p. 573) and *descriptive coding* (Gibbs, 2007, p. 45) in which the participants' wordings were incorporated to a certain extent to summarize the content of the citation. Examples of how quotes were coded are presented in the following table:

EXAMPLES OF CODES	
CODES	CITATION FROM THE TRANSCRIPTS
AI frees us from tedious work we do not want to do anymore	*"So I think it's really good for that kind of thing, the tedious things that we don't want to do anymore"* (A7, P1 53:01)
Using AI to kickstart ideas	*"I'm more like playing a little bit with it, making it kickstart ideas for me, I feel like that's the good way"* (A7, P4 30:17)
Middleman before using AI output Fact-checking AI output before trusting	*"That's why I'm the middleman before it gets sent to any user or any client or anything. So I can't trust it. I have to read whatever it gives me first and make a decision if I actually I don't trust it with facts or anything like that, but I could ask it for what would be some good ideas to check up on, on facts maybe"* (A7, P4 30:17)

Table 19: Examples of in vivo and descriptive codes (Appendix 7)

As seen in Table 19, we allowed for multiple codes for the same quote to summarize different insights in the same quote that could be useful in dividing themes in the next phase of thematic analysis. Eventually, 272 different codes emerged from the transcriptions in which 308 citations were extracted (initial codes can be seen in Appendix 9).

To strengthen internal reliability, both researchers went through an entire interview collaboratively to align the coding approach. The remaining transcriptions were divided between the two researchers to be coded which was then followed up by both researchers collaboratively going through all the transcriptions and codes together to align and ensure the reliability, of the codes. During this procedure, we also started to *search for initial themes* by discussing the links between the different codes.

The codes were assessed by *searching for themes*. Based on our familiarization with data and extensive coding process, we were able to link different codes with each other based on their coherence. Essentially, we analyzed the codes to consider how they might combine in overarching themes. The codes were piled into level 1 themes which we refer to as *microthemes*. The procedure was iterative and codes were rearranged multiple times due to new discoveries in the data. Essentially, 30 microthemes emerged from the initial search for themes (see microthemes in Appendix 9).

Based on the former phases, *themes were reviewed* and codes were rearranged. In this phase, we linked different microthemes based on their ability to perform a coherent pattern in level 2 themes which we will refer to as subthemes. Based on a higher level of themes, microthemes were reviewed and a new level of understanding the data emerged. Figure 18 is an example of how microthemes are grouped to form a subtheme:

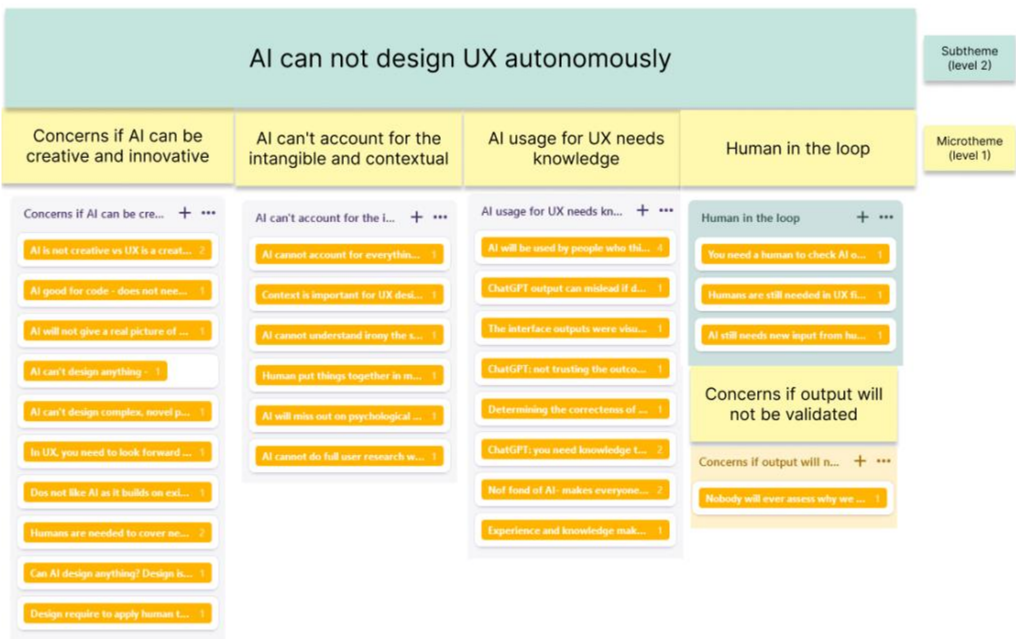


Figure 18: Example of the subtheme: “AI can not design UX autonomously” (locate all subthemes in Appendix 9)

The structured approach of Braun & Clarke's (2006) six phases of thematic analysis can strengthen the internal reliability, as it provides a systematic way to identify and organize themes. Furthermore, it reduces the likelihood of researcher bias and it might increase the consistency of themes across both of the researchers.

3.6 Ethical considerations

It is an obligation to assess ethical issues that might arise in the course of performing social research to ensure the integrity of the study and treat the research subjects with respect (Bordens & Abbott, 2011, p. 197; Bryman, 2016c, p. 120). Discussion of ethical principles can involve different foci based on the research objective and subjective. For instance, the *Belmont Report* emphasizes protecting people with regard to their autonomy (*respect for persons*), well-being (*beneficence*), and equal burden between researcher and participant (*justice*) (Belmont Report, 1979, pp. 4–6). In relation, the *APA Ethical Principles of Psychologists and Code of Conduct* emphasizes rights for participants to participate voluntarily, provide informed consent, withdraw participation, obtain results, and confidentiality (American Psychological Association, 2017). In the following section, we will present how we addressed the ethical issues in our course of performing research with UXPs.

To secure the study's integrity, we have provided informed consent in the survey and obtained a signed consent form in the SICI (Appendix 6). In both cases, we have made sure to inform the participants about the purpose and procedures of the study, while providing our contact information in case of questions and/or withdrawal from the study at any time.

In both the survey and the SICI, we have ensured each participant's anonymity and confidentiality. From our pilot studies, we knew that UXPs oftentimes have a responsibility to keep company information anonymous. In relation to this, we made a risk assessment in which we ensured that the UXPs have permission from their company to minimize the risk of privacy violations. The protection of privacy has been accommodated by the application of GDPR in securing the data safely (see

Appendices 4 & 6) and removing names, companies, and other personal identifiers (eg. faces from recording) to protect the identities.

To accommodate ethical issues of autonomy, we have contacted the participants based on their own provision of email addresses at the end of the survey. We have reached out politely to ask if they were still open for an interview, while providing opportunities to participate either online or on-site. Furthermore, we send the consent form beforehand in which withdrawal from the research is written explicitly as an option anytime. In the session, we ensured autonomy based on the open questions in which we ask the participants to perform their normal work activities. However, due to our focus on AI, we asked specifically to observe and inquire about AI which we were aware of during the contextual inquiry phase. Here, we focused on the natural use of AI systems while not pressuring them.

Finally, we have assessed our own biases in the analysis of the data provided by the research subjects. We are aware that our researcher bias might influence the framing of statements made by participants. To accommodate this, we transcribe the interviews and process the data inductively by staying as close to the participants' own words with citations in the thematic analysis. Moreover, we performed inter-coder reliability coding by collaboratively coding the transcriptions to discuss our biases of the dataset to remove subjectivity and misinterpretations.

4. Results & Findings

In this section, we will present the findings from the qualitative and quantitative approaches:

§ 4.1 Quantitative Analysis

§ 4.2 Qualitative Analysis

4.1 Quantitative Analysis

This section presents a quantitative analysis of the insights obtained from a survey administered to 64 UXPs (see § 3.3.2 and Appendix 4). The aim of the quantitative analysis is to provide insights on RQ2 and RQ3 by providing a quantitative overview of all the respondents' perceptions of AI in UX (N=64) including their experience in using AI in the design process which was limited to 52% of the respondents (N=33, see § 3.4.1).

4.1.1 Perceived challenges in the design process

In the survey, one of the questions aimed at exploring the perceived challenges that the UXPs faced in the design process. The distribution of the biggest challenges faced by the UXPs in relation to the design process is visualized in Figure 19.

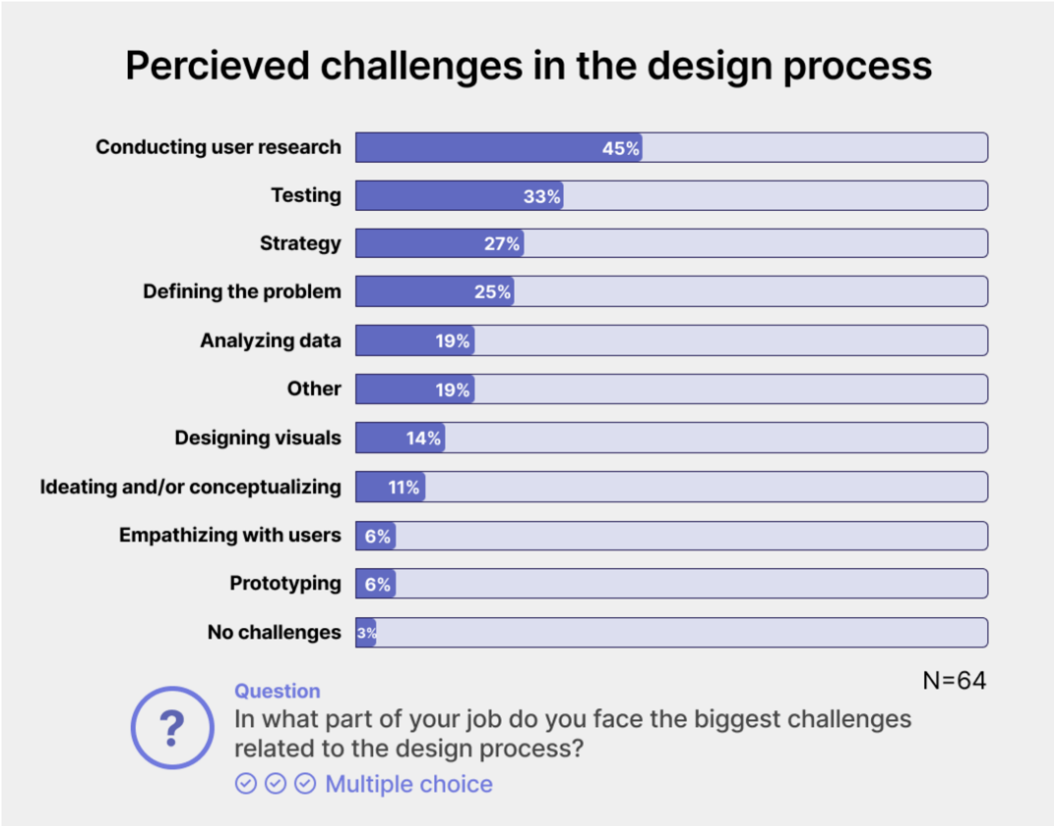


Figure 19: The biggest challenges divided by UX activities in the design process as perceived by UXPs. The percentages are based on the total amount of respondents (N=64).

According to findings in Figure 19, the most significant challenges reported by the UXPs are conducting *user research* (45%) and *testing* (33%). This shows that activities related to user involvement are prominent challenges in the design process. In relation to the design phases of *user research* and *testing*, 19% of the respondents found difficulties in analyzing data, while 6% of the UXPs find trouble empathizing with users.

Other noteworthy insights from Figure 19 are the challenges related to *strategy* (27%) and *defining the problem and/or requirements* (25%) which are challenges related to *problem setting*.

Finally, 14% of the respondents encounter difficulties in *designing visuals*, while 11% find challenges in the *ideation process*, and only 6% face problems in building *prototypes*. Based on the answers, a relatively small amount of UXPs find challenges related to *design conceptualization and development*.

4.1.2 UXPs' usage of AI in the design process

When asked about in what part of their job AI was used, UXPs with AI experience (N=33) provided the following insights as shown in Figure 20:

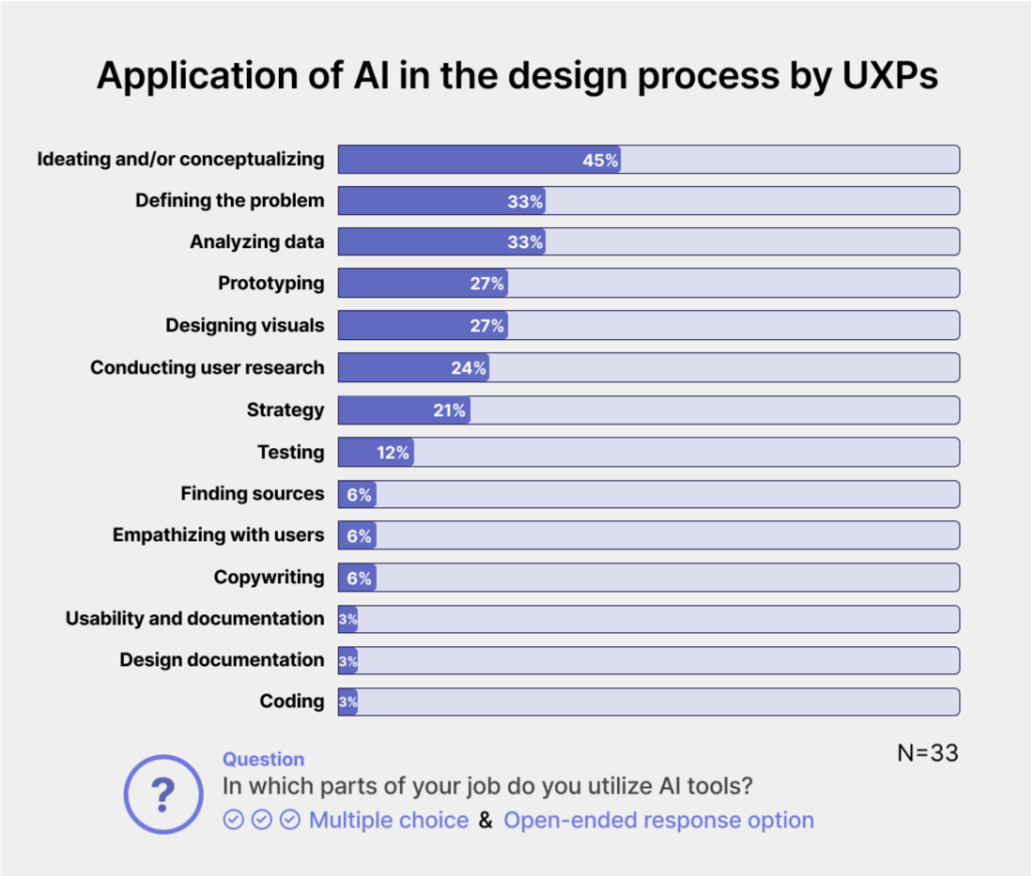


Figure 20: Usage of AI in the design process divided by UX activities.
Percentages are based on the total amount of respondents with AI experience (N=33).

Respectively, 45%, 27%, and 27% of the total responses from the respondents with AI experience are in connection to *ideation/conceptualization*, *prototyping*, and *designing visuals*. This shows that a relatively huge amount of the current AI usage is related to the design phase of *design conceptualization and development*.

In relation to *problem setting*, the data shows that 33% of AI utilization is regarding *definition of problems* which belongs to the design phase of *problem setting*. In close proximity, 21% of AI usage is connected to *strategy*. These results indicate that AI is being used to a certain extent for *problem setting*.

In relation to the design phase of *user research,* 24% of the respondents used AI to *conduct user research*. Additionally, AI is also used, however in much lower cases, for *finding sources* (6%). Overall, the results in Figure 20 show relatively few cases of AI utilization in *user research* and *testing* compared to the phases of *problem setting,* and *design conceptualization and development.* However, 33% of reported cases where AI is utilized are in connection to analyzing data which might take place in all stages of the design process and thereby challenge that finding.

Compared to the perceived challenges in the design process (Figure 19), a relatively small amount of the UXPs found challenges in the third phase of design (*design conceptualization and development),* whereas AI is mostly used for this specific phase of design. Furthermore, many UXPs find challenges in user research while relatively few cases were reported for using AI for research on users. These findings might indicate a correlation between challenges and AI usage. However, calculations of the correlation between these factors are not valid due to our small sample size.

UXPs' use of GenAI

When asked to identify the specific AI tool(s) and the aspect of their work that it supports, UXPs with prior AI experience disclose the following:

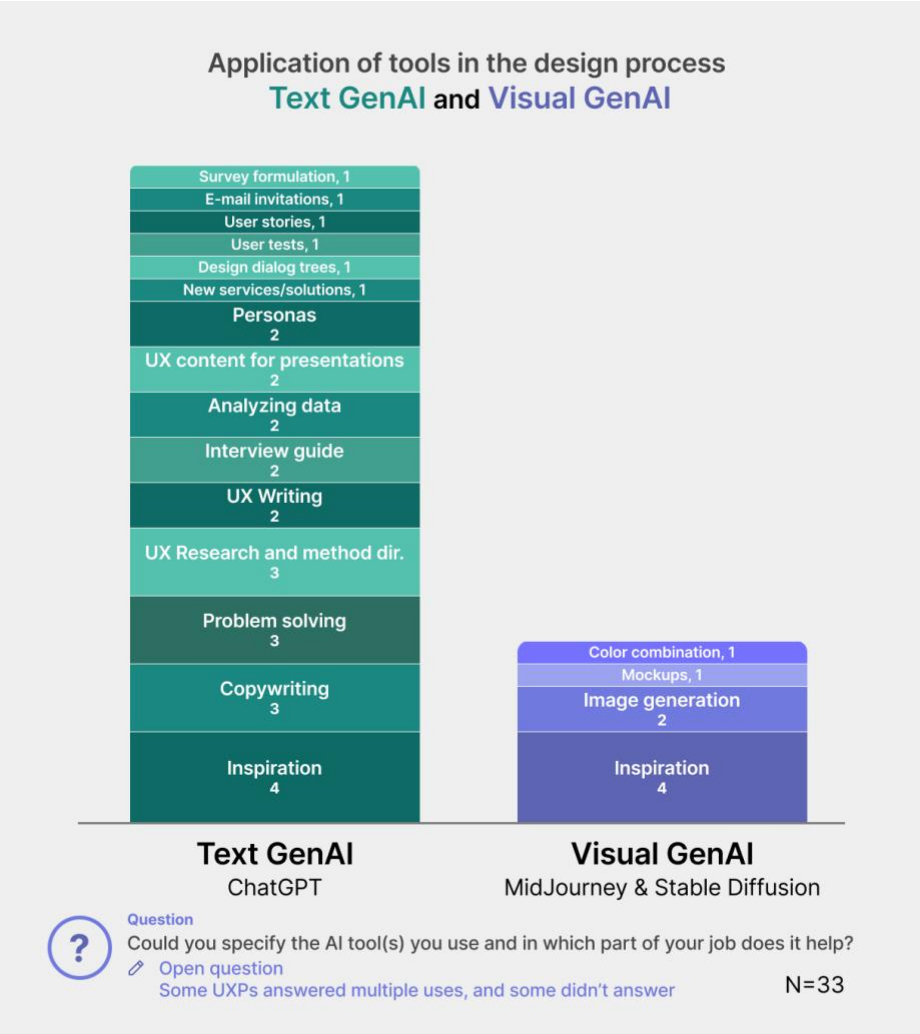


Figure 21: Application of Text and Visual GenAI in the design process. The digits refer to a number of cases for the specific AI application reported by UXPs with AI experience (N=33)

While out of 33 respondents with AI experience, 24 explicitly mentioned using ChatGPT as Text GenAI in their work practices, only 6 respondents indicate using visual GenAI, specifically mentioning Midjourney and Stable Diffusion. Based on Figure 21, it can be observed that the range of Text GenAI application is more diverse than that of Visual GenAI. However, our data do not provide further insights into the duration of the engagement with AI or the extent of the impact utilization of AI has on UXPs' work practices. Therefore, despite the lower diversity of reported cases of visual GenAI, we can not exclude the possibility that Visual GenAI might have a more significant impact on UXPs' work practices in comparison to text GenAI.

In addition, the cases of ChatGPT application show similarities with the findings from Figure 21 in connection to *ideation/conceptualization* and *defining the problem,* namely *inspiration, copywriting,* and *problem-solving*. Similarly, Visual GenAI is mostly used by UXPs for *inspiration* and *image generation.*

4.1.3 Perceived advantages and challenges of using AI

To understand the reasoning behind why UXPs use AI in their work practices, we asked them to specify the advantages and challenges of using AI. To clarify and quantify the collected data, we have collected the answers with similar traits into groups of advantages and challenges:

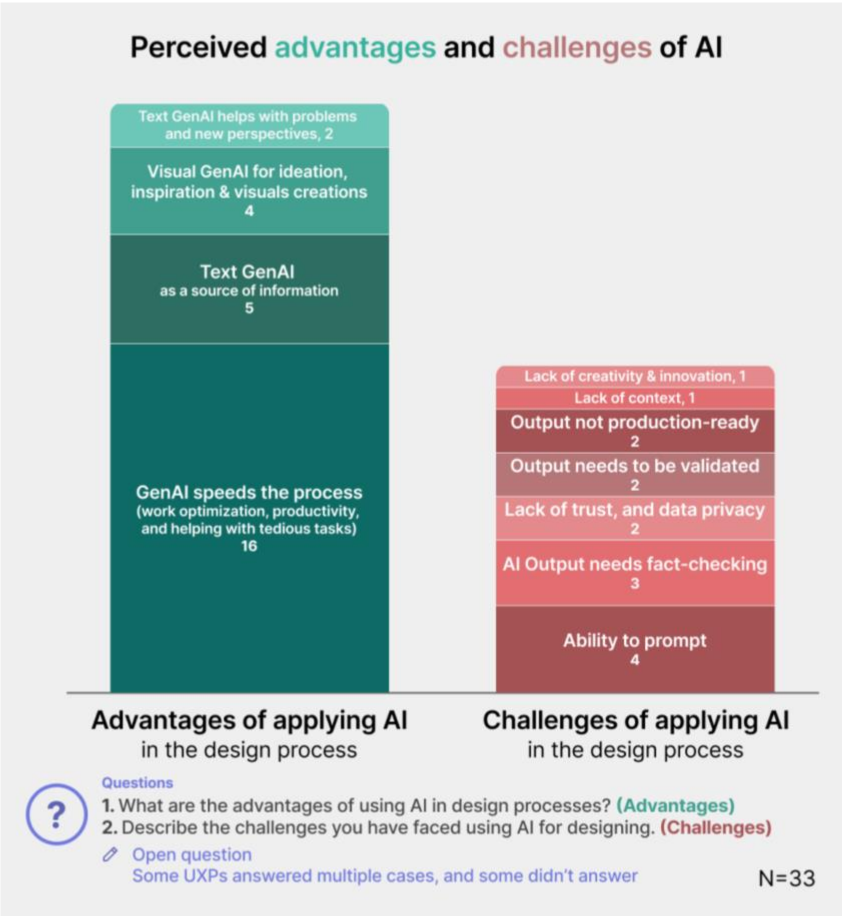


Figure 22: UXPs' perceived advantages and challenges of AI. The digits refer to a number of cases the specific advantages and challenges were reported (N=33).

According to the findings in Figure 22, it is evident there is a higher perceived level of benefits in comparison to challenges. The disparity between them is more than half (58%). As we do not have additional insights, it can not be excluded that the lower number of reported challenges can be attributed lack of ethical concerns or a lack of AI literacy.

Figure 22 shows that the most commonly perceived benefit of AI utilization is *speed* which was reported 16 times. Under this category, we have included also reported cases of *optimization, productivity improvement*, and *support with tedious tasks* in terms of time. While Text GenAI is reported to be beneficial as a source of information in 5 cases, Visual GenAI is perceived as useful for *ideation* and *inspiration* in 4 cases.

In comparison, the most common perceived challenge is the *ability to promp*t to avoid generic output. This could be attributed to the timing of the questionnaire that was conducted in February/March 2023 when the use of AI might still is relatively novel among UXPs, as it was shown also by the proportion of 52% of UXPs reporting utilizing AI in our survey (Figure 17).

Out of 15 reported challenges, 7 of them were related to ethical aspects such as *privacy, transparency,* and *trust*. The need of validating AI output to decide if to further fact-check the AI output is related to the lack of trust and transparency. Meanwhile, the perceived liability of visual GenAI output comes down to its low maturity causing its inability to be used directly in production.

Although the most common AI usage by UXPs is related to the design phase of *design conceptualization and development,* we can not conclusively determine whether the reported benefit of process speed-up is associated specifically with this design phase.

4.2 Qualitative Analysis

This section presents the results and findings derived from the thematic analysis of the SICI sessions with six UXPs. By systematically analyzing the qualitative data collected from the participants in an inductive approach (§ 3.5.2), we identified four overarching themes, each containing subthemes. In the following, we will provide an overview of the themes and subthemes which are the results of the qualitative analysis that will be presented and explained in § 4.2.1-4.2.4.

THEMES AND SUBTHEMES	
THEMES	**SUBTHEMES**
A. Practical usage of GenAI in UX § 4.2.1	**A1**. Practical usage of text GenAI **A2**. Practical usage of visual GenAI
B. AI as an asset in UX practices § 4.2.2	**B1**. AI can inspire and support UXPs **B2**. AI augments UXP's abilities
C. Concerns about applying AI in UX practices § 4.2.3	**C1**. AI output needs validation due to trust and transparency **C2**. AI cannot design UX autonomously **C3**. The Importance of real users, human intuition, and empathy in HCD
D. AI's impact on the future of the UX domain § 4.2.4	**D1**. Hype and reliance on AI **D2**. Practical implications of applying AI in UX **D3**. UXPs might remain in the field of UX

Table 20: Overview of the themes and subthemes from thematic analysis.
The themes and subthemes are presented in § 4.2.1-4.2.4.

4.2.1 Theme A. Practical usage of GenAI in UX

One of the focal points of our study has been to uncover the current UXP work practices of applying AI. In this section, we will present the overarching theme A, which encompasses the *Practical usage of GenAI in UX*. The findings are divided based on the subthemes A1. *Practical usage of Text GenAI* and A2. *Practical usage of Visual GenAI*.

Subtheme A1. Practical usage of text GenAI

Subtheme A1, *Practical usage of text-generative AI,* explores the range of tasks UXPs use AI to generate text which will be referred to as *text-generative AI*. Despite a variety of text-generative AI applications, the most prevalently used by the participants is *ChatGPT-3* (A7, P1 07:17; P2 04:04; P3 07:44; P4 05:32; P5 03:53; P6 02:25). Other AI applications which the UXPs use are *Nichess* (A7, P1 31:49), *Grammarly* (A7, P5 1:01:15), *Wordtune* (A7, P1 09:17), *Jasper* (A7, P4 21:08), and *Copy.ai* (A7, P1 35:40). While some use AI tools, e.g. ChatGPT, on a monthly basis (A7, P5 36:57), others use it daily and consider AI as one of the main tools (A7, P2 09:01; P3 07:44; P4 03:08). The analysis is limited to the AI systems being used by the UXPs in our study which can be located in Table 23. When we refer to generative AI text tools, it is mainly ChatGPT and to a smaller extent Wordtune, Copy.ai, Jasper, and Grammarly even though the latter tools were not used enough to conclude on. We do not include other AI tools in the analysis because they were not a part of our participants' work practices which is a limitation to our findings which will be discussed further in § 5.5.3.

Our insights show that UXPs use text-generative AI tools for the following tasks: *UX writing, solving design problems, copywriting, user research, refining with design intent, visual ideation,* and *getting directions.* UX writing covers not only cases when UXPs use chatGPT for creating headlines, slogans, or short sentences (A7, P1 14:35; P4 23:54; P5 3:53), but also UX copies (A7, P1 34:39; P3 22:23, P4 21:08; P6 02:25), and the situations when the AI tool assists UXPs to expand their initial text on certain UX topics (A7, P4 26:56; P5 17:30).

Copywriting refers to blogs on UX topics (A7, P5 3:53), creating text for Social Media (A7, P1 09:17), and helping with grammar or (re)phrasing the text in a more presentable way (A7, P1 09:17; P4 26:56; P5 11:21).

In relation to the user research and testing category, the UXPs use AI for writing user tasks and tests (A7, P5 14:43), interview guides (A7, P2 16:25), writing email invitations for the surveys (A7, P2 05:09), and calculating p-values (A7, P5 16:04). One UXP uses ChatCPT in the process of refinement of their design intents and generating what type of questions the audience might ask after reading such a document to prepare for potential questions and address them in advance (A7, P6 2:25).

Some use ChatGPT when they have *"some design problem that I'm lost about"* (A7, P3 53:48) and to get a more contextual answer, such as *"getting directions where I could look or some links or some articles"* (A7, P1 07:17, P2 21:53) that might further inspire them to do additional research using other tools such *Google Scholar, Google* or *Dribble* (A7, P1 07:17; P3 53:48). One UXP uses ChatGPT for writing user stories and generation of a user journey to put user stories in more perspective (A7, P3 23:11), whereas another UXP utilizes ChatGPT for visual tasks, such as exploring color combinations (A7, P1 07:17).

It is not possible to describe the usage of generative AI tools without mentioning the prompting process. While some UXPs understand the importance of a precise prompt and will try to provide as much context in the initial formulation to avoid misunderstanding (A7, P1 09:17; P3 11:43) and look for tips on Social Media on how to prompt the best way (A7, P1 10:17, 11:17), other UXP formulates their prompts very simple and would write the same prompt as when searching on Google: *"very often [...] almost the same as I'll put into a Google search"* (A7, P5 13:39).

In pursuit of receiving a valuable answer, UXPs provide the backstory, the context, specify the personality, style of writing, even the length of answer (A7, P1 09:17; P2 12:20, 19:12; P3 11:04, 11:43) and reread and clarify the prompt to ensure that the prompt can not be *"understood in different ways"* (A7, P3 11:43). One participant also underpins the different forms of prompting when using Google and ChatGPT. When searching on Google, they need to formulate the prompt in keywords to get a good answer, while when interacting with the ChatGPT they would formulate a normal question which makes it flexible and easy to use GenAI (A7, P1 20:42).

Despite understanding the importance of providing a more contextual prompt to receive more useful answers, some UXPs write a very general prompt and argue that they just look for an idea or inspiration (A7, P5 09:29; P6 10:54) which is linked to, and will be unfolded in, the subtheme of *AI can inspire and support UXPs*. This approach was observed when UXPs prompt ChatCPT to generate a blog post about a certain topic or when asking for rephrasing design intent. When prompting for a blog or design intent, UXPs already have *"some sort of a synopsis"* (A7, P5 09:29) or *"first draft"* (A7, P6 02:25) ready and they look for a way to improve them.

In cases that UXP receive an answer which is wrong, or they want to elaborate or modify specific parts further, they would provide instructions to ChatGPT on how the answer should be corrected, specified, or improved (A7, P1 17:26; P2 10:25; P3 11:43; P5 09:29; P6 02:25). Further insights of AI output validation will be presented in subtheme *how UXPs validate textual and visual AI output before using it*. When they are satisfied with the output, they copy and paste it somewhere else, e.g. Figma or a Word document, to edit and ideate further until it meets the required standards (A7, P1 17:26; P2 20:10; P3 12:52; P6 09:54, 11:52). What UXP appreciate about the prompting and editing process is that it feels like a human interaction (A7, P1 20:43; P3 11:43; P6 02:25), which will be further explored in the subtheme *AI as a tool and sparring partner*.

Subtheme A2. Practical usage of Visual GenAI

In subtheme A2, *Practical usage of Visual GenAI,* participants mention several visual GenAI applications such as *Dall-E* (A7, P2 6:38; P3 28:45, P4 05:32), *Midjourney* (A7, P1 23:50; P3 28:45; P4 05:32; P6 16:30), *Stable Diffusion/DiffusionBee (Stable Diffusion App)* (A7, P4 05:32; P6 16:21), *Figma AI plugins* (A7, P1 35:40), *Khroma* (A7, P4 17:11) and *Uizard* (A7, P1 37:24; P3 36:05; P4 33:02; P6 17:40). It is important to note that only three UXPs (50%) have utilized visual-generative AI applications in their daily work practices and not all of them where used to a high enough degree to draw conclusions. Therefore, when we discuss visual-generative AI applications, we refer to either Dall-E, Midjourney, or DiffusionBee.

Compared to text-generative AI, the usage of visual Gen AI applications is not as extensive, due to the perceived concerns about lack of good UX in the visual AI output which is unfolded and explained in the subtheme of *AI cannot design UX autonomously*. Usage of visual generative AI varies between populating the wireframes with illustrative content to avoid empty image holders with Figma AI plugins (A7, P1 35:40), generating visual assets (A7, P1 23:50; P4 05:32), inspiration, and color-picking to assist with the interface ideation process (A7, P1 25:14; P3 30:23). Generating visuals assets include images, logos, and icons (A7, P1 23:50, P2 06:38, P4 05:32). Text-to-image also helps with getting inspiration and finding colors for building mood boards (A7, P4 05:32). Two UXPs reported using generated small images and backgrounds in production (A7, P4 05:32) and visual content creation with marketing purposes (A7, P1 23:50).

Despite describing the prompting process as experimental (A7, P1 29:50), some UXPs are intentionally getting inspired by specific artists' prompts or exploring others' prompts in the channel (A7, P1 29:50; P4 12:44). While some provide a very specific prompt from the beginning with style specification (A7, P1 23:50; P4 11:14), others might have a more general prompt (A7, P3 30:23). Examples and descriptions of the iterative prompting process can be seen in Appendix 11.

Conclusion: Practical usage of GenAI

To sum up, our findings show that while the use of visual AI generative output is not yet extensive, all six UXPs have already successfully implemented text Gen AI into their work practices and use it for a variety of tasks such as UX writing, solving design problems, copywriting, user research, refining with design intent, visual ideation, or getting directions. Our insights reveal the difference in how UXPs treat the prompting which is reflected in how much satisfied they are in the outcome.

Table 21 shows how the application of AI in terms of textual - and visual output was used in the different stages of design.

AI APPLICATION IN DESIGN STAGES		
DESIGN STAGES	TEXT GENERATIVE AI	VISUAL GENERATIVE AI
User research	Interview guides Email invitation for research Generating user journey Data summarization Data analysis UX methodological inspiration	
Problem setting	Defining design problems Problem-solving	
Design conceptualization and development	UX writing (UX copy, headlines) Copywriting (social posts, blogs) Refinement of design intent Writing user stories Generating questions for meetings Color combinations	Color combinations Mood boards Logos Icons Visual assets (backgrounds, marketing) UI interfaces
User testing	User tasks & tests Calculating p-values	

Table 21: Overview of GenAI output as used by UXPs in the design stages

The focus of theme A, *Practical usage of generative AI in UX*, was to describe how the UXPs use AI in practice whereas the following themes aim at explaining the perceived abilities to apply AI (§ 4.2.2), the concerns about applying AI in UX practices (§4.2.3), and the practical implications (§ 4.2.4).

4.2.2 Theme B. Advantages of AI in UX practices

Based on the UXPs' reflections on their AI usage, presented in the theme A, *Practical usage of generative AI output UX,* the overarching theme B which is about the *Advantages of AI in UX practices* emerged. Theme B reveals how UXPs perceive AI and how AI supports UX practices. This theme is supported by two subthemes that unfolded from the data: B1. *AI can inspire and support UXPs* and B2. *AI augments UXP's abilities.*

Subtheme B1. AI can inspire and support UXPs

Subtheme B1, *AI can inspire and support UXPs,* focuses on how the UXPs apply AI to *"kickstart ideas"* (A7, P4, 30:17), *"jumpstart my own brain" (A7, P6, 28:09), "generating ideas" (A7, P4, 5:32),* and *"give me a new idea"* (A7, P6, 6:51) while also serving as *"inspiration"* (A7, P1, 34:39, no. 5 11:21) and "as a starting point" (A7, P1 8:59). This subtheme underpins the potential for AI to serve as a sparring partner to augment the UXPs' creativity in the design phase of *Ideas, develop, and building*. The participants emphasized that the AI output is not used directly, previously discussed in *Practical usage of generative AI in UX,* but rather served as an inspiration to further explore and stimulate their creative processes (A7, P5 11:21; P1 38:35). The interactions between the output of AI and the UXPs show how a collaborative, iterative design process can augment human creativity, rather than replacing it with AI which will be further explored in the theme of *AI's impact on the future of the UX domain*.

When analyzing the UXPs' perception of AI applications, we discovered that participants sometimes perceive AI as a tool and sometimes as a sparring partner. All participants refer to *AI as a tool* (A7, P1 07:17; P2 09:01; P3 40:58; P4 03:08, 29:35, 38:18; P5 11:21; P6 21:38, 31:58). Some UXPs insist that AI (ChatGPT) is not replacing the previous methods, but in contrast, it adds to their the toolbox of methods and represents a *"new research method"* (A7, P3 40:58, 53:48) or a *"nice extra add-on"* (A7, P5 06:52). This perception underlines AI having a *"supporting role"* (A7, P5 06:52), serving as a *"supporting tool"* (A7, P1 07:17), *"fun tool"* (A7, P2 09:01), *"editing tool"* (A7, P6 06:51) and by comparing it to the similar an assisting tool as were Pantone cards in the past (A7, P4 29:35; 38:18).

The role of AI is highlighted by how it is supporting UXPs in their daily activities. For example, the participants note that AI is applied as an approach to remember important aspects of UX methods and activities such as sending consent forms before an interview (A7, P2 10:25) and points to be included in an email or presentation (A7, P2 14:03; P6 13:27). Moreover, one participant reflected on using AI as *"a supporting tool"* to draw meaning by performing research and analyzing data (A7, P3 43:54). The context in which the UXPs define AI as a sparing partner is when arguing that AI helps them to *"augment my own ability"* (A7, P6 29:50) or ideate and spare (A7, P4 29:35, 35:58; P5 10:24; P6 02:25; 06:51, 19:23), specifically in cases when there is a lack of feedback (A7, P1 08:59; P3 26:54; P5 10:24; P6 12:02) and/or during remote work (A7, P5 10:24). In addition, AI imitates the situation when *"you're just standing and drinking coffee with someone, and then you're like 'Hey, can you read this?'"* (A7, P6 12:02) and it feels like *"humankind of interaction"* (A7, P1 20:43), *"conversation"* (A7, P3 11:43) or having a "*good companion"* (A7, P4 35:58). In contrast, the visual generative AI applications that appeared in this research do not have the same conversational feeling for the UXPs and therefore it might be the reason why some UXPs consider them more as tools (A7, P3 34:53; P4 29:35).

Subtheme B2. AI augments UXP's abilities

Subtheme B2, *AI augments UXP's abilities,* highlights the AI's ability to solve tasks fast and efficiently to enhance the UXPs' work practices. Participants highlight that their application of AI can solve *"trivial tasks"* (A7, P6 5:22) and do a *"tedious task"* (A7, P1 41:09). The UXPs emphasize that AI can assist with more repetitive and generic aspects of the design process (A7, P2 25:55; P4 26:56) and they can *"skip the boring parts"* (A7, P1 54:56) which the UXPs, for instance, refer to as copywriting (A7, P6 2:25; P2 25:55) and color matching (A7, P1 7:17).

Additionally, the UXPs noted that AI can do tasks *fast* (A7, P1 34:39; P2 6.38; P4 26:56; P5 1:01:15) and *efficiently* (A7, P1 48:33; P2 32:59) which highlights the potential for AI to reduce the UXPs' time and effort to complete certain trivial and tedious tasks which enable UXPs to spend their time on more important activities (A7, P2 45:19). Based on this, the third subtheme is closely linked to the microtheme *Using AI to solve trivial tasks & tedious work.* In addition, one participant also perceives AI as *smart* due to the conversational and contextual format in which the AI output can be tailored to a specific need (A7, P2 18:21) such as writing emails (A7, P2 5:09).

Conclusion to advantages of AI in UX practices

Overall, the findings suggest that AI has the potential to be an advantage for UXPs, but the application of AI must be balanced with human expertise and creativity. UXPs can leverage the benefits of AI as a starting point and inspiration while maintaining the essential human aspect of utilizing the AI output to augment their own abilities, save time, and focus on important tasks as opposed to trivial and tedious ones that AI is able to solve. While there is the tendency to label visual-generative AI as a tool, the text-generative AI is perceived by UXP sometimes as a sparring partner and sometimes as a tool depending on the context of the tasks.

4.2.3 Theme C. Challenges of applying AI in UX practices

An analysis of the UXPs' application of AI revealed the overarching theme C which is about *concerns about applying AI in UX practices.* Theme C shows how AI might be a liability in opposition to theme B (*Advantages of AI in UX practices).* Theme C highlights the liabilities of AI application in UX practices and is supported by three subthemes: C1. *AI output needs validation due to trust and transparency,* C2. *AI cannot design UX autonomously,* and C3. *The Importance of real users, human intuition, and empathy in HCD.*

Subtheme C1. AI output needs validation due to trust and transparency

In subtheme C1, *AI output needs validation due to trust and transparency*, our findings revealed underlying microthemes to structure the analysis: 1) *validation of textual AI output before usage, 2) biased datasets* and 3) *lack of transparency* which directly influence the trust of UXPs.

In our first microtheme, *validation of AI output before usage*, the UXPs underline that they do not use AI output directly (A7, P1 17:26; P2 15:03,19:12; P3 15:10; P4 26:56; P5 11:21; P6 15:15). As the participant does not trust the AI outcome, they refer to themselves as *"middleman"* (A7, P4 30:17) and would try to validate the AI output before using it (A7, P1 15:37; P2 15:03; P3 15:10; P4 30:17; P5 09:29; P6 08:59). One UXP describes treating the AI output as a source of information in the same way as they treat information on *Wikipedia*, in which the information needs to be *"reevaluated"* (A7, P6 15:15). As a result of AI output validation, one participant reported a very bad quality of AI-generated blogs on UX-related topics and admit that they would never allow it to be published under their company name (A7, P5 03:53, 05:32). According to some participants, if a UXP does not know much about the UX field, they might read through the AI output and think it is good enough (A7, P3 15:10; P5 05:32; P6 25:35), but *"then if you know a bit, then you're just like, ah, this is just off"* (A7, P5 05:32). That raises the question of how to deal with the AI output from the field one lacks expertise in (A7, P5 05:32). To address this, the UXPs emphasize that it is important to talk with people, either colleagues (A7, P3 19:20; P6 07:32) or users, customers, and experts, who posses more in-depth knowledge and enable UXPs to make sense of the AI output and gain their perspective to be able further use the AI-generated outcome, e.g. for design ideation (A7, P3 16:27, 24:54).

The second microtheme, *biased datasets,* reveals that one of the reasons why UXPs can not trust AI outcome is the ambiguity surrounding the extent to which the data used to train AI models is biased (A7, P1 43:36, 46:50; P3 56:41; P6 28:09). In addition, one UXP points out that AI has a tendency to prefer outliers in the data analysis and misses out on the middle values which they perceive as *"red flags"* (A7, P5 02:49). As a consequence of that mistrust, participants would rather use search engine for a specific question than AI due to emphasis on actively deciding what sources they trust (A7, P5 11:21; P6 28:09) which is related to the microtheme presented below.

The third microtheme, *lack of transparency,* introduces an additional reason besides biased datasets and low quality which causes trust issues for UXPs. The UXPs prefer to know the sources of information (A7, P3 56:41; P5 21:09; P6 25:35), as that would support them in validating the AI outcome and deciding if there is a need to fact-check it further (A7, P1 15:37; P3 56:41; P4 30:17; P5 17:30; P6 25:35). The UXPs admit that there are cases which do not require to fact-check the AI output, referring to (re)phrasing tasks (A7, P1 22:40; P4 43:58). One participant reflects that the emphasis on fact-checking may be due to their *academic background*; they can not take something without knowing the sources because otherwise it would be *"copying"* (A7, P5 11:21).

Subtheme C2. AI cannot design UX autonomously

Subtheme C2, *AI cannot design UX autonomously,* highlights the concerns regarding AI's ability to autonomously: a) *be creative and innovative,* b) *account for the intangible and contextual,* and c) *design a UI with a good user experience*. One UXP pointed out skepticism towards AI being innovative (A7, P5 6:52, 50:37), especially regarding generating visuals, due to AI's training data that will rely on existing solutions (A7, P5 18:05) or outdated data (A7, P5 33:07). This results in AI not being able to create novel products (A7, P5 35:37). Furthermore, one UXP consider the AI output as a part of their own ideas through the prompts that are written iteratively (A7, P4 33:46) which indicates a high sense of ownership over the AI output. One UXP also points out that there is a "sweet spot" for rephrasing and changing the output through prompts after which the pattern of the AI text output starts to be repetitive and similar (A7, P1 19:45). Furthermore, participants questions whether AI will be able to *design* which requires an intention to solve a problem (A7, P6 21:38) which relates to AI's lack of accounting for the intangible and contextual aspects that need to be involved in a design process, such as observing users (A7, P2 42:04; P5 34:36), the person-to-person interaction of team members discussing the design in the real world (A7, P6 34:27, 51:29), and include multiple contextual aspects of an ecosystem (A7, P5 1:08:30).

Reflections in relation to AI being able to perform HCD or not, one participant expressed that *"it's [AI red.] not human centered, then we need to call it something else"* (A7, P5 26:29) due to the lack of human intentionality if the UXP is excluded. Some UXPs insist that AI should remain a tool and not be the main force driving user research and user involvement (A7, P5 38:32, 50:37) or being assigned *"responsibility or decision-making"* (A7, P6 31:58). Another UXP highlighted the difference between the output and intentions related to applying AI (A7, P6 23:48) in which it is emphasized that a tool might not be HCD by default but the UXP using the tool can be an HCD (A7, P6 21:38). Additionally, AI applications might not be HCD but they can support UXPs by providing guidelines for best practice in an HCD approach (A7, P1 42:41; P5 35:37) which is related to the subthemes *AI can inspire and support UXPs*.

Moreover, the UXPs perceive that current visual-generative AI outputs are not useful enough because the UX is not accounted for (A7, P1 38:56; P3 28:45). In addition, UXPs emphasize that even though the visuals might look beautiful or have interesting patterns, there is no worth or sense from a UX perspective in it (A7, P1 38:56; P3 32:22; P529:23) which is the reason to validate the output. The UXPs empathize that the same or better results of getting inspired by UIs can be achieved by browsing online libraries, such as *Google* or *Dribble* (A7, P1 38:56; P3 33:10).

Subtheme C3. Importance of real users, human intuition, and empathy in HCD

Subtheme C3, *Importance of real users, human intuition, and empathy in HCD,* underpins the importance of including real users, human intuition, and empathy. Reflecting on whether AI can have an HCD approach or not, the UXPs highlight the importance of including real users and their data in the UX design and research process as opposed to including synthetic users for testing or relying on AI-driven virtual participants (A7, P1 56:06; P5 22:19, 1:05:09). In relation to using synthetic AI-generated users for testing, one UXP notes that people, in general, are unpredictable, especially when it comes to usage of complex digital products that stands out from more generic user interfaces such as *E-com sites* (A7, P5 35:37). Moreover, it is also highlighted that a user test without real users cannot replace normal user tests because then it might not be human-centered (A7, P1 56:06; P5 24:02).

In relation to the importance of including real users in an HCD approach, the role of empathizing with users is an important aspect of designing (A7, P2 42:04; P5 31:25). While some UXPs highlights their concerns about AI's ability to empathize with users due to AI's constraints of including all the contextual and intangible (A7, P2 42:04; P5 1:05:09; P6 25:35), one UXP implies that AI might be able to learn patterns of empathy in the same way people can learn it (A7, P3 47:13). Even though empathy is deemed important, one UXP also points out that they are not always having an HCD approach due to limitations of time and resources in which they need to prioritize certain tasks rather than empathizing with users (A7, P6 26:18). Some UXPs reveal many solutions are not tested anyway and therefore argue that AI-generated synthetic users could provide some insights as opposed to no insights at all (A7, P4 43:58; P5 24:02). One UXP also highlights that real user tests might also be misleading if users are in a certain mood (A7, P3 51:30).

In continuation of concerns regarding AI-driven user research, one UXP highlights the potential for the lack of an empathic relationship between the UXP and the user. For example, if an interview was performed by an AI with a real user, AI might be able to show empathy but the user might not care enough to elaborate due to a lack of human interaction with the researcher (A7, P3 49:29). Furthermore, using AI to empathize with users, as opposed to a UXP, might lead to a deficiency in the UXP's emotional connection and care towards the user resulting in not fully understanding the intangible and contextual aspects of a given problem in the user's current situation (A7, P5 26:29).

Conclusion: Challenges of applying AI in UX practices

To summarize, the UXPs do not fully trust AI output due to lack of transparency and biases in the generative AI applications. As a consequence, they validate the generative AI output to decide if there is a need for further fact-checking before using it. While text-generative AI output is, in general, considered useful, visual-generative AI outcome lacks true value for the UXPs, and alternative UI libraries provide the same if not far better results than the visual GenAI applications in their current state. The findings suggest that AI might not be able to perform UX activities autonomously, but rather serve as either a supporting tool or sparring partner to perform HCD activities that involve human creativity, intuition, presence, and empathy in close relation with UXPs.

4.2.4 Theme D. AI's impact on the future of the UX domain

Based on the UXPs' reflections on the perceived abilities and liabilities of AI, theme D emerged, *AI's impact on the future of the UX domain,* in which three subthemes unfolded: D1. *Hype and reliance on AI,* D2. *Practical implications of applying AI in UX,* and D3. *UXPs might remain in the field of UX*.

Subtheme D1. AI hype and reliance on AI

The UXPs note that the abilities of AI are hyped (A7, P1 40:15; P4 57:55; P6 52:29) which might cause a rapid decline in interest and investment in AI due to expectations exceeding the ability of AI (A7, P4 49:33, 57:55). The hype of AI might cause an over-reliance on AI-driven UX practice affecting the UXP's ability to perform best practices of UX design and research in the future resulting in losing competencies over time if not actively stimulated and performed, eg. designing prototypes, and defining and solving problems (A7, P6 39:26). In relation, if companies rely heavily on AI to design UX, there might be ethical considerations regarding the design that need to be accounted for, such as AI applying design to manipulate users (A7, P4 39:31).

Subtheme D2. Practical implications of applying AI in UX

In subtheme D2, *Practical implications of applying AI in UX,* the UXPs emphasize that generative visual AI output can not be included directly in existing digital products due to the constraints represented by the existing visual identity and design system of the product (A7, P5 35:37; P6 3:53, 16:30). The UXPs point out that aspects like these might be a liability when implementing AI autonomously in the production chain (A7, P4 37:20; P6 34:27, 51:29). Another point in relation to implementing AI in UX is that with the ability to design digital products fast, the groundwork and decision-making towards a well-defined design might be overlooked. Some UXPs claim that in the best practices of UX, there is a need for simplicity and specific content, for instance using less complex features that users might not need (A7, P5 52:30) or nice-looking UI without considering the user experience (A7, P6 38:49). According to one UXP, some basic UX principles are not solved and the quickly AI-generated outputs might just exaggerate the issue further (A7, P6 34:27). Based on this, *"[...] it emphasizes that we [UXPs red.] need to be intentional about what we're creating more than ever"* (A7, P6 52:29).

Subtheme D3. UXPs might remain in the field of UX

Subtheme D3, *UXPs might remain in the field of UX*, is based on the UXPs' reflections on how AI might impact the field of UX, focusing on their own role as UXPs in relation to the emerging role of AI. Despite AI's perceived abilities to be fast, efficient, and smart, UXPs highlight that current UX practices, tools, libraries, and methods will still be applied. For instance, low-fidelity paper prototypes (A7, P5 1:06:58), user research and tests (A7, P3 55:09; P5 24:02), well-established software tools for collaboration on wireframes (A7, P3 6:39), and UI libraries for inspiration (A7, P1 39:19; P3 33:10).

In general, the UXPs note that AI can lift UX design and research to a higher level if it is controlled by a UXP with a certain degree of knowledge and expertise (A7, P3 39:05; P5 44:09) which can be related to the importance of human creativity, intentionality, presence in the real world, and empathy in UX design and research (§ 4.2.3), including the UXP' reflections on *Advantages of AI in UX practices* (§ 4.2.2). In relation to the future role and activities of UXPs, the participants highlight the importance of keeping up with trends (A7, P1 59:29), getting better at their jobs (A7, P4 45:21), and not falling behind other UXPs (A7, P3 39:05).

Conclusion: AI's impact on the future of the UX domain

The results and findings suggest that AI has the potential to be a valuable advantage for UXPs, but the application of AI must be balanced with human creativity, intuition, presence, and empathy. The application of AI can support UXPs to perform HCD activities rather than replacing them in which AI can serve as either a supporting tool or sparring partner. UXPs can leverage the benefits of AI as a starting point and inspiration while maintaining the essential human aspect of utilizing the AI output to augment their own abilities, save time, and focus on important tasks as opposed to trivial and tedious tasks. Despite the perceived benefits of AI, current UX practices, methods, and tools will remain in the field of UX. Implementing AI in the production chain might be complex due to existing constraints and over-reliance on AI output without validation might result in bad, complex digital products.

To provide an overview of the advantages and challenges of applying AI in UX practices, Table 22 serves as a summary of our findings in the qualitative analysis related to the stages of UX design:

ADVANTAGES AND CHALLENGES OF APPLYING AI		
DESIGN STAGES	AI AS AN ADVANTAGE IN UX PRACTICES	CHALLENGES OF AI IN UX PRACTICES
User research	As a source of information Augmenting UXP abilities (analyzing collected data) AI helps with tedious and trivial tasks (to focus on higher level tasks)	AI output need to be fact-checked (lack of transparency) AI lack of accountability for the contextual and intangible Lack of empathy (person-to-person relationship)
Problem setting	AI as a source of information Text-generative AI as a sparring partner	AI output to be validated (biases in data and lack of transparency) Lack of accountability for the contextual and intangible
Design conceptualization and development	Text-generative AI as a starting point for inspiration Visual-generative AI as inspiration Text-generative AI as a sparring partner	Lack of best UX practice in visual-generative AI Not production ready due to existing visual identity constraints Lack of creativity and innovation Lack of intentionality
User testing	Text-generative AI augmenting UXP abilities (generating content to be used for real user tests)	Ethical concerns and biased datasets (manipulating users, and synthetic users) Lack of accountability for contextual and intangible Lack of empathy (person-to-person relationship)

Table 22: Overview of the perceived advantages and challenges of GenAI applications in UX work practices

5. Discussion

The aim of the discussion is to provide critical reflections on the research findings and results in light of the existing literature and research objectives. The discussion is a platform to give perspective on the implications, significance, and limitations of our study, while also suggesting possibilities for future research directions. The subjects of discussions follow the structure:

§ 5.1 The UXP-AI relationship
§ 5.2 Perspectives on AI's abilities
§ 5.3 Ethical concerns and AI Literacy
§ 5.4 The role of users and empathy in design
§ 5.5 Limitations to our study

The discussion section aims at answering RQ3 and RQ4 by balancing and comparing insights from existing literature with the findings in a critical reflection.

5.1 The UXP-AI relationship

In our research, we found that AI has the potential to be a valuable advantage for UXPs in the design process based on how GenAI supports, inspires, and augments the UXPs and their abilities (§ 4.1.3; § 4.2.2). In this part of the discussion, we highlight how the UXPs use and perceive GenAI in relation to their rationale for deciding on AI to perform UX activities by including insights from the literature review (§ 2.2, 2.3, and 2.4).

5.1.1 The role of AI as a designerly tool

The findings on AI as an advantage (§ 4.1.3; 4.2.2), can be related to results from similar studies on designing with AI included in the third subtheme, *creativity and* *innovation* (§ 2.4.3). There is a resemblance between AI's opportunities in various case studies on designing with AI (Bakaev, Heil, et al., 2022; Bakaev, Speicher, et al., 2022; Y. Hu et al., 2020; Karahasanović et al., 2021; Main & Grierson, 2020; Malsattar et al., 2019; X. Sun et al., 2022) and our findings on AI's ability to inspire and support UXPs (§ 4.2.2). The findings of AI's capability of augmenting human abilities also relate to different perspectives presented in § 2.3.3 Human-AI relationship. The majority of the participants refer to GenAI as a sparring partner that they interact with to get inspiration and create content (§ 4.2.2) which can be related to the perspectives of *human-AI co-creativity*, *hybrid-intelligent-systems*, and *AI as a partner*. These perspectives highlight how an AI system and a human being work together in tandem as equal contributors. However, the participants' practical AI application reveals that the GenAI output is merely used as a starting point to be validated and edited before usage (§ 4.2.3). Therefore, the current UXP-AI relationship is closer related to the perspective of keeping a *human-in-the-loop*. The UXPs use AI as a tool to augment their own abilities by leveraging the advantages of GenAI to save time for important tasks, get inspiration, and solve tedious tasks rather than treating AI as an equal partner in a co-creative process. The participants also highlight their *sense of ownership* of the AI output which they use to a certain extent (§ 4.2.3). Based on these insights, GenAI serves more as a *designerly tool* by supporting the designer in both *thinking* and providing *outcome* in a creative process (§ 2.2.2), such as *artifact creation* (§ 2.3.1), rather than AI being a partner. The reason to perceive AI as a partner might come down to the fast, human-like interactions and conversation provided by text GenAI. To further analyze and understand the underlying meaning of the UXPs' reference to AI as a tool or sparring partner, a *discourse analysis* could supply the findings and discussion.

5.1.2 UXPs' rationale for deciding on AI as a designerly tool

The UXPs seem to choose and use AI as a designerly tool in line with Stolterman & Pierce's (2012) rationales for picking tools and methods. AI is picked due to its *effective* and *efficient* nature as AI can support the UXPs to solve trivial and tedious tasks fast

(§ 2.3.1; § 4.2.4). Additionally, AI is deemed *easy to use* in a *flexible* setup with the ability to iterate on the outcome with the purpose of thinking or creating an output (§ 4.2.1). Finally, AI supports an *individual approach* that arguably also encompasses an interpretive *team approach* due to the conversational, sparring nature of text GenAI (§ 4.2.2). Based on this, text GenAI might be able to exceed the categories of designerly tools as presented by Stolterman et al. (2009). AI is generally a *software,* but it is also able to perform a simulation of *theoretical* work such as mind maps and the category of *other* due to text GenAI's conversational capability.

In general, AI and its capabilities are hyped in the design community (§ 4.2.4), and the reason for UXPs to apply AI might also come down to gaining *respect* or *status* (Stolterman & Pierce, 2012, p. 28) amongst other UXPs. However, due to our findings, there are no indications of this being the reason to apply AI. The way AI augment their abilities suggests that AI is chosen based on the opportunities rather than boosting their professional identity in the organization or UX community. UXPs still apply non-AI designerly tools that suit the *purpose* and *activity* of the current situation in the design process. This might be related to the *Tools-In-Use-Model* which highlights that designers define the purpose for an activity before a designerly tool is picked. Our findings indicate that despite the perceived abilities of AI, UXPs still apply other UX tools, methods, and approaches that best fit the current design situation (§ 4.2.4). However, the reality of choosing a designerly tool is more complex than the tools-in-use-model and rationale for choosing a tool, such as time constraints and ease of use (Stolterman et al., 2009, p. 10; Stolterman & Pierce, 2012, p. 27). If AI is prioritized as a designerly tool solely based on its efficient and convenient traits as opposed to other UX tools, methods, and approaches, there might emerge concerns regarding the tool's prescriptive nature and lack of exploring divergent possibilities with other approaches (Stolterman & Pierce, 2012, p. 27). Furthermore, if a tool is picked based only on its efficiency to reach a certain goal efficiently, rational and positivistic problem solving might be picked over a pragmatic problem setting. Nevertheless, based on our findings, AI is merely used to a certain extent to augment their abilities and solve tedious tasks, brainstorm, and as inspiration, while being aware of AI's limitations (§ 4.2.3). This indicates that UXPs use AI based on a pragmatic process in an overall judgment grounded on the perceived benefits and limitations of using a specific designerly tool, method, or approach.

5.2 Perspective on AI's advantages and challenges

This part of the discussion focuses on the impact AI might have on the design of information technology and the UXPs' work practices. We explore the consequences of applying AI in the design process by discussing its efficiency; problem setting ability; and creativity and innovation.

5.2.1 The impact of AI's efficiency

In relation to AI's ability to produce a vast amount of content fast, our participants highlight their concerns regarding GenAI's ability to create specific, simple content that reflects reality (§ 4.2.4). It can be discussed, whether AI's efficiency to solve tasks fast is positive or negative. On the positive side, the efficiency makes the design process more agile and iterative with AI which eventually might reduce the limitations of time, effort, and budget expenses in the process of designing information technology. On the contrary, new information technology, features, and content can be produced at such speed with AI that it might not be validated, evaluated, or tested before it is implemented. This might cause rapid growth in new IT systems, features, and content, while also raising ethical concerns if certain phases of the design process are neglected. If user research or testing is rushed, there might be a lack of important user insights and considerations that need to be addressed before deployment to avoid or mitigate certain ethical issues (§ 2.3.2). Additionally, if problem setting is neglected, there might be a lot of solutions that emphasize solving the problems *right* rather than naming and framing the problem to solve the *right* problems (§2.2.1).

AI is capable of automating certain UX work practices, such as performing qualitative or quantitative data analysis (§ 2.4.3), and the UXPs will have more time and mental capacity to elevate the overall user experience. However, if GenAI becomes an integral part of the UXPs' work practices to automate certain UX activities in design processes, the UXPs might lose their abilities to perform them. It could be argued, that is not problematic to lose some abilities if certain UX activities can be done by AI because it will make UXPs able to focus on more important areas of the design process. However, the importance of data groundwork to get familiarized with data, such as data analysis, should not be neglected because it might impact the overall understanding of the insights (Braun & Clarke, 2006, p. 87). Reading a ready-made analysis by AI, rather than getting familiarized with the data and performing the analysis themselves, might impact the UXPs' ability to understand the implicit meanings of the data. Arguably, the UXP's distance from the raw user data might affect the UXPs' ability empathize with users and extract the underlying user needs. This can be related to Schön's (1983) metaphor on the *swampy lowlands*. Rather than staying on the *high ground of rigor*, the practitioner should *"[…] descend to the swamps where he can engage the most important and challenging problems"* (Schön, 1983, p. 42). There is a complementary relationship between doing and thinking, and it is the complex details that are important to solve wicked problems in which data familiarization and empathizing might serve as essential components. These claims could be substance for further research on how AI's automation of UX work tasks influences the UXPs' abilities to understand, and empathize with, the users.

5.2.2 AI and problem setting in an HCD approach

One of the topics of interest throughout our research have been the role of AI in an HCD approach. The core of the design is dealing with wicked problems from a pragmatic perspective which requires an inquiry process (Dewey, 1938). With problem setting and reflection-in-action, Schön (1983) emphasizes the importance of the researcher being situated in the context of practice to construct a unique case, independent of established techniques. Additionally, Stolterman (2008) highlights the designerly approach as a human activity, situated in practice to deal with the richness and particular of reality to create and design new ideas (§2.2.1). Arguably, Dewey's, Schön's, and Stolterman's pragmatic perspectives on design are reflected in the UXPs' insights on AI's lack of being able to account for the intangible in the context of practice (§ 4.2.3). One might argue, that AI encompasses a technical rationality approach that enforces objectivity, causality, and systematic methods which are the core of a positivist approach to deal with design. Based on how AI is trained on existing data which makes it limited to the causality of the deliberation of means, depending on prior established ends. Based on AI's output that builds on existing data and solutions, the output might result in a universal solution (§ 2.2.1), or a solution that might not reflect reality due to misrepresentation and biases (§2.3.2). In AI's current state with its lack of being situated in the context of practice to account for the intangible, might serve as a valid argument for why it cannot design autonomously in a HCD approach. Nevertheless, design in the context of information technology covers a wide variety of tasks on different levels of abstractions. AI can be used as a designerly tool in the different levels of abstraction in the design process to a lesser or higher degree - from finding the perfect color palette to dealing with wicked problems. Especially, the tedious, trivial tasks were solved by AI, eg. color matching or copywriting (§4.2.2) which can be labeled as low levels of abstraction. These types of AI outputs were used more or less directly in the design process after validation. On the contrary, in relation to higher level of abstractions in problem setting, the AI output was merely used as inspiration or as a source of information to inform the decisions amongst other inputs. Moreover, the findings from the qualitative interview revealed, that AI might not be able to design novel, complex products (§ 4.2.3). These findings might be rejected due to the UXPs' lack of AI literacy, such as prompting abilities, use of less-suited AI tools, or similar factors. It can be argued that it is not the AI system that needs to perform the problem setting, or be human-centered autonomously. Rather, it relies on the UXP to develop AI literacy (see §5.X.X) and take AI's capabilities into the context of problem setting and HCD. Designerly tools, methods, and approaches are not necessarily prescribed as either human-centered or not. Arguably, in tandem with including the human perspectives, eg. by doing user research and testing in the design process, the use of GenAI can still act within an HCD approach to inform the UXPs and support them in an inquiry process of naming and framing to deal with the wicked problems.

5.2.3 Creativity and innovation

According to our findings, the applied visual GenAI AIs lack the ability to design for a good user experience when it comes to generating UIs (§ 4.2.1). It was also emphasized by the UXPs, that AI is not creative and innovative due to relying on existing and outdated data (§4.2.3). However, AI still supports the creative process through its ability to support UXPs with inspiration in the design conceptualization and development phase (§ 4.1.2; 4.2.2). Nevertheless, it can be argued, that AI needs to be informed to an extensive degree with context based on user insights, such as user needs, their work practices, and outliers in the user base, before AI might be able to design a UI with a good user experience. Design comes down to iterations which include user research, problem setting, design conceptualization and development, and testing which require interactions between divergent and convergent thinking (§ 2.2.1). One of the limitations to the findings on visual GenAI not being creative can be highlighted with the UXP's AI literacy and use of AI systems (Midjourney, Stable Diffusion, and DALL-E) that generate images rather than creating engaging UIs. Some AI tools, eg. *Uizard*, focus on creating digital products based on text prompts (Uizard, n.d.) which might impact the UXPs' perception of AI's creativity and ability to design a comprehensive user experience. To accept or reject some of the UXPs' perceptions that AI is not creative and innovative, we need to further research how GenAI works and compare it to what creativity and innovation are through related work and established theories. For now, we can point out that the generative abilities of AI are still evolving due to the current stance of AI development and we can assume that this will continue in the near future (§ 2.3.1).

5.3 Ethical Concerns & AI Literacy

In this section, we highlight and discuss the findings from our research and literature in connection to the UXPs' perceived challenges of utilizing AI and the ethical concerns addressed in the literature. Throughout the discussion, we will identify opportunities for further research to expand the insights on our findings.

The findings from the qualitative and quantitative analysis show the prevailing tendency of UXPs to perceive more benefits over challenges in applying AI within the design process (Figure 22). This relates to a lack of competencies to critically evaluate AI and can be linked to a lack of *AI literacy* (§ 2.3.2; § 2.4.3) defined by Long & Magerko (2022). Based on the survey findings, UXPs consider the *lack of ability to prompt* GenAI as the most challenging part of AI utilization causing their dissatisfaction with the GenAI output (§ 4.1.3) that was further confirmed in qualitative analysis (§ 4.2.1; § 4.2.3). Our qualitative findings show that the issues with prompting were caused by the *prompts lacking contextual background* (§ 4.2.1). In the late stages of our thesis, we found an empirical study that points out that the way of prompting and watching the prompt history is crucial. Furthermore, it highlights that a human being prompting is always fully responsible for the received AI output (Burger et al., 2023, p. 238). Therefore, despite UXPs' dissatisfaction with text GenAI output, it can be argued that it is due to their lack of AI literacy and understanding of how to achieve better AI output rather than the GenAI's inability to generate. On the other hand, UXPs' reported dissatisfaction with the visual AI output due to the lack of a good user experience can be explained by using AI for a task that the AI system might not be able to perform based on its output format. For instance, generating UIs in an AI tool made for generating images (Midjourney, DALL-E, and StableDiffusion) might also be linked with the UXPs' lack of understanding of visual GenAI's capabilities and limitations (§2.4.3).

Among the UXPs' identified liabilities of applying AI, in both qualitative and quantitative analysis, are those related to the ethical aspects such as *privacy, transparency, bias,* and *trust* which are also at the center of discussion within academic literature (§ 2.3.2) and the policymakers' activities (§ 2.3.2). The increased focus on *AI Ethics* can be seen in the demand for *AI Ethical standards* to ensure reliable and safe AI systems (§ 2.3.2). Our qualitative findings show that UXPs prefer if the AI system provided transparent and visible information about the output's origin(s) to make the UXP's validation of the AI output less troublesome (§ 4.2.3). This is supported by the literature emphasizing the importance of communicating the *trustworthiness cues* embedded in the interface and providing local explanations to facilitate gaining trust and trustworthiness in AI systems (§ 2.3.2). This is also in direct connection to the current tendencies within *XAI* to improve the *explainability, interpretability,* and *transparency* of AI systems (§ 2.3.2). Literature shows the beneficial aspects of combining *XAI* and *human-in-the-loop* to increase more reliable and informed AI outcomes (§ 2.3.3) and suggests implementing *ten modes of AI interactions* (Table 10) to further advance human-AI capabilities by challenging, negotiating, and informing AI's decisions (§ 2.3.3). Based on the discussion, transparent communication and local explanation about the AI output would increase UXPs' trust and trustworthiness in AI output to strengthen the UXP-AI relationship and further augment their abilities.

Furthermore, our qualitative findings suggest that the UXPs are aware of *biased datasets* and the *misrepresentations* caused by them, and therefore would appreciate knowing more about datasets on which AI was trained (§ 4.2.3) to avoid *black boxes* (§2.3.2). Academic literature links the problem of biased datasets to a *lack of fairness* when building AI systems and this issue has still not been sufficiently addressed (§2.3.2; §2.4.1). Despite the academic community's focus on ways how to improve human-AI interactions and address AI ethical concerns, the praxis does not emphasize these issues in a similar way (§2.4.1). Our findings suggest that the UXPs are not concerned about AI not being safe to use. However, they highlight the importance of reliable and trustworthy AI systems in their way of editing, validating, and fact-checking the output (§4.2.3). To our knowledge, no literature has focused on examining the alignment between UXPs' ethical values; workplace values and priorities; and requirements set by AI ethics which we believe would help further examine and address ethical aspects of AI in UXPs' work practices.

Finally, to implement a more *pragmatic approach* in our study, we would develop specific and practical recommendations for UXPs on how to effectively utilize AI in the HCD process while addressing ethical considerations. This might include guidance on proper prompting to increase satisfaction with the AI outcome and recommendations on how to make ethical decisions. By offering practical and actionable insights, the study could contribute to improving the application of AI in the UXPs' work practices.

5.4 The role of users and empathy in design

According to our qualitative findings, UXPs believe in the importance of involving real users in the UX design and research process as opposed to relying on AI-generated users (§ 4.2.3). In the following discussion, we will present four reasons that could expand this perspective: 1) *Accuracy and biases*; 2) *Overlooking outliers*; 3) *HCD;* and 4) *Empathy*.

The first reason, *accuracy and biases,* is due to the qualitative findings suggesting UXPs' uncertainty surrounding the validity of AI systems. For instance, the possible biases that come with the use of *synthetic users* to test a system (Synthetic Users, n.d.), or a system that performs a simulation of eye-tracking and produces attention heatmaps (Uizard, n.d.). The uncertainty can be linked back to *biased datasets, a lack of trust, transparency,* and *explainability* in AI systems (§ 2.3.2). Our qualitative findings are in close proximity to the literature (§ 2.3.2), both vocalizing concerns to which extent the biased datasets might further amplify the misrepresentations and biases. The second reason, *overlooking outliers,* emerged from qualitative findings where UXPs believe that AI's approach to analysis overlooks outliers (§ 4.2.3). This perception is supported by an empirical study showing that ChatGPT appears to label more items into fewer categories compared to human UX Researchers (Schiavone et al., 2023). The third reason, *HCD,* is the UXPs' belief that user tests need to be conducted with real users in the context of including perspectives on all the affected human beings. Otherwise, the design process can not be called *human-centered* (§ 4.2.3). In a recent discussion conducted by Ward (2023) about using AI-generated users, UXPs argue that if a product is going to be used by humans, it should be real humans UXPs need to understand. In addition, humans play also a role in co-designing and validating the outcomes (Ward, 2023) which also further supports the idea of users providing feedback within *human-in-the-loop* concept (§ 2.3.3). While literature underlines the importance of UXPs (and HCI) applying human-centered values (§ 2.4.1), there is a need to allow UXPs to have control over the design and prioritize HCD in the development (§ 2.4.1). Our findings reveal that HCD is not always possible due to the time and resource limitations and therefore, AI-generated users have the potential to offer some insights as opposed to no insights at all (§ 4.2.3).

Furthermore, the determination of whether AI can be considered *human-centered* depends on the UX design team deciding on a design approach, selected based on the situational context, and evaluation of perceived benefits connected with a specific approach (§ 2.2.2).

The fourth reason is *empathy*. While some UXPs are concerned by AI's inability to empathize with users due to AI's contextual and intangible limitations, others believe that AI can learn patterns of empathy (§ 4.2.3). On one hand, the literature highlights a potential for *enhancing the UX capabilities of AI systems* by leveraging accurate and ethically acquired information about users, context, and behaviors. That would allow AI systems to process and act on the knowledge and further support UXPs in their practice (§ 2.4.3). Another aspect that our findings suggest is that using AI to empathize might denote UXPs' emotional connection and care toward the users resulting in a lack of understanding of situational context (§ 4.2.3). While some empirical studies showed that having an AI system in the design process helped UXPs to gain context, familiarity, and empathy (§ 2.4.3), there are warning that text GenAI is still manipulative (§ 2.3.1). A study suggests that GenAI performs better in cognitive empathy than emotional empathy (Lahnala et al., 2022, p. 9). However, to draw more concrete findings would require investigating empathy and the relationship between toxicity and empathy in conversational AI.

5.5 Limitations to our study

In the following section, we will outline potential limitations to our study. We explore the study limitation from a validity and reliability point of view.

5.5.1 Validity

In general, validity refers to the extent to which the findings of the study are well-founded in the conducted research. There are different perspectives on validity: *1) ecological validity; 2) external validity; 3) internal validity;* and *4) measurement validity* (Bryman, 2016, p. 47- 48).

Ecological validity is concerned with the *"[...] naturalness of the research approach"* Bryman, 2016, p. 48). From an ecological validity standpoint, our pragmatic approach with emphasis on acquiring knowledge in practice has been achieved by conducting contextual inquiry allowing UXPs to showcase their knowledge and usage of AI in their work practices. Based on our pragmatic approach, we argue that ecological validity is strengthened. However, it is important to acknowledge that the online format might challenge the study's ecological validity as we did not observe the UXPs directly engaged in their work environment and practice. We asked our participants to perform their regular UX activities but asked them to focus on activities that they normally would use AI to perform. These instructions might weaken the ecological validity. Nonetheless, the UXPs' active showcase of their work practices including AI tools rather than only relying on describing their AI usage in a semi-structured interview enabled us to collect comprehensive, intangible data and record the participants' real work context of applying AI in their UX activities in a manner closely resembling reality.

In the context of *external validity* and the ability to *generalize* beyond the context of our study (Bryman, 2016c, p. 47), we need to address the role of emerging phenomena and contextual boundaries. While examining the use of AI in UXPs' work practices represents an opportunity to study emerging phenomena, it also introduces challenges to the study such as *data scarcity, lack of clarity* regarding issue relevance, and *causal ambiguity* (Yadav, 2018, p. 363). Part of the challenge in the process of investigating the use of AI has been its rapid development resulting in new AI tools emergence and potential changes in the way how UXPs work within a short period of time. For instance, since ChatGPT-3's release in November 2022 till February 2023, ChatGPT-3 has been titled as one of the overall fastest-growing consumer applications ever (K. Hu, 2023). Therefore, we acknowledge that UXPs might use AI differently than the ones we recorded. Furthermore, based on the limited period (February-April 2023) of data gathering, AI tools and integrations were fast-growing. As a result, our study can be considered as a snapshot of UXPs' use of specific examples of AI in their practices within the Copenhagen Metropolitan Area between

February and April 2023. Therefore the findings may not be generalized to a broader UXPs' community. In addition, we are aware that our study is based on a limited number of participants which restricts the overall generalizability of our findings. Overall, we acknowledge there is a need to be cautious when applying our findings to broader contexts, AI systems (tools), and time periods. Moreover, while the use of social media as the respondents' recruitment platform might not accurately represent UXPs, we argue that our sample was representative and heterogeneous to cover UXPs across seniority, attitudes towards AI, and different use of AI. Furthermore, we acknowledge a small sample size in connection to examining the use of visual GenAI which further challenges the external validity of our study.

In terms of the *internal validity* of our study in regard to the causality between variables (Bryman, 2016c, p. 47), we believe that we have applied a structured and reflexive approach to our research to minimize potential biases from our side as researchers. We have employed in vivo and descriptive coding to align our interpretations and stay close to the participants' wording in an inductive coding approach. This is specifically crucial in the interpretivist phase of our study. Due to the structured and transparent data collection, and thematic analysis process, we account for the precautions of minimal impact of researchers' biases on our findings and secured the consistency in codes and themes based on our inductive approach.

Reflecting on the *measurement validity* as a way to question the adequacy of measure (Bryman, 2016c, p. 48), we believe that while the questionnaire was suited for measuring the proportion of AI usage by UXPs and getting an initial understanding of UXPs' use and attitude toward AI, the SICI sessions enabled us to understand the practical context and experience of the use of AI. Furthermore, it uncovered the perceived advantages and challenges of AI in the context of work practice. Finally, we acknowledge, that by using the questionnaire, some of our data can be biased due to the approach to our recruitment of SICI participants who were sampled from the questionnaire. However, this way of applying the questionnaire is closely aligned with the *case-selection variant of explanatory sequential design* (Creswell

& Plano Clark, 2018) enabling us to select the best fitting participants for SICI to further examine the use of AI by UXPs in their work practices.

Finally, we are aware that there are other quantitative methods that could have been used aside from a questionnaire, such as *text mining*, to extract information from Social Media about the use of emerging AI tools that we would further process by using *sentimental analysis* to determine UXPs' overall emotional state towards AI. However, the technical and legal restrictions prevented us from applying them as data collection and analysis methods.

5.5.2 Reliability

R*eliability* within qualitative research is concerned with the *repeatability* of the study (Bryman, 2016c, p. 46). As *internal reliability* relates to assessing the consistency of coders across the research (Bryman, 2016, p. 390), we have addressed *inter-coder reliability* (Bryman, 2016, p. 714), within our collaborative approach in the coding process related to the thematic analysis. Through the collaborative coding process, we have aligned the way we made the inductive codes. We acknowledge that as both researchers are also UXPs themselves, our subjective stances might have an impact on framing participants' statements. To accommodate the subjectivity, we have been taking proactive measures in the form of a collaborative and systematic approach, regular meetings, and open reflective discussions.

To address *external reliability* which relates to the consistency of the methodological approach to be *replicated* (Bryman, 2016, p. 390*)*, we provide a transparent and detailed description of the study's methodological approach. We include all related research materials in the appendices, eg. the questionnaire design; SICI design; and documentation of thematic analysis, to strengthen the replicability of our research.

As the focus of our study is investigating the emerging phenomenon, UXPs designing with AI, not much research has been done in this area (§2.4.3). However, based on our literature review we have been able to draw connections with the existing studies and research carried out in the related fields to our study which further strengthens the external reliability of our study.

We acknowledge that the population of UXPs in our study is defined broadly to accommodate different roles existing in the field of UX. As our selection of SICI participants was constrained by the condition that UXPs should have relatively extensive experience with applying AI in their work practices, we lacked the UX Researcher's perspective. Therefore, we propose that further research might focus on a more specific UX role, rather than trying to encompass the various UX roles and activities that come with the term UXP.

5.5.3 Limitations of AI systems

In our study, we have observed the use of various AI systems. In the following, we present the different versions of the tools that we have encountered.

AI SYSTEMS APPLIED BY UXPS IN THE STUDY	
AI SYSTEMS AND VERSIONS	**GENERATIVE AI TYPE**
OpenAI ChatGPT-3	Text GenAI
OpenAI GPT-4	Text & Visual GenAI
DALL-E 2	Visual GenAI
Midjourney V4	Visual GenAI
StableDiffusion version V2.1	Visual GenAI
Diffusion Bee V1.7.4	Visual GenAI

Table 23: AI systems and their versions during the research period (February-April 2023)

It is important to take into account, that our findings are limited to the versions as listed in Table 23.

5.5.4 A perspective on the research limitations

Despite the mentioned limitations of our research, we believe that our study contributes to Yadav's (2018) four recommendations for how to make an emerging phenomenon a research priority, namely *1) enhance observability; 2) enable early structuring; 3) encourage initial conceptualization;* and *4) accelerate data availability* (Yadav, 2018, p. 363). With our pragmatic approach to the findings from SICI, we are *enhancing the observability.* Our study provides findings related to UXPs' use of AI in work practices and by that offers the knowledge for further researchers to follow-up. Furthermore, through knowledge collection and analysis we provide a *structure* to the studied phenomena to increase its clarity. As a part of connecting our research to the existing literature, we also establish a set of *concepts* to be further investigated in connection to the use of AI in UX, e.g. UXP-AI relationship, AI's ability to problem setting in an HCD approach. And finally, by addressing the use of AI in UXPs' work practices in the early limited period (February-April 2023), we believe we contribute to accelerating data availability and further *encouraging* exploration of the use of different AI systems by different UXP roles.

6. Conclusion

The overall aim of the thesis is to answer the problem statement:

> *How are Artificial Intelligence (AI) systems currently being applied by User Experience (UX) practitioners when designing information technology and how will the recent advancement of AI systems transform the UX practices?*

By reviewing related work in the fields of UX, AI, and including the intertwinement of AI in UX practices, we identified a research gap within the academic literature regarding UXPs' practices of designing information technology with AI. We have conducted an explanatory sequential mixed method study, combining quantitative and qualitative approaches when examining how UXPs apply AI in their work practices and gaining insights into how AI impacts the field of UX.

In the field of designing information technology, UXPs are approaching system development with an HCD approach to creating UX that serves as an umbrella term to encompass UI and interaction design. Overall, the UX design process consists of user research, problem setting, design conceptualization, and testing. When defining AI, we found out that there is no standard definition. While AI refers to an extensive domain, it is mostly defined in connection to AI systems and their capabilities. AI refers to intelligent systems with capabilities that make AI systems goal-driven, usually embedded in larger systems. Latest advances in AI development have resulted in the emerging GenAI in which the AI system learns from content (eg. text and image) with the aim of generating text (text GenAI) or images (visual GenAI).

Based on a survey (N=64), we found that approximately half of the UXPs have experience in applying AI systems to design with. While AI can be applied in all stages of the design process, the most common use of AI is related to UX activities in the stages *problem setting* and *design conceptualization and development.* Overall, we found that the UXPs in our study had a positive attitude towards AI, and they perceive more advantages as opposed to challenges in their AI utilization within the design process. Based on the study of current practices of applying AI in the UX domain, UXPs are applying AI systems as a designerly tool for inspiration and sparring purposes. They apply GenAI systems to design with because it supports them in solving trivial and tedious tasks. Furthermore, AI augments the abilities of the UXPs and AI's efficiency provides opportunities for UXPs to focus on other important UX tasks with a higher level of abstraction. Ultimately, we found that the advantages of applying AI in UX are aligned with studies in related work.

The reason why UXPs primarily use the GenAI output only as inspiration is due to ethical concerns regarding trust, biases, and lack of transparency. As a consequence, the AI output needs to be validated and/or edited before the UXPs might use it directly in the design. In general, the UXPs prefer to use text GenAI systems because it provides sparring and useful outcomes to a certain extent. On the contrary, the UXPs experienced that visual GenAI systems do not account for the user experience when generating a UI. The findings suggest that AI, in its current state, cannot autonomously design novel products and solve wicked problems with a high level of abstraction. Based on the UXPs' perceived challenges, the use of AI must be balanced with human creativity, intuition, presence, and empathy. This suggests that AI can support UXPs to perform HCD activities rather than replace them. However, the UXPs' perceived disadvantages of AI's ability to be creative, innovative, and empathic might be false due to a lack of AI literacy, or because the UXPs applied AI systems that did not fit the purpose of their tasks.

AI's efficiency makes the design process more agile and iterative which reduces the limitations of time, effort, and budget expenses in the process of designing information technology. However, AI's efficiency and automation of certain UX activities, such as data analysis, might result in a decrease in the UXPs' abilities to empathize with users and understand their needs if they stop familiarizing themselves with data. Furthermore, the UXPs indicate that HCD without real users is not human-centered. They suggest that AI lacks the prerequisites to account for the contextual, intangible real-life situations regarding user involvement and accounting for all involved human actors in an HCD approach. The UXPs believe that using AI-generated personas or synthetic users based on biased datasets might further amplify the misrepresentations and biases of real users. Overall, the findings indicate that despite the perceived advantages of AI, current UX practices, methods, and tools will remain in the field of UX in which AI can be applied as a supplement to augment the abilities of UXPs.

6.1 Concluding remarks

Due to our sample size, the nature of the emerging phenomena (AI), the rapid development and advancement of AI systems, and the UXPs’ limited use of different AI systems, our study can be considered as a snapshot of UXPs' use of specific examples of AI systems in their practices within the Copenhagen Metropolitan Area between February and April 2023. Therefore, we acknowledge that the findings may not be generalized to a broader UXP community. Furthermore, our findings and results are based on how UXPs perceived the advantages and challenges of applying AI to design information technology. Therefore, further research needs to address AI’s ability to be creative, innovative, empathic, design autonomously, and human-centered to determine if the UXPs’ perceived disadvantages of AI are valid. Our contribution to the research of the emerging phenomena of AI is to provide findings related to the current application of AI in UX work practices, acknowledging the rapid advancement of AI which might implicate the results. Finally, to research the topic further, we propose to focus on a more specific UX role, rather than trying to encompass the various UX roles and activities that come with the term UXP.

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