Artificial Intelligence (AI) for User Experience (UX) design: A systematic literature review and future research agenda

Abstract

Purpose

The aim of this article is to map the use of AI in the user experience (UX) design process. Disrupting the UX process by introducing novel digital tools such as Artificial Intelligence (AI) has the potential to improve efficiency and accuracy, while creating more innovative and creative solutions. Thus, understanding how AI can be leveraged for UX has important research and practical implications.

Design/Methodology/Approach

This article builds on a systematic literature review approach and aims to understand how AI is used in UX design today, as well as uncover some prominent themes for future research. Through a process of selection and filtering, 46 research articles are analysed, with findings synthesized based on a user-centred design and development process.

Findings

Our analysis shows how AI is leveraged in the UX design process at different key areas. Namely, these include understanding the context of use, uncovering user requirements, aiding solution design, and evaluating design, and for assisting development of solutions. We also highlight the ways in which AI is changing the UX design process through illustrative examples.

Originality/value

While there is increased interest in the use of AI in organizations, there is still limited work on how AI can be introduced into processes that depend heavily on human creativity and input. Thus, we show the ways in which AI can enhance such activities and assume tasks that have been typically performed by humans.

Keywords: artificial intelligence; machine learning; user experience; user interface; design; user centred design process; systematic literature review

1 Introduction

When developing a digital artifact or service, designers need to create an overall user experience (UX) that meets end-user requirements and expectations (Chen et al., 2018). In fact, cases of bad UX have resulted in non-use by end-users and have been associated with technostress, fatigue, and misuse (Hart & Sutcliffe, 2019; Nisafani et al., 2020). End users of digital solutions have high standards for what they demand of an application or service, and software success is often linked to how well designers manage to understand and translate requirements into corresponding functionality and appropriate aesthetics (Silva-Rodríguez et al., 2020). Following an iterative user centred design process, and having qualities of creativity, problem- solving, sense-making, empathy, and collaboration, is shown to result in user friendly and innovative solutions (Oulasvirta et al., 2020). However, the process of designing still requires a lot of time, experience, and resources. The task of designers becomes increasingly complex when considering that they are required to simultaneously understand what to create (problem setting), and develop the solution (problem solving) (Q. Yang, 2017). To understand the task at hand, designers need to gather information on how the users will utilize the developed solution, often analyzing data from users interacting with the system. Nevertheless, in many cases there is an absence of such data which makes the task even more complex.

The recent uptake of artificial intelligence (AI) has sparked a debate on how the design processes surrounding UX design can be enhanced, providing designers with tools that enable them to design better digital artifacts, within shorter cycles and a lower cost (Oh et al., 2018). Practical applications as well as research on AI for UX is growing rapidly in the last few years. Using data sets containing for example user data or GUI elements, enables AI applications that automate design tasks, as well as facilitate the creation of adaptive interfaces that dynamically evolve based on changing user requirements (Johnston et al., 2019). As such, the field of AI-supported UX is fundamentally changing what was possible in designing digital artifacts. Since the field of AI consist of many sub-fields with different application areas and domains of specialization, there is a multitude of possibilities for creating data driven solutions that aid or drive UX processes. Nevertheless, to date there is a lack of a comprehensive understanding of how the use of AI has changed and will change UX design. Exploring this nascent area of research is of high importance for the domain of Information Systems (IS) since the success of digital tools relies heavily on how well they conform with user requirements and expectations (Chatterjee & Kar, 2017).

The introduction of AI has already caused fundamental changes in the design process around UX, so it is important to understand how such technologies can be developed and integrated into the design process. In a recent literature review, Abbas et al., (2022) provide an overview of the challenges faced by UX designers when incorporating machine learning (ML) into their design process. In their findings, the authors suggest several tools, algorithms, and techniques that can be used to overcome emerging challenges. In effect, the study of Abbas et al., (2022) provide a complementary perspective which seeks to identify the major challenges UX designers face when trying to learn about ML and incorporate it in their work. Nevertheless, there is less of a focus in their work on how ML can be utilized during the different phases of the UX design process. The introduction of new digital tools such as AI in the UX design process has been argued to entail important changes for the nature of work of designers (O'Donovan et al., 2015). Such shifts have been argued to result in radical news ways of working, as well as some potentially negative and unintended consequences (Gaffney, 2017). Among others, AI use in UX design process has been argued to be a potential risk factor for lack of control and autonomy, UX design misalignment, performance losses, as well as increased stress and frustration of designers over the fear of job displacement (Gaffney, 2017). As such, it is argued that for AI to be a useful tool in the UX design process, there is a need to understand both the technical and human related elements throughout the process (Koch, 2017). Thus, it is important to take the UX design process as a starting point and identify how AI is introduced at the different stages.

The objective of this article is to identify how UX design has changed with the introduction of AI during the past years by overviewing existing academic literature, as well as what challenges and opportunities it creates. We therefore build on a systematic literature review approach to synthesize existing work, to better understand how and to what extent AI is creating changes in the design process. Grounded on this synthesis, we then proceed to explore current gaps of research and promising areas for future studies. We therefore develop a comprehensive research agenda which is aimed at highlighting important areas that have yet to be researched concerning human-AI collaboration in UX design. Specifically, this research builds on two main research questions:

RQ1. *How is AI currently used to support or enable the UX design process?*

RQ2. *What are some current gaps and important research avenues to enhance human-AI collaboration in UX design?*

These two research questions correspond to our synthesis of the current literature, and the critical assessment and development of the research agenda. In the next section we introduce key related work pertaining to definitional aspects of AI as well as the design process. These two sub-sections serve as a foundation of our systematic literature as they define the scope of this article and the type of design we focus on. In sequence, section 3 provides a synthesis of current research by mapping key areas on the design process framework. Through this synthesis we explore some important areas of AI use in the design process, as well as some concerns and challenges in leveraging AI. Section 4 then develops a research agenda with actionable directions for future scientific inquiry. In closing, section 5 discusses the theoretical and practical implications of this work and outlines some limitations.

2 Background

2.1 User Experience (UX) Design Process

Design is the part of innovation focusing on decision where people create ideas and solve problems (Verganti et al., 2020). Verganti et al. (2020) defines design practice as ”the phenomenology of design in a specific context: its process (“how” design decisions are made; through which phases, methods, tools, or collaborative practices) and the object of design (which design decisions are made; which novel solution it creates, whether a good, service, or process)”, and design principles as ”the perspective and philosophy that inform the act of designing, and that constitute an ontology of what design is”. UX is defined by Yang et al. (2020) as:”…an *overall experience, which includes all aspects of user interaction with products or services”*. On the other hand, UX has been defined as *”…a person’s perceptions and responses resulting from the use and/or anticipated use of a product, system or service, including all the users’ emotions, beliefs, preferences, perceptions, physical and psychological responses, behaviors and accomplishments that occur before, during and after use”* (ISO 9241-210:2010). A common denominator of these definitions is the focus on the user, and how they experience the designed digital solution.

The process of designing the UX has been a topic of considerable focus over the last years. A. Schmidt and Etches (2014) defines UX-design as *“the process of supporting user behavior through usability, usefulness, and desirability provided in the interaction with a product”*. A critical part of designing the UX is following a predefined and established process where piloting, testing and refining are key elements of the process (Wilson, 2013). The user-centred design is a framework of process that focused on putting users at the centre of product design and development. It is one of the most used techniques for designing UX for digital solutions (Pandian & Suleri, 2020). In addition, each phase in the process can be related to different UX-activities, thus providing more detail on how such process change with the introduction of AI (Park et al., 2013; B. Yang et al., 2020). Preece et al. (2015) defines user-centred design as a “design process, which consists of identifying the needs and requirements of the user, generating ideas, and evaluating them to satisfy the needs and requirements”. A key element of user-centred design is that it is an iterative (as seen in Figure 1), as the steps can be revisited if the result does not meet the user requirements after each iteration. The user centred design process facilitates a dynamic interplay between the user and the designer, by allowing UX-designers to conceptualize, communicate, and evaluate their design before creating the final solution (Pandian et al., 2020).

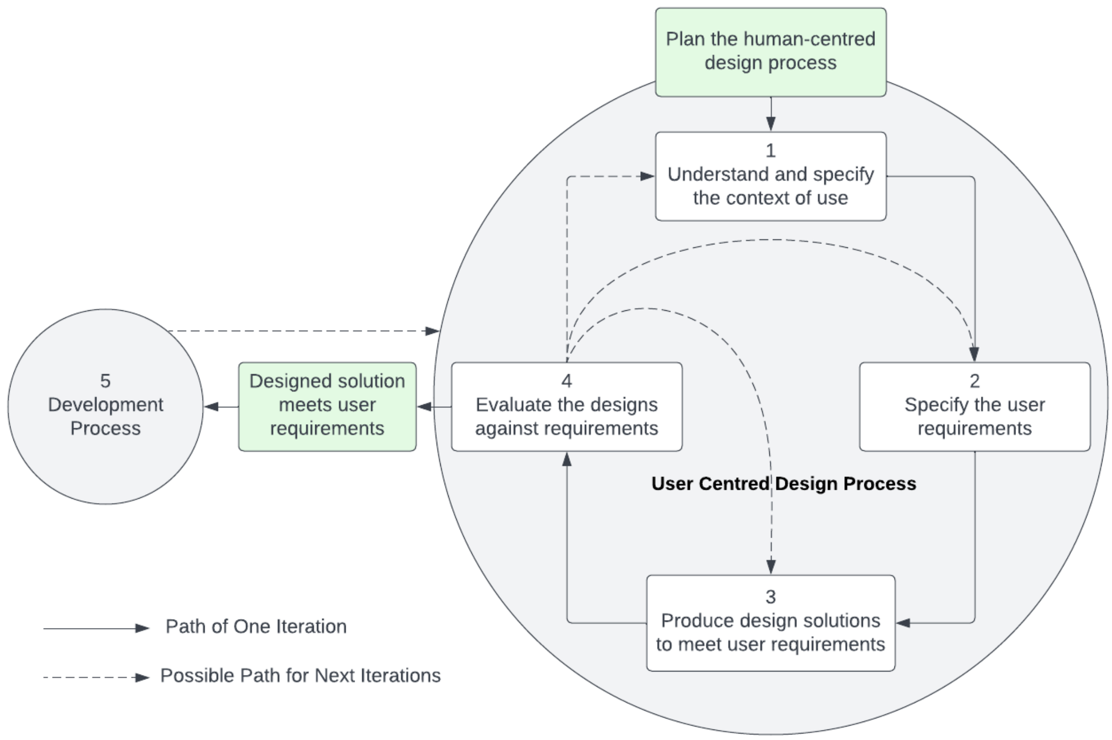

Figure 1. User centred design and development process.

2.2 Artificial Intelligence (AI) in Design of UX

Despite a breadth of definitions around the concept of AI, a comprehensive and inclusive one was provided by Nilsson (1998) stating that AI is *"concerned with intelligence behavior in artifacts. Intelligence behavior, in turn, involves perception, reasoning, learning communicating, and acting in complex environments. AI has one of its long-term goals in the development of machines that can do these things as well as humans can, or possibly even better"*. In their literature review, Enholm et al. (2021) look at different definitions of AI, and state that *"there is a consensus that AI refers to giving the computer human-like capabilities, meaning that computers are able to perform tasks that normally require human intelligence"*. Owing to the manifold strengths of AI as demonstrated by latest applications in practice, there is increased interest in how AI can be used to enhance or even radically change the design process of digital solutions (Agner et al., 2020, pp. 3–17). Specifically, AI has been hailed to provide many important affordances including enabling greater customization at scale, more precise analysis of usage of digital solutions, and also aiding in the creative process of designers (Oh et al., 2018).

As the use of AI for design purposes has grown, concepts to describe this phenomenon has evolved. Some of these concepts describe the entire idea of AI for design, while others are used as a measure of how well the AI is performing at, e.g., generating new and creative ideas. One such concept is artificial design intelligence (ADI). This refers to AI that has developed design knowledge, by using ML to predict design trends and generate designs (Li, 2020). Another example is called computational creativity, which is an AI sub-field where the system exhibit behaviour that would be deemed creative in humans (Feldman, 2017a). Following in this direction, yet another sub-field is that of AI interacting with art design in intelligent design. The field includes, among other things, artificial intelligence aided design, artificial design intelligence system, user experience design of artificial intelligence products and artificial intelligence product manager (Li, 2020). Yet, while there is significant promise in the use of AI during the design process, the field remains fragmented. This makes it difficult to develop a holistic understanding of how AI is currently used in the design process, how its use can be optimized, but even more importantly how the spring of AI might radically change the design process entirely as we know it. For this reason, we conduct a systematic literature review which builds on this cross-disciplinary domain. The aim is to map the current status of knowledge and develop a forward-looking research agenda which can help aid both researchers and practitioners. Specifically, we aim to contribute to emerging field of human-AI collaboration and understand how interactions of humans with emerging AI technologies develop. As AI applications are becoming increasingly embedded in different tasks, including that of UX design, it is important to understand how processes and interactions evolve in order to optimize collaboration patterns.

3 Methodology

In this section, we present our approach to conducting our systematic literature review, adopting the methodology proposed by Tranfield et al.'s (2003) . We started off the preparation stage by establishing our research questions, the focus of the review, and our search strategy and relevant inclusion and exclusion criteria. We then screened the initial pool of papers and removed duplicates, and non-relevant papers, which was followed by an assessment of all papers remaining in the pool, based on quality, and relevance to our research questions. The final stage included the analysis of the papers in the final pool. These stages are discussed next in more detail. Figure 2 presents an overview of our approach.

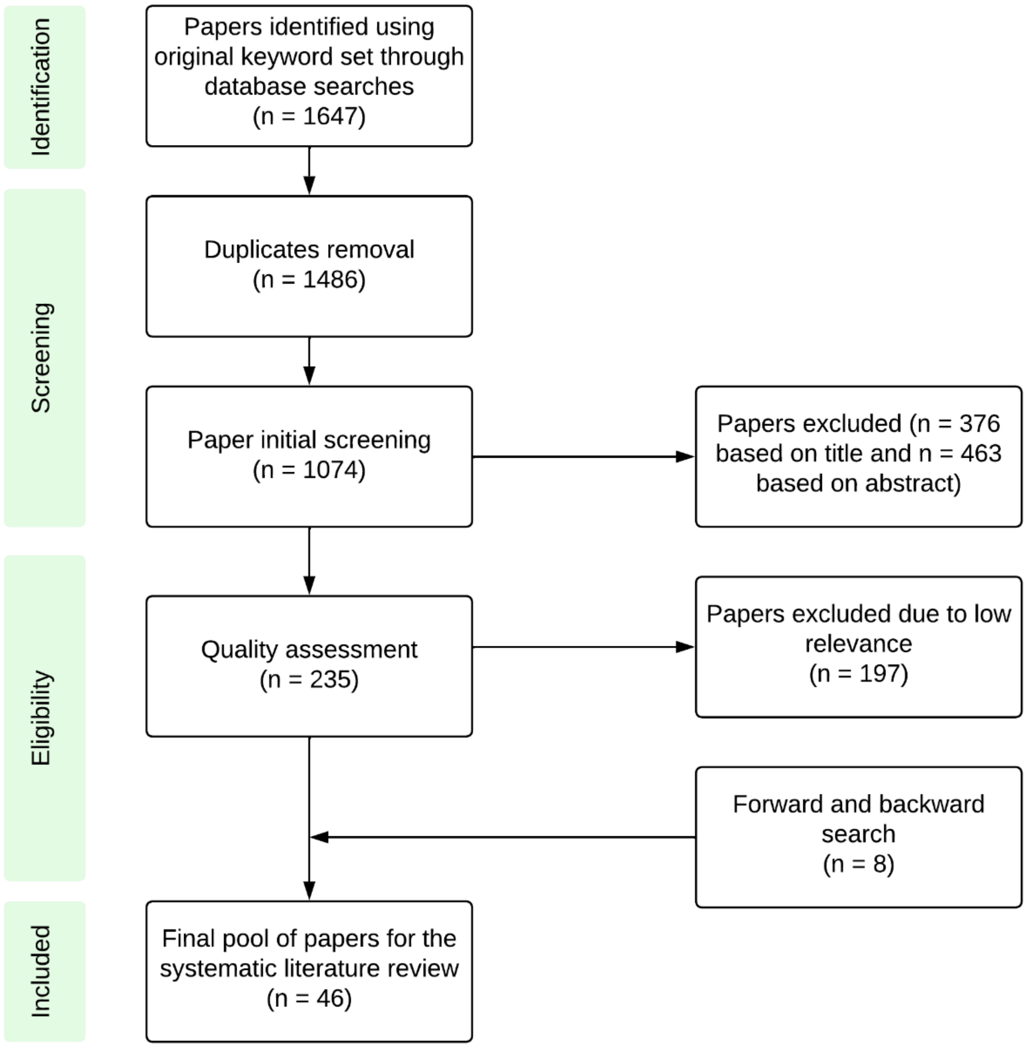

Figure 2. Methodology for the systematic literature review

3.1 Preparation

The preparation stage entailed articulating our research questions clearly and planning and formalising our search strategy. We initiated this stage by conducting a preliminary examination of the available literature to sensitise and familiarise ourselves with the domain and the potential gaps that exists in the literature in relation to AI uses in UX and user centred design studies. This step illustrated the need to provide a systematic review of the current state of the art and allowed us to identify relevant keywords during the selection stage.

3.2 Selection and screening

In order to identify papers that discuss AI as part of user centred design and UX, we established our exclusion and inclusion criteria. Selected papers had to focus on the use of AI in a design process, and specifically they had to discuss how AI was/could be used to supplement or replace the work of a designer or a front-end developer, i.e., not focused on how AI can support end users to customise a design solution nor how to design AI solutions. In addition, our search strategy entailed that studies should have been:

- Published after 2015;
- The right type of output: journal paper, conference paper, book chapter;
- Published in peer reviewed and reputable journals and conference proceedings.

We identified keywords based on a preliminary investigation of the literature, reflecting the focus of our study and the inclusion criteria. These are found in Table 1.

Table 1. Keywords for the systematic literature review.

Categories	Keywords
AI	Artificial Intelligence, AI, Machine Learning, Deep Learning, Artificial Design Intelligence
Design	User Experience, UX, User Interface, UI, User Customisation, UX Design, Design Prototyping, Human Computer Design, Human Computer Interaction, Co-creation, Intelligent Design, User-centred design, Usability

Following this, we began our search through Google Scholar using all keyword combinations. We chose to use Google Scholar because it has proved to be a convenient and easy to use platform for identifying peer reviewed studies, as well as minimising publication bias (i.e., identifying studies published in outlets that are not always indexed) (Yasin et al., 2020). In addition, in order to ensure that we had identified all relevant publications with the given combinations of keywords we extended our search to several other databases including among others Scopus, ACM digital library, AIS library, IEEE Xplore digital library, as well as search engines of publishers (e.g., Taylor and Francis, JSTOR, Springer). We conducted the search and selection of articles between October 29, 2022 and November 27, 2022. This resulted in 1647 articles overall, which we extracted into a reference manager software (Zotero) to facilitate screening.

Screening entailed examining the 1647 papers for relevance based on our inclusion criteria, whereby we removed papers that were not peer reviewed journal papers, conference papers, or book chapters. We retained some important papers such as doctoral dissertations and reports in a separate folder for use in key facts in the introduction as well as for aiding us in uncover promising areas of future research, but not for the main synthesis of articles. We also screened papers on the basis of their titles and abstracts. All in all, after removing duplicates, applying our exclusion criteria, and screening, only 38 papers remained in the pool. By performing a forward and backward search, 8 more articles were identified and included in the total pool of 46 papers. We note that these articles were not found during our original search because they used specialist or alternative terms to refer to specific techniques of AI (e.g., feedforward artificial neural networks), which we had not included in our set of keywords, or they were not referring to any of these in the abstract or keyword set.

3.3 Quality Assessment

During quality assessment, we examined the papers with regards to relevance, rigor, and credibility. We examined relevance by assessing whether or not a study fits in terms of our research questions, and we examined relevance on the basis of whether a study has been peer reviewed as well as its publication outlet. We then examined credibility by thoroughly reading each study and on the basis of consensus within the team. This was done through identification of themes among two of the co-authors in and independent manner, and a consensus discussion with the addition of five research assistants. This assessment resulted in 38 papers being included in the final pool. To ensure that relevant papers were not missed in our search, we conducted a forward and a backward search, by examining the reference list of each of the 38 papers passing through quality assessment. We identified 8 relevant, rigorous and credible papers that had not been picked up during the search phase, which we then included in our final pool of papers. This resulted in 46 papers overall being examined as part of this systematic literature review.

3.4 Data Extraction

To facilitate data extraction, we developed a concept matrix to organise the analysis of the papers. Building on a concept matrix can be useful as it helps characterising the pool of papers, and synthesising the findings of each article on the basis of the focus of the review (Nayernia et al., 2021). Specifically, for our concept matrix we extracted the title, the abstract, its main theme, and the respective research question(s), relevant definitions, the research method used, key findings and contributions to the field, and limitations and steps/avenues for future research. The analysis of the collected papers is based on this matrix where we extracted Table 2, Table 3, Table 4, and Table 5 directly from it. Similarly to the process used during the paper selection, two of the co-authors independently coded the contents and themes within the papers using a concept matrix. These concept matrixes were then compared between them and further discussed with five research assistants. This process helped form a common understanding of the content and the relevant themes.

3.5 Data analysis and synthesis

The majority of the papers that were retained for further analysis have been published in 2021 (17 papers) and 2020 (13 papers). These articles are predominantly conference papers (29 papers), as typically, authors working in the domain of UX and user centred design o publish their work in conferences, such as HCI and ACM SIGCHI. From the wordcloud shown in 3, it is evident clear that in their majority, studies are mostly looking into using AI and its applications for automation, exploring and developing personas and interfaces, and prototyping more generally. Following this descriptive analysis, we conducted a qualitative analysis of the articles, by leveraging the concept matrix and synthesising the results along the main areas of user centred design, namely: context of use; requirements analysis; solution design; design evaluation; and development. These themes were based on the framework for user-centred design presented in Figure 1.

Figure 3. Word cloud using the total of keywords used in the identified articles per type of output (darker and larger words represent higher frequency in the corpus).

4 Findings and Analysis

In this section, we present the findings of our analysis of the 46 identified studies, and we focus on our study's research questions. Specifically, we examine the current state of the art with regards to the use of AI within the context of the digital design process, and we elaborate on gaps and important research avenues for enhancing human-AI collaboration in UX design. We do this, by adopting the User Centred Design Framework earlier introduced, which allows us to identify and elaborate on AI uses within the distinct components of the framework as well as on more comprehensive uses as part of the process.

4.1 AI and the digital design process

Our analysis of the identified articles indicates that AI is mostly used for producing the design solution (step 3 in the user centre-design and development process, Figure 1), with a little over one third of the articles (35%) focusing on this step. The second most common use for AI is automatically developing the solution (step 5 in the user centre-design and development process, Figure 1) with 31 % of the articles focusing on this. The remaining articles focus on evaluating the design solution via AI and understanding automatically the context of use of the envisaged solution. We note that we did not identify any articles focusing on the specification of requirements.

4.2 AI uses for understanding the context of use

Besides the use of AI for specific steps during the design process, some studies propose the use of AI tools and AI-enabled approaches for helping designers understand more effectively and more efficiently the context of use of their digital solutions. As context of use, we refer to the "combination of social, physical, task, technical and information" (Tokkonen & Saariluoma, 2013, p. 791) factors that influence the user experience. Understanding the context of use of a digital solution is particularly important, as in essence it entails understanding who the targeted user is and what is their personal context, how, when and where they may use the digital solution and what might be done to improve their experience of interacting with said solution (Korhonen et al., 2010). Often, this information gets captured and analysed through user personas or user portraits, on the basis of available datasets (Yuan, 2023), and it is then used to inform low fidelity prototyping of interfaces and products (Christoforakos & Diefenbach, 2019). Therefore, studies that focus on this aspect of the design process (summarised in Table 2) propose AI tools and methods for automating those parts of the design process that are geared towards proving a better understanding of the context of use of the digital solution.

First, developing user personas to understand the characteristics of the targeted end user requires accessing relevant datasets that can inform the construction of such personas, in terms of demographics, and other characteristics that might be important for certain solutions (e.g., especially for personalisation and making recommendations purposes). Often such datasets get produced via market research approaches and their analysis can be crucial for understanding better what the digital solution needs to support or not in terms of behaviours and affordances.

This approach to developing user personas however can be particularly time-consuming and might require expertise beyond the skillset of the designer. Therefore, Salminen et al. (2019) propose automating this part of the design process by automatically generating personas and profiles using ML. The authors analysed think-aloud transcripts of conversations with research and marketing professionals and found that the advantages of automating the personas, relate to speed and currency of the results. They also note, however, that automatically created personas seem to share the same disadvantages as their manually developed counterparts, namely usability, perception, credibility and relating to information content (Salminen et al., 2019). In other words, the underlying issues are not necessarily solved.

Second, designers often develop low fidelity prototypes (e.g., sketches) which they then use for showcasing tentative solutions, as well as for understanding better how a user might interact with the proposed solution. When the design of the low fidelity prototype has stabilised, it is time for the designer to increase the level of detail and move from a low fidelity, to mid and high fidelity prototypes (i.e., executable UI code). However, moving between these levels of prototyping can be challenging, because low fidelity prototypes allow users to evaluate digital solutions based on personal visions, which will differ from person to person, and often high fidelity prototypes do not represent clearly the original concept produced during ideation (Christoforakos & Diefenbach, 2019). This then entails numerous iterations, which can be resource-expensive in terms of costs and time. Suleri et al. (2019) propose the use of deep neural networks for moving between low, mid and high fidelity prototyping, which allows automated and quick iterations between the stages, thus simplifying the process and enabling showcasing how e.g., a UI might look like on the basis of a preliminary sketch.

Table 2. AI uses for understanding the context of use.

Source	Research Method	Type of AI and solution	Key findings
Suleri et al. (2019)	Usability evaluation using SUS-schema with 15 designers. Workload analysis using NASA-TLX with 8 participants.	Prototyping workbench where designers can sketch out their ideas. The solution then uses deep neural networks to create a mid-fidelity prototype, and then the executable UI code.	AI can address the frustration designers experience when they need to move from a low fidelity to mid and high fidelity prototypes (as evidenced via the NASA-TLX test). Current tools approach switching from low to mid to high fidelity prototyping as distinct steps, but they are interconnected, and AI

			can provide comprehensive support.
Salminen et al. (2019)	Eye-tracking user study, using automatically generated persona profiles.	Automatically generated personas (AGP) using online analytics data.	AGP can be developed rapidly and can be behaviourally very accurate; they also enhance communication with the client/organisation.

4.3 AI use for user requirements specification

Our review did not yield any studies that focus on automating the specification of user requirements. We posit that this is due to the nature of the requirements specification process, that often involves activities such as role playing, focus groups and in-depth interviews for capturing design guidelines, and functional and non-functional requirements for a particular product.

However, we also note that the challenge lies primarily with how a designer can meet the identified requirements, which allows them to understand what needs to be created early on in the design process (Zhou et al., 2020). Along these lines, Koch (2017) suggests that possibly AI can be used to ”[discuss] the stated requirements with the system, which in turn suggests first ideas, similar projects, or inferred information. Based on the designer’s feedback, the system adapts its understanding and presents it to the designer for further discussions”. As such, AI can be used for capturing important information with regards to a task from the designer through such a dialogue, which can then help the designer to understand and engage with the preliminary requirements better.

4.4 AI use for solution design

User centred design entails designing solutions that address user requirements. This typically entails using design principles for generating prototypes that are iteratively modified for developing detailed solutions. Table 3 summarises existing research that focuses on using AI for this step within the user centred design process, i.e., for producing solutions that address user requirements.

In their majority, existing studies focus on the uses of AI that either help designers to move from a low to high fidelity solution (e.g., Pandian et al., 2020) or to optimise their designs. For example, both O'Donovan et al. (2015) and Duan et al. (2020) put forward a machine learning approach that can automatically change and improve a design. Further, within the industry, Microsoft and AirBnB developed pilot solutions whereby paper-based sketches are converted into GUI code with the help of AI (Buschek et al., 2021). However, such approaches have received to date mixed feedback. Specifically, such solutions have been criticised because ML-based solutions that convert UI sketches to code suggest much less control over the final solution (Pandian & Suleri, 2020), which is something desired by designers (Duan et al., 2020; O'Donovan et al., 2015) and which indicates that a designer-AI collaboration would be preferrable (Duan et al., 2020).

Other approaches indeed focus more on ensuring that designers lead the design process, by allowing them to choose the input for the AI component (Chaudhuri et al., 2022b). For example, a study shows that AI can provide acceptable suggestions for optimisation on the basis of a designer-produced sketch, because this entails that the designer is offered a range of alternatives to choose from rat6jher than just one (Todi et al., 2016). In addition, scholars mostly agree that AI should not be used for automating the entire process but rather offer to designers the tools that can make the design process easier and more accurate (e.g., Feldman, 2017b; Gardey et al., 2022). For instance, supervised machine learning can be used for enabling designers identify design patterns that perform better in terms of usability (Silva-Rodríguez et al., 2020) and deep learning techniques can improve design performance when iterating initial designs (Chaudhuri et al., 2022b; Zhou et al., 2020)).

Table 3. Uses of AI for designing solutions

Source	Research Method	Type of AI and solution	Key findings
Duan et al. (2020)	Experiment using 108 different layouts of a photo editing UI	ML is used for updating UI layouts based on designer feedback, task performance, time completion and error rate.	Optimising layouts using ML is time efficient and leads to new ideas, but requires human involvement for refining the solution be aesthetically pleasing. The recommendation is to have a designer-AI collaboration rather than relying on the one or the other.
Buschek et al. (2021)	Case study and user test on a working prototype.	Sketch plugin that matches paper-based GUI elements and produces a digital	AI does not consider design conventions and best practices (e.g., aligning elements, placing them exactly on the same

		version and creates the wireframes using ML.	coordinates as in the hand drawing). The authors indicate that it is important to evaluate the output design for such instances and they recommend using ML as the glue between the different design steps, not for replacing designers but rather allowing them to spend more time on creative work.
Feldman (2017a)	Experimental procedure using qualitative techniques and designer feedback.	Evolver, a Creative Artificial Intelligence System (CAIS) that is based on genetic algorithms and designer-controlled constraints.	AI helps designers to augment their creativity and to create something that neither the designer nor AI could do alone. CAISs are efficient and effective, but do not understand the entire problem, and they lack human skills like empathy and emotion. Based on their findings, the authors suggest that the designer cannot be replaced but they will need to use new tools to evolve the design process.
Gomes & Preto (2018)	Conceptual article and artifact design	Focuses on interactions that are boosted by AI and specifically emphasized on the importance of a design oriented approach	A design oriented approach for emotional user experience depends on the interactions that the artefact encourages which are offered to the user per physical and digital interfaces.
Todi et al. (2016)	Two empirical studies involving 20 end users and 10 designers.	Tool for integrating real-time optimization in the design tool. A designer sketches first the layout and receives AI-enabled suggestions to explore design alternatives.	The AI-enabled tool delivers solution similar to what the designers would develop on their own, reducing the overall time necessary, and findings suggest that exploring alternatives like this can be positive.
O'Donovan et al. (2015)	AB testing: comparison of a baseline design to an automatically adapted one. The empirical entailed 20 designers developing 200 design and then 2 designers evaluating the final output.	DesignScape allows for interactive layout suggestions or automatically adapting the design, using a form of ML.	Users overall disliked the adaptive feature because they felt that they were losing control over the design and they preferred being able to ignore optimisation suggestions. Looking at the final output, 63,4% preferred the adaptive design over the baseline, with only 34,1% not having used any suggestions.

Pandian and Suleri (2020)	Conceptual – the paper proposes different solutions for using AI to automate UI design.	MetaMorph: a UI element detector that uses deep neural networks. Blu: a UI layout generator taking screenshots as input and creating blueprints and editable graphics.	As the design process consists of many steps, a designer should not use AI for automating and collapsing all steps into one. MetaMorph and Blu automate parts of the process and allow for customization.
Pandian et al. (2020)	Qualitative study with 10 UX designers undertaking tasks based on prespecified tasks, completing an After-Scenario Questionnaire (ASQ) and participating in interviews.	MetaMorph is used in combination with Eve (Suleri et al. 2019) to help the transition from low-fidelity to high-fidelity prototypes.	MetaMorph detects elements from low-fidelity sketches with mAP of 63,5%, and above averaged answers to all ASQ questions. These results suggest that the process was quick and easy with enough information for completing each task. Part of the recommendations entail allowing designers to correct the detected elements when the later are wrong, to manually detect undetected elements, and include only those elements with high accuracy.
Silva-Rodrıguez, Nava-Munoz et al. (2020)	Experimental evaluation of interaction design patterns recommendation mode.	Model for recommending design patterns based on design-level requirements, using supervised ML (logistic regression, multinomial Naive Bayes, linear support vector machine (SVM), and random forest) to help designers choose patterns.	Design patterns increase usability and UX, but selecting the right patterns can be a hard task, especially for inexperienced designers. The implementation of the pattern can reduce the time spent finding the correct patterns. While the study used a small dataset, the findings suggest that ML can be useful for solving this problem.
Zhou et al. (2020)	Design experiment with 11 students and evaluation by 3 experts.	Deep learning solution and field intelligence for helping designers during the iterations of the initial design input.	AI could improve designers' performance in fluency and stylisation, but flexibility and originality did not improve.
Gardey et al. (2022)	Evaluation experiment where 3 UX experts evaluated interaction with widgets across 6 websites.	The authors used decision trees (a type of ML technique) to predict the effort involved in interacting with the widgets.	AI tools and techniques can be used to accurately capture and assess the effort involved in interacting with digital solutions, thus supporting UX evaluation.

4.5 AI uses for design evaluation

After a prototype is complete, it needs to be evaluated with regards to whether it meets the user requirements. This step often includes user tests, or evaluating user data. Table 4 summarises the existing literature that explores how AI can be used to automate or conduct this step of the design process.

Most of the literature evaluates UX using e.g., a SUS-schema, whereas only one study that explores automating the process using AI. In more detail, Yang et al. (2020), exploring mobile applications, use user data to assess UX, which can be then used to help designers appreciate whether there is need for further iterations in the design process. The findings suggest that, even though this approach can be used for simulating UX to some extent, and therefore resulting in improved efficiency toward identifying the optimal design, it cannot improve learning and effectiveness (Karimi et al., 2018). This suggest that deep learning during the evaluation process may be not suitable. Indeed, an important aspect of design evaluation is by directly including the end user in the process, e.g., through user testing and walkthroughs, which requires qualitative techniques for evaluating whether user requirements have been met and thus produces qualitative data (Desolda et al., 2020). While we did not identify any study engaging with such an approach for AI-enabled evaluation, there are some studies that supplement user testing with more qualitative techniques, for assessing user feedback and identifying patterns via AI. For example, there are studies that use AI in order to measure how a user may react to a design (Swearngin & Li, 2019; Zhou et al., 2020) and scholars have argued that this approach may be considered good enough for replacing the traditional user testing, because such automated techniques can reduce costs (financial, time etc.) (Swearngin & Li, 2019). However, Wallach et al. (2020) argue that this should not be the end goal, because usability testing as a method is irreplaceable for identifying barriers and hindrances, and therefore evaluating user experience. Ideally, and because predictive models can give valuable insights beyond user testing, it is posited that a hybrid approach that builds on synergies between AI and the designer can yield the best results.

Table 4. Uses of AI for designing evaluation

Source	Research Method	Type of AI and solution	Key findings
Swearngin and Li (2019)	Informal evaluation of a solution on the basis of testing for accuracy by 7 interaction designers.	TapShie: a tool that uses deep learning to model how 'tappable' an element is according to a human user.	Automated techniques to cut costs of user studies. Reasonable accuracy in matching how likely a human will think UI element is tappable. The interaction designers saw potential in this solution but expect more functions (e.g., 'tappability' of different screens).
Wallach et al. (2020)	Multiple case studies, using AI for prototyping UI models and evaluated using synthetic designers (machine generated)	ACT-R for ANTETYPE: an extension to the prototyping tool that simulates human behaviour based on cognitive architecture and acting as the designer's "best friend". The designers asks the ML for help and receives performance predictions for a given scenario.	The weakness of AI is linked to low trust, loss of manual skills and lack of situation awareness. This solution supports designers by providing a quick performance analysis of different design variables. The goal is not to replace user testing (which gives rich qualitative insights) but to use AI for gathering quantitative data as well, thus making for a mutually beneficial relationship between UX and AI.
Yang et al. (2020)	The study follows the Artificial Intelligence-Aided Design framework, doing user testing of the old and the new application with 6 participants.	AI application using click behaviour for assessing UX.	The solution is able to simulate UX to a certain extent, resulting in improved efficiency of optimal design, but it is unable to improve learning and effectiveness. It can be used to assist designers, but it is not an omnipotent tool.
Zhou et al. (2020)	Empirical study with 500 participants labelling their preferred solution, the later then used for updating the final model. 20 people later evaluated real-life examples from the Baidu mobile app.	FEELER: an ML approach to explore and evaluate design solutions. It uses collective learning for predictive modelling based on user feedback and measuring preference scores to help designers quickly and conveniently adjust UI modules.	The findings indicate that the solution can help designers to identify the best design solutions, to improve UX, to understand the hidden rules for good design and to test out more options for UIs.

4.6 AI uses in the development process

After the designer has created a solution, the developer will have to code the user interface and often, there are important discrepancies between the prototype (UI as designed by the designer) and the actual UI code (UI as developed by the developer). These discrepancies are typically addressed by the developer so that the coded UI can still meet the user requirements ingrained in the prototype (Nguyen & Csallner, 2015). Along these lines, these discrepancies can be delegated to AI applications, by automating the process, and converting the prototype to code while supporting the designer to have greater involvement during development. In Table 5 we summarise studies that propose the use of AI for the development process.

Table 5. Uses of AI for development

Source	Research Method	Type of AI and solution	Key findings
Nguyen and Csallner (2015)	Empirical evaluation of 488 screenshots from 100 popular apps.	REMAUI: a tool that identifies interface elements using computer vision and character recognition. It is used for generating user interfaces that are similar to the initial screenshot.	First technique to automatically reverse engineer a mobile application user interface with an average run time of 9 secs.
Beltramelli (2018)	Accuracy testing of a proposed solution.	Converting high-fidelity prototype (screenshots) to code by using deep learning to reverse engineer user interfaces from a single input image.	The solution was trained on a small data sets and supports few parameters, but proved to be able to learn the layout and achieved 77% of validation accuracy. There were problems with colour selection, the correct GUI style and modelling GUIs with long lists.
Chen et al. (2018)	Accuracy testing and generalisation and usefulness evaluation of a proposed solution. UI-exploration effectiveness is measured using the Monkey tool (developed by Google) and user stories were piloted with 8 PhD students.	Stoat: a system that transforms UI design image to a GUI skeleton using computer vision and machine translation. It creates an automated GUI exploration framework for building datasets for training purposes.	Large datasets were used and tested and the solution achieved high speed, reliability, accuracy and generalisation. During pilot testing, it achieved 90% satisfaction and the results indicate that this solution saves time when used as a baseline, and being updated based on results.

Asiroglu et al. (2019)	Accuracy testing of a proposed solution.	The solution automates code generation of low-fidelity prototype (hand drawn mock-ups) via object detection, object cropping, object recognition, and HTML building. It uses computer vision and deep learning using CNN.	The solution achieved 96% method accuracy and 73% validation accuracy.
Fernandez-Garcia et al. (2019)	Case Study	Recommender systems using neural networks that help end users choose what is displayed and adapting in real time.	The solution simplifies the process when there is a large number of components to choose from. Neural network model achieves 80% performance accuracy.
Latipova et al. (2019)	Review of child computer interaction educational projects.	The focus was on examining FloydHub, Pix2Code and Sketch2Code to identify how neural networks can be used for child computer interaction educational projects by automatically creating GUIs.	Automatically generating code can make it easier to include children in the design process, because they are able to interact with their ideas faster, with lower costs and greater ease of use. Challenges of neural networks include accuracy, and needing suitable data sets.
Souza Baule et al. (2020)	Literature review of 20 approaches for using code automation for GUI design.	Mapping of studies that automate code based on GUI design im- ages using deep learning and computer vision.	The review shows that ML can facilitate and speed up the design process, whereby designers will still be able to remain creative during the initial steps of the design process. Different approaches are used for automating code (from classic ML to CNNs), and the review identifies some common weaknesses.
Moran et al. (2020)	Empirical study on accuracy testing via interviews with industrial practitioners.	ReDraw: a system that automates the move from GUI to code via detection, classification, and assembly using computer vision and neural networks.	The solution achieves average component classification accuracy of 91%. It accurately detects components, and creates a visually similar solution with reasonable code structure with reasonable hierarchies. Only two mock-up artifacts were examined.
Dave et al. (2021)	Review of 3 ML-based approaches.	The study compares different ML methods (low-fidelity HTML Code	All three methods aims to reduce the effort and time so as to facilitate rapid prototyping and

		Generation, sketch2code and pix2code) for converting UIs to code.	good results. The different approaches apply to different levels of prototype, and therefore each has different drawbacks and benefits.

As explained, the main focus during development is on transforming a prototype into code. Indeed, our analysis indicates that most studies focus on the development step. All studies employ ML for transforming prototypes to code, and in their majority, they use computer vision for identifying components. Computer vision seems therefore very useful as its object detection ability can be used for detecting GUIs and generating code (Souza Baulé et al., 2020).

In our analysis, we identified numerous ML types being used, from the more traditional ML techniques to more complex ones, such as CNN. The use of ML within the design process domain seems to be following the trend of using such algorithms for automating tedious and lengthy processes (Dave et al., 2021). The extensive use of ML indicates that ML has great potential in the field, particularly because all examined approaches managed to identify design components, and convert a prototype into code, whereby most of the solutions manage to create code that preserves the hierarchical structure of the graphical elements (Beltramelli, 2018). Moran et al (2020) for example use neural networks that allow moving from GUI to actual code and Asiroglou et al (2019) use deep learning and CNN to move from low to high fidelity.

At the same time, however, there are some common weaknesses across all proposed AI uses, the first being that many of these solutions are able to identify only a small number of components (e.g., Aşıroğlu et al., 2019). In addition, in many cases, the researchers either did not test their solution with actual end users and designers, or such testing was limited (e.g., Moran et al., 2020). Instead, they focused on testing and measuring the accuracy of the ML algorithm (e.g., Aşıroğlu et al., 2019; Beltramelli, 2018; Chen et al., 2018) which can result in false positive results. Other common weakness include (Chen et al., 2018; Souza Baulé et al., 2020):

- The merging of design elements when these are close together – the same applies for texts positioned close together when they use similar fonts;
- Incorrect classification of smaller design elements;
- Incorrect implementation of the alternative GUI elements;

- Incorrect classification/misclassification of progress bars and toggle buttons when the design uses multiple styles;
- Low accuracy and simplistic GUI skeletons; and
- Non recognisable GUI elements when they are not fully visible.

On the basis of the above weakness, several authors (e.g., Beltramelli, 2018; Chen et al., 2018; Latipova et al., 2019) suggest that automated code generation should only be employed as a supplement for design and development for the purpose of saving time before they engage with improving, and updating their design and finalising development themselves.

As earlier explained, most studies focus on using ML for automatically coding a prototype during the development process. However, Fernandez-Garcia et al. (2019) propose the use of a recommendation model for supporting end users to choose what is displayed to them, which indicates another potential for employing AI use during development, that of user customization.

4.7 How AI changes the digital design process

After reviewing the identified articles, we observe that, across them, there are some important emerging themes with regards to how AI might influence and change the digital design process.

As AI is a field that consists of several sub-technologies, it is interesting to note that all identified studies leverage some type of ML algorithms. An underlying reason for this is possibly the fact that the use of weak AI, powered by ML, can provide significant benefits for designers and developers (Verganti et al., 2020). Such benefits relate to requiring fewer resources and easing implementation, because weak AI is easier to develop and use when compared to strong AI. As such, weak AI is a reasonable starting point for designers, especially when they may be lacking advanced skills in this area. However, AI experiences unprecedent growth and the sub-technologies that underpin AI promise a wide variety of applications and a comprehensive toolset. As an indication, neural networks, deep learning and DNNs are becoming very popular and these, together with computer vision, can be used as part of the design process. An issue that the use of such novel and complex technologies might lead to is that designers and end users might have limited understanding in terms of how these technologies can influence the design process but also its very outcome, i.e., the digital solution. This is not necessarily an issue that pertains to skills, or the lack thereof, but rather, an issue that relates to AI being a black box technology without the ability to provide explanations in terms of decision making (Asatiani et al., 2020); as such, even if AI enabled digital solutions are accurate, designers and end users will not be readily able (at least for the medium term) to understand the causal relationships that underpin them, which is an important point of departure in terms of how the design process takes place today, via close collaboration between designers and end users.

Another aspect that the analysed studies highlight is that of the role of the designer in an AI-enabled design process; however, they offer conflicting perspectives. Some argue in favour of AI being an instrument that can act as a good designer on its own (i.e., possibly replacing the human designer), whereas others are supportive and argue in favour of a symbiotic relationship between the human designer and the AI (i.e., the two forming a human-AI partnership). Kaiser (2019), for example, argues that while AI can indeed automate the design process by leveraging large datasets and building robust models with the potential to mimic the processes human designers follow, it is probably unlikely that this will lead to the complete removal of the human designer from the design process. Indeed, the first steps in the design process (understanding and specifying the context of use, and specifying user requirements), require the interaction of the design with the end users, which are resource intensive activities (i.e., prone to automation) and yet very few studies thus far focus on these two steps. As such, it is more likely that UX designers and AI will need to collaborate, where AI augments the work of the human to develop AI-enabled solutions (2019). Such collaborative human-AI partnerships will be integral for successfully integrating AI in the design process. This is because AI cannot straightforwardly understand an use the tacit knowledge that feeds into designing digital solutions. However, such a partnership will require that UX designers enrich their skillset with AI and ML sills so as to understand what problems AI can or cannot solve (Sun et al., 2020; Yang, 2017).

Further, we consider that AI will more likely be used to automate the more repetitive aspects of the design process. This is because low fidelity prototypes can be easily used as input for the AI tool, which can then more easily produce the executable code (Aşıroğlu et al., 2019). This can result in significant resource efficiencies, especially changes in the prototype are required. This is because automating repetitive tasks will allow designers to claim back their time and focus on developing their creativity, skills and capabilities (Buschek et al., 2021; Verganti et al., 2020), on focusing more on their end users, and on making sense of what problems they need to address and how. However, the design process involves problem setting and problem solving, whereby the later involves ideation, prototyping and iterations, and a critical analysis of the solution, which may lead to continuous adaptations until an optimised solution is identified (Sun et al., 2020). Yet, not all of these can or should be automated, and therefore the entire design process should not be considered as a single AI-enabled process. Instead, it is important to differentiate between identifying what problem needs to be solved ("getting the right thing", through exploration and ideation) and what might be the best solution in terms of performance and usability ("getting the thing right") (Yang, 2017, p. 410).

4.8 Looking ahead

While there are undoubtedly many potential areas of the UX design process that will be revolutionized through the deployment of AI, recent developments, particularly in the domain of generative AI have signalled a new wave of opportunities (Gozalo-Brizuela & Garrido-Merchan, 2023). The new wave of generative AI promises to dramatically change how designers of digital solutions design, develop, and test their applications. Early applications of generative AI have shown that these tools can provide outputs of text, code, images, and other media forms that are comparable to those of highly skilled professionals. In fact, there is a growing number of publications highlighting how to effectively utilize tools like ChatGPT to generate code for different types of applications, which helps reduce the time it takes to launch new digital designs (Tian et al., 2023). At the time of writing this review article, there are very few scientific publications concerning the ways generative AI are leveraged within the UX design process. Nevertheless, a look at recent news articles and practitioner reports tells a story of very promising applications and areas of use.

A growing trend that is observed in using open generative AI tools is that they allow for a broader base of users to engage in outcomes that require a specialization in a domain, such as coding and design for example. As a result, solutions that previously required highly skilled professionals become more accessible to individuals. This phenomenon is analogous to the early days of the world wide web, where the development and design of websites was a task only a small number of highly specialized individuals could undertake. This does not mean that the UX design process will be substituted by generative AI tools, but rather that there will be a greater democratization of design with the aid of such tools. In addition, generative AI tools have shown to be incredibly good in collecting and analysing different forms of data and in generating insight. Such applications can prove to be very useful in understanding user requirements and effectively translating them to design artifacts. Furthermore, generative AI applications can also take on the role of testers, or even help identify issues of design or functionality assuming different personas. For instance, when it comes to universal design, generative AI can help identify or even generate different design alternatives to fit user requirements, and also provide recommendations that may have been overlooked by human designers. Thus, we are likely to see different forms of conjoined agency of UX designers and generative AI in the years to come, as well as automation and transfer of many design tasks through generative AI services enabling greater accessibility to unskilled individuals to design digital artifacts.

5 Research Agenda

Based on the synthesis of the existing literature in Section 4, we identified three emerging themes (Section 4.7) in terms of how AI might influence the digital design process in the future. In this section, we consolidate these into a research agenda, which builds on open issues and key assumptions, with a view to serve as a starting for future research and practice. Each of the three research themes presented aim to highlight existing research gaps as well as proposed ways for addressing them in pursuit of AI constructively supporting the design process. We explore why these research themes are important for the discourse of AI use in the digital design process and we then forward a number of research questions within each theme that can spark further research.

The themes along with some open research questions within each of these are summarized in Table 6 below.

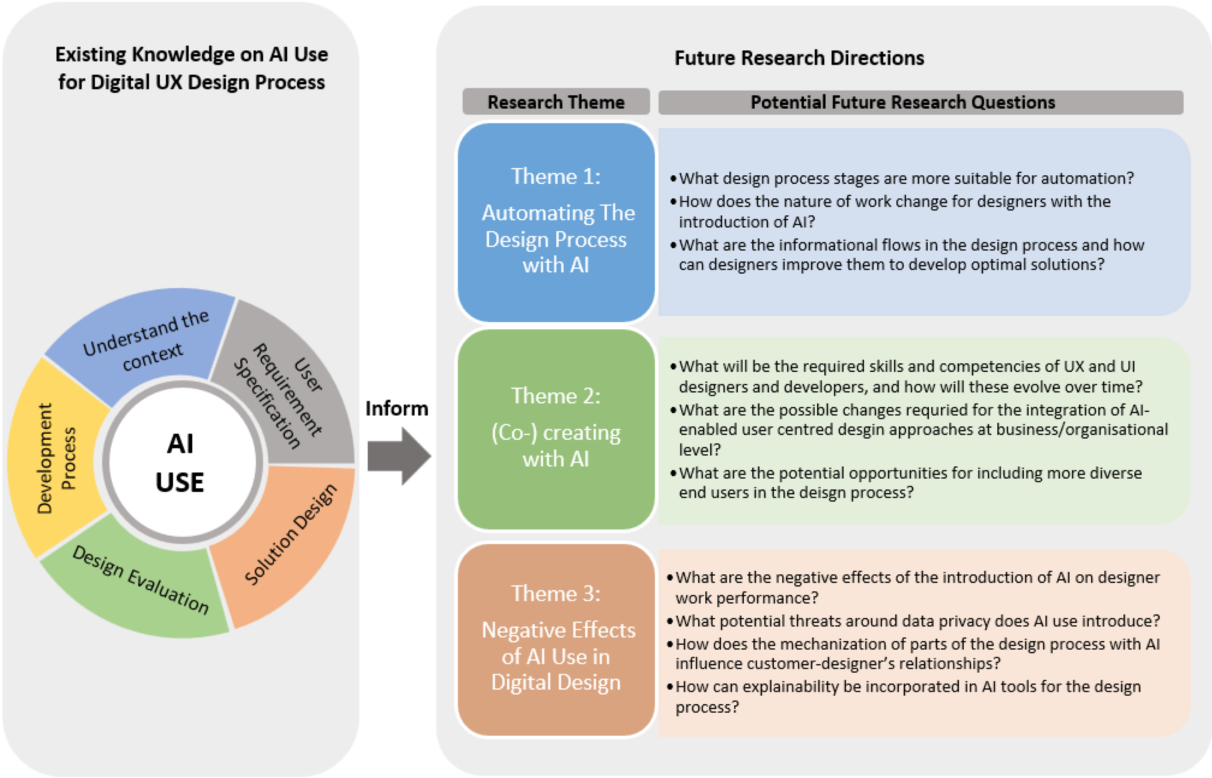

Diagram 1. Synthesized existing knowledge on AI use for UX design process and future research directions

Table 6. A Research Agenda for the use of AI in the digital design process

Theme	Open issue	Research Question
Theme 1: Automating the design process with AI	- Limited knowledge of which parts of design should be automated - Unclear understanding of how the nature of work for designers' changes when automating parts of the design process - Lack of knowledge about strengths and weaknesses of AI vs humans in certain design process steps - Limited understanding of how to streamline data integration throughout the design process when using AI tools	– What design process stages are more suitable for automation? – How does the nature of work change for designers with the introduction of AI? – What are the informational flows in the design process and how can designers improve them to develop optimal solutions?
Theme 2: (Co)Creating with AI	- Unclear understanding what will be the required skills and competences for those involved in an AI-enabled user centred design process.	- What will be the required skills and competencies of UX and UI designers and

	- Limited understanding of how end users should or could participate in the design process.	developers, and how will these evolve over time? - What are the possible changes required for the integration of AI-enabled user centred design approaches at business/organisational level? - What are the potential opportunities for including more diverse end users in the design process?
Theme 3: Negative effects of AI use in digital design	- Lack of knowledge regarding responsibility of projects with the introduction of AI - Limited understanding of how AI use in the design process influences project outcomes - Lack of understanding of how AI use in the design process may influence designer involvement - Lack of explainability can create problems in collaboration between designers and customers	– What are the negative effects of the introduction of AI on designer work performance? – What potential threats around data privacy does AI use introduce? – How does the mechanization of parts of the design process with AI influence customer-designer's relationships? – How can explainability be incorporated in AI tools for the design process?

5.1 Theme 1: Automating the design process with AI

To date, the use of ML in the digital design process is often driven by data availability with a limited focus on a user-centred approach (Buschek et al., 2021). Further research into how to systematically integrate AI into defining design patterns, education of designers, and prototyping of tools is needed (Buschek et al., 2021). Such automation in key stages of the design processes is an aspect that has currently not received enough attention despite the high practical interest for it. Buschek et al. (2021) points out of the importance of not using AI technology just because it is possible to do so. Specifically, it is argued that AI technologies should only be used to automate processes that have high overhead and require considerable manual work. This holds particularly true for utilizing AI into creative design work. It is important to identify what challenges designers face during the design process, what tedious and repetitive tasks they need to complete, and how exactly AI can be used to automate these and provide cues for the creative process. Such a focus requires a thorough understanding of the specific tasks and everyday work of designers within different contexts and a prioritization of AI applications in automating tasks that are of heightened importance. In addition, it highlights the need for incorporating AI for generating ideas or patterns that can enhance the workflow of designers by augmenting their creativity.

As the design process consists of many steps and activities, it is also important to understand how the potential automation of certain parts will change the nature of tasks performed by the designer and the process as whole. As illustrated earlier, the introduction of AI requires that designers provide the necessary input about what need as digital design outcomes. As such, designers do not only focus on layout, but also on the knowledge of formalizing conceptual, structure-based, functional, and aesthetic aspects of design (Oulasvirta et al., 2020). This process, requires creativity, problem-solving, sense-making, empathy, and collaboration (Oulasvirta et al., 2020). Understanding how parts of these activities can be delegated to AI systems, as well as how doing so changes the type of work designers do is important in the further assimilation of AI technologies in the design process.

In a recent article by Buschek et al. (2021), the authors argue about what practices cannot or should not be automated through AI technologies. The logic behind their argumentation is that in certain elements of the design process either the human or AI technologies may have an advantage, so it would make little sense to shift this distribution of work. On the other hand, there are ample opportunities for applying AI technologies in cases where traditionally non-digital solutions have been used. For example, the faster conversion from paper mock-ups to digital prototypes can enable earlier testing and collection of usage data.. Understanding how this shift in the process influences final design and usability therefore is of high interest. Furthermore, tracking how the use of AI for automating certain aspects of the design process depends on the type of industry or other internal factors can help expand our knowledge about the potential contingencies around deployment of such tools (Verganti et al., 2020). The goal of figuring out how to develop tools that eliminate the tedious aspects of designing and testing, while enhancing the creative tasks is a fruitful area of future research (O’Donovan et al., 2015).

From the research conducted so far, there are also very limited studies that examine the entire design process. This has resulted in many different tools automating the tasks of designing. Thus, a future avenue of research would be to examine how the fragmentation of the design process and the subsequent tools influence the outcomes. Further research can focus on if best results are gained from using multiple AI-tools, or if integrated solutions offer better data flow and thus better results. Some articles such as that of Moran et al. (2020) suggest further work should focus on the ability to convert the entire process. Dave et al. (2021) substantiates this by pointing out that "*the scope for improvement is immense and as machine learning algorithms improve, the horizons of intelligent automation, specifically in the domain of website creation, will vastly broaden*".

5.2 Theme 2: (Co)creating with AI

The introduction of AI in the design process will inescapably lead to changes of the design process and the workflow. Such changes will have to do with who can and should be part of the design process itself. On the one hand, such changes relate to automating the design process with AI, while on the other hand they will also lead to further changes in the skillset and competences of designers.

Today, the design process, and especially when it comes to user centred design, entails the participation of UX and UI designers and developers, who are responsible for the ideation phase of a product or service, its design and later on as part of its actual development. At the same time, this process often involves a number of stakeholders, such as the client who commissioned a product/service and increasingly it involves future end users. Specifically, over the years, the user centred design process has moved from perceiving the 'user as subject' to the 'user as partner', whereby future end users are involved throughout design and development, whereby they co-produce the final output with designers and developers (Sanders & Stappers, 2008).

However, there are many obstacles and limitations during such co-creation processes. Focusing specifically on designers in this context, they often need to operate not merely as designers, but also as researchers, observing user behaviours, supporting the creativity of the end users (Sanders & Stappers, 2008), and facilitating their interaction with the various AI tools used for the purposes of design. However, designers and developers may or may not have the required experience and expertise to support such participatory approaches. In addition, the use of AI tools as part of the design process requires hard skills as well, i.e., familiarity and knowledge to work with and manipulate said tools. For example, Yang et al. (2020) have discussed that UX designers, for example, lack important knowledge with regards to DNNs. As such, it is really important we understand what the required skillset and competences of UX and in UI designers and developers will be in the short and the long term, so that they can keep up with the pace of continuous advancements in the AI space. At the same time, as companies and businesses transition from human-intensive to AI-intensive innovation systems (Verganti et al., 2020), it is expected that further changes will have to be implemented internally, i.e., with respect to those business processes in particular that interface with design processes, whereby the latter draw from AI techniques and tools. In the field of Industry 4.0 and specifically in relation to human-centred design and the increased use of AI, Ngoc et al. (2022) have indeed found that the value chain of a business has to be adapted so as to formally and usefully integrate the role of humans as well as that of the AI. Therefore, future research endeavours could focus on the type of changes that will be required, as well as the impact of such changes on businesses and organisations.

There are however, critical opportunities enabled by the introduction of AI in the design process. Latipova et al. (2019) discuss that the introduction of AI can facilitate the inclusion of a broader range of end users in the design process, with reference to children, and people with disabilities, by making it more accessible, and therefore more inclusive. Indeed, user centred design requires time and budget, which often pose constraints on how designers engage with diverse users. One of the techniques to address this shortcoming has been the use of simulators, that manage to represent different impairments (such as visual and hearing impairments), thereby informing designers about users' capabilities (Cardoso & Clarkson, 2012). The introduction of AI, however, in the design process can support more tailored solutions, both for the benefit of the designer, by offering recommendations for activities (Wallach et al., 2020), as well as for the benefit of the end user, leading up to more useful and easier interactions for requirements specification purposes (Zimmermann et al., 2017). While research is only beginning to emerge in this area, it will be important to further explore what potential AI has for supporting and for facilitating or informing recent initiatives for inclusive user research (e.g., McKenna-Aspell et al., 2022), whereby the potential unintended consequences of such uses are also considered.

5.3 Theme 3: Negative effects of AI use in digital design

Understanding the weaknesses or potential negative effects of introducing AI tools in the design process can give us useful insight into how to incorporate and develop such tools. A viable way of exploring this issue could be done by including designers in the research and understanding the restrictions that AI imposes on their work. In addition, the changing nature of their work could in fact entail negative consequences, such as increased stress due to working with new technologies or added barriers in utilizing these tools in practice. Furthermore, the automation of parts of the design process may yield negative effects on the quality of end products or may even lessen the sense of responsibility that designers have on the final digital solutions they deliver. Hence, it is important to understand what the potential negative implications of AI use in the digital design process are in order to develop appropriate practices of deploying them.

To date the examination of potential negative effects of AI use in the context of digital design has been limited to studies examining the performance of developed digital products. Although digital products might fulfil the requirements of customers, it is possible that projects implementation may deviate substantially. Thus, there is a need to understand the entire lifecycle of development in relation to customer and designer collaboration, and how the use of AI impacts this relationship. For instance, data-driven AI applications may place strong requirement for customers to provide quantitative data towards designers or pose a requirement to transfer potentially sensitive information. In addition, the high cost of newly developed AI applications may have ripple effects on the total cost of providing digital design solutions to customers, which may impact project success negatively. Hence, there is a need to understand the broader context of AI use, not only within the design process, but within the entire relationship between customer and service provider.

Finally, a potential negative outcome of incorporating AI in the design process is nicely illustrated by Buschek et al. (2021) who argue that using such tools may render designers as merely users of tools that automatically produce outcomes. Thus, without understanding how they derived to certain insights or design principles, designers may be inclined to override their own judgment in terms of what AI tools propose. This issue is further exacerbated when considering that on a design project there are typically several stakeholders involved. This requires that tasks that are automated by AI should be more credible and consistent, as well as contain common information definitions (Salminen et al., 2019). Enabling a common understanding and central rules of how these systems operate is an important element of providing transparency of the process and adoption. Furthermore, embedding explainability in insights or proposed solutions enables designers to understand why and how AI tools propose certain solutions. It also mitigates the risk of blindly incorporating AI suggestions as it enables more reflexivity from the side of designers. Hence, a fruitful research stream is to understand in which way incorporating explainability in AI algorithms can enable designers to improve their work performance.

6 Discussion and Conclusion

Users of digital solutions nowadays expect professional and user-friendly experiences, requiring designers and developers to constantly evolve and deliver products of high quality. Designing solutions that meet such standards, often involve a time-consuming iterative design process, balancing originality and following universal design principles. To aid this process, researchers and developers have looked at how AI can be used. In this article, we have synthesised existing knowledge on how AI might be used in the future, thus changing the design process of digital solutions.

Specifically, we followed the systematic literature review approach to identify and document relevant evidence from the existing literature, and we then documented and presented our findings based on the User Centred Design Framework, tracing effectively the major steps of the design process. In doing so, our aims was to present findings in a way that highlights the major proposed uses and applications of AI for designing digital solutions, as well as documenting the particular AI tools and techniques proposed. The focus has been on presenting the current state of the art in terms of AI use as well as envisaged AI uses from the perspective of a designer.

In terms of theoretical implications, our findings provide researchers with a concise presentation of the phases of UX design and development, and the ways in which AI can be incorporated across all or some of them. Specifically, we have presented our findings in seven distinct parts, whereby the first five parts correspond to the five steps of the user centred design process, and where the other two present AI uses for multiple steps and across the entire design process. This approach showcases better the great range of AI uses and the emerging possibilities, as we believe that adopting the viewpoint of the designer and carefully examining the major activities that form part of UX design and development provides a more nuanced understanding of the current status of AI use, as well as the main challenges and shifts it is creating for the different stakeholders. It also enables researchers to integrate and contextualize theories and methods from other domains and disciplines that can prove useful in the study of AI for UX design.

In addition, through our research agenda, we identify a number of areas that require further research so that we can better understand how AI can be used, and how it should be and should not be used as part of the UX design process. The proposed research agenda does not represent an exhaustive list of themes that researchers should focus on; however, it does steer and provides orientation towards some of the most important themes that are likely to be in the centre of attention in the coming years.

From a practical perspective, the study presents practitioners the state-of-the-art in terms of our knowledge of how AI can be utilized for UX design. Designers and developers can build on this body of knowledge to launch new products or services or identify areas that are of high significance. For example, our findings highlight that aspects of UX design can be automated under certain circumstances, further indicating where relevant the technologies and techniques that can be used. Some of these technologies are already in use, as for example for website design, and we posit that, depending on the context and its specificities, such tools can also be used in software engineering and interface design.

While this paper has attempted to overview the field of AI use in relation to UX design process, it also comes with some limitations. First, we have based our overview of the UX design process on the user-centred design process. While this process is widely used, especially in the academic domain, it is not the only process that professionals work with. Thus, future research can explore alternative ways in which UX designers implement their design process, or perhaps build on entirely new processes that incorporate AI. In addition, our study was limited based on the available published work. Since the field of AI is advancing rapidly, and especially with the proliferation of generative AI, it is likely that the latest developments in UX and use of AI are still not available in academic articles. Thus, an interesting potential area of research would be to collect primary data from professionals that are utilizing such tools in their everyday work. It is likely that such a research approach could result in the identification of novel types of practices of working with AI to inform UX design.

Concluding, we reiterate that our findings and agenda are based on a systematic literature review of existing studies, and this poses certain limitations. First, most protocols for systematic literature reviews entail the use of keywords to form search strings and conduct queries via databases (Tranfield et al., 2003b); typically, such queries are limited at paper title and abstract level (e.g., Nayernia et al., 2021). This means that inescapably, studies that do not refer to the predefined keywords at the title or abstract can be easily missed and inadvertently excluded from the final pool of papers. In this study, we have attempted to address this issue through forward and backward searches, through which we identified and analysed additional articles which were using different terminology rather the predefine keywords. A rather more important limitation is that systematic literature reviews, by their nature are retrospective as they build on the pool of knowledge available up until a defined point in time. As the field of AI is rapidly advancing, it is very likely that seminal articles published after this defined point in time will radically change the way we think about AI for UX design.

7 Declarations

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8 References

Abbas, A. M. H., Ghauth, K. I., & Ting, C.-Y. (2022). User Experience Design Using Machine Learning: A Systematic Review. *IEEE Access*, *10*, 51501–51514. https://doi.org/10.1109/ACCESS.2022.3173289

Agner, L., Necyk, B., & Renzi, A. (2020). Recommendation Systems and Machine Learning: Mapping the User Experience. In A. Marcus & E. Rosenzweig (Eds.), *Design, User Experience, and Usability. Design for Contemporary Interactive Environments* (pp. 3–17). Springer International Publishing. https://doi.org/10.1007/978-3-030-49760-6_1

Asatiani, A., Malo, P., Nagbøl, P. R., Penttinen, E., Rinta-Kahila, T., & Salovaara, A. (2020). Challenges of Explaining the Behavior of Black-Box AI Systems. *M I S Quarterly Executive*, *19*(4), 259–278.

Aşıroğlu, B., Mete, B. R., Yıldız, E., Nalçakan, Y., Sezen, A., Dağtekin, M., & Ensari, T. (2019). Automatic HTML Code Generation from Mock-Up Images Using Machine Learning Techniques. *2019 Scientific Meeting on Electrical-Electronics & Biomedical Engineering and Computer Science (EBBT)*, 1–4. https://doi.org/10.1109/EBBT.2019.8741736

Beltramelli, T. (2018). pix2code: Generating Code from a Graphical User Interface Screenshot. *Proceedings of the ACM SIGCHI Symposium on Engineering Interactive Computing Systems*, 1–6. https://doi.org/10.1145/3220134.3220135

Buschek, D., Anlauff, C., & Lachner, F. (2021). Paper2Wire – A Case Study of User-Centred Development of Machine Learning Tools for UX Designers. *I-Com*, *20*(1), 19–32. https://doi.org/10.1515/icom-2021-0002

Cardoso, C., & Clarkson, P. J. (2012). Simulation in user-centred design: Helping designers to empathise with atypical users. *Journal of Engineering Design*, *23*(1), 1–22. https://doi.org/10.1080/09544821003742650

Chatterjee, S., & Kar, A. K. (2017). Effects of successful adoption of information technology enabled services in proposed smart cities of India: From user experience perspective. *Journal of Science and Technology Policy Management*, *9*(2), 189–209. https://doi.org/10.1108/JSTPM-03-2017-0008

Chaudhuri, N. B., Dhar, D., & Yammiyavar, P. G. (2022a). A computational model for subjective evaluation of novelty in descriptive aptitude. *International Journal of Technology and Design Education*, *32*(2), 1121–1158. https://doi.org/10.1007/s10798-020-09638-2

Chaudhuri, N. B., Dhar, D., & Yammiyavar, P. G. (2022b). Automating assessment of design exams: A case study of novelty evaluation. *Expert Systems with Applications*, *189*, 116108. https://doi.org/10.1016/j.eswa.2021.116108

Chen, C., Su, T., Meng, G., Xing, Z., & Liu, Y. (2018). From UI design image to GUI skeleton: A neural machine translator to bootstrap mobile GUI implementation. *Proceedings of the 40th International Conference on Software Engineering*, 665–676. https://doi.org/10.1145/3180155.3180240

Christoforakos, L., & Diefenbach, S. (2019). Idealization Effects in UX Evaluation at Early Concept Stages: Challenges of Low-Fidelity Prototyping. In T. Z. Ahram & C. Falcão (Eds.), *Advances in Usability, User Experience and Assistive Technology* (pp. 3–14). Springer International Publishing. https://doi.org/10.1007/978-3-319-94947-5_1

Dave, H., Sonje, S., Pardeshi, J., Chaudhari, S., & Raundale, P. (2021). A survey on Artificial Intelligence based techniques to convert User Interface design mock-ups to code. *2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS)*, 28–33. https://doi.org/10.1109/ICAIS50930.2021.9395994

Desolda, G., Esposito, A., Lanzilotti, R., & Costabile, M. F. (2020). *Interplay between AI and HCI for UX evaluation: The SERENE case study*.

Duan, P., Wierzynski, C., & Nachman, L. (2020). Optimizing User Interface Layouts via Gradient Descent. *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–12. https://doi.org/10.1145/3313831.3376589

Enholm, I. M., Papagiannidis, E., Mikalef, P., & Krogstie, J. (2021). Artificial Intelligence and Business Value: A Literature Review. *Information Systems Frontiers*. https://doi.org/10.1007/s10796-021-10186-w

Feldman, S. (Salevati). (2017a). Co-Creation: Human and AI Collaboration in Creative Expression. *Proceedings of the Conference on Electronic Visualisation and the Arts*, 422–429. https://doi.org/10.14236/ewic/EVA2017.84

Feldman, S. (Salevati). (2017b, July 1). *Co-Creation: Human and AI Collaboration in Creative Expression*. Electronic Visualisation and the Arts (EVA 2017) (EVA). https://doi.org/10.14236/ewic/EVA2017.84

Fernández-García, A. J., Iribarne, L., Corral, A., Criado, J., & Wang, J. Z. (2019). A recommender system for component-based applications using machine learning techniques. *Knowledge-Based Systems*, *164*, 68–84. https://doi.org/10.1016/j.knosys.2018.10.019

Gaffney, G. (2017). The Revolution Will Not Be Handheld. *Journal of Usability Studies*, *12*(3), 92–94.

Gardey, J. C., Grigera, J., Rodríguez, A., Rossi, G., & Garrido, A. (2022). Predicting interaction effort in web interface widgets. *International Journal of Human-Computer Studies, 168*, 102919. https://doi.org/10.1016/j.ijhcs.2022.102919

Gomes, C. C., & Preto, S. (2018). Artificial Intelligence and Interaction Design for a Positive Emotional User Experience. In W. Karwowski & T. Ahram (Eds.), *Intelligent Human Systems Integration* (pp. 62–68). Springer International Publishing. https://doi.org/10.1007/978-3-319-73888-8_11

Gozalo-Brizuela, R., & Garrido-Merchan, E. C. (2023). ChatGPT is not all you need. A State of the Art Review of large Generative AI models. *arXiv preprint arXiv:2301.04655*.

Hart, J., & Sutcliffe, A. (2019). Is it all about the Apps or the Device?: User experience and technology acceptance among iPad users. *International Journal of Human-Computer Studies*, *130*, 93–112. https://doi.org/10.1016/j.ijhcs.2019.05.002

ISO 9241-210:2010. (2010). *ISO 9241-210:2010(en), Ergonomics of human-system interaction—Part 210: Human-centred design for interactive systems*. https://www.iso.org/obp/ui/#iso:std:iso:9241:-210:ed-1:v1:en

Johnston, V., Black, M., Wallace, J., Mulvenna, M., & Bond, R. (2019). A Framework for the Development of a Dynamic Adaptive Intelligent User Interface to Enhance the User Experience. *Proceedings of the 31st European Conference on Cognitive Ergonomics*, 32–35. https://doi.org/10.1145/3335082.3335125

Kaiser, Z. (2019). Creativity as Computation: Teaching Design in the Age of Automation. *Design and Culture*, *11*(2), 173–192. https://doi.org/10.1080/17547075.2019.1609279

Karimi, P., Grace, K., Maher, M. L., & Davis, N. (2018). *Evaluating Creativity in Computational Co-Creative Systems* (arXiv:1807.09886). arXiv. https://doi.org/10.48550/arXiv.1807.09886

Koch, J. (2017). *Design implications for Designing with a Collaborative AI* (Technical Report SS-17-04; The AAAI 2017 Spring Symposium on Designing the User Experience of Machine Learning Systems, p. 4). Association for the Advancement of Artificial Intelligence. https://www.aaai.org/ocs/index.php/SSS/SSS17/paper/viewFile/15382/14577

Korhonen, H., Arrasvuori, J., & Väänänen-Vainio-Mattila, K. (2010). Analysing user experience of personal mobile products through contextual factors. *Proceedings of the 9th International Conference on Mobile and Ubiquitous Multimedia*, 1–10. https://doi.org/10.1145/1899475.1899486

Latipova, A., Gasenko, A., & Sim, G. (2019). On 'Artificial Intelligence-User Interface' Approach. *2019 International Multi-Conference on Engineering, Computer and Information Sciences (SIBIRCON)*, 0446–0451. https://doi.org/10.1109/SIBIRCON48586.2019.8958406

Li, S. (2020). The Trend and Characteristic of AI in Art Design. *Journal of Physics: Conference Series*, *1624*(5), 052028. https://doi.org/10.1088/1742-6596/1624/5/052028

McKenna-Aspell, J., Wang, Y., Rutter, S., & Zamani, E. D. (2022). *Facilitating inclusive spaces for sharing untold stories from diverse perspectives*. ASIS&T European Chapter IST 2022. Information Science Trends 2022: Untold Stories in Information Science, Sheffield, UK.

Moran, K., Bernal-Cárdenas, C., Curcio, M., Bonett, R., & Poshyvanyk, D. (2020). Machine Learning-Based Prototyping of Graphical User Interfaces for Mobile Apps. *IEEE Transactions on Software Engineering*, *46*(2), 196–221. https://doi.org/10.1109/TSE.2018.2844788

Nayernia, H., Bahemia, H., & Papagiannidis, S. (2021). A systematic review of the implementation of industry 4.0 from the organisational perspective. *International Journal of Production Research*, 1–32. https://doi.org/10.1080/00207543.2021.2002964

Nguyen Ngoc, H., Lasa, G., & Iriarte, I. (2022). Human-centred design in industry 4.0: Case study review and opportunities for future research. *Journal of Intelligent Manufacturing*, *33*(1), 35–76. https://doi.org/10.1007/s10845-021-01796-x

Nguyen, T. A., & Csallner, C. (2015). Reverse Engineering Mobile Application User Interfaces with REMAUI (T). *2015 30th IEEE/ACM International Conference on Automated Software Engineering (ASE)*, 248–259. https://doi.org/10.1109/ASE.2015.32

Nilsson, N. J. (1998). *Artificial Intelligence: A New Synthesis* (1st Edition). Morgan Kaufmann.

Nisafani, A. S., Kiely, G., & Mahony, C. (2020). Workers' technostress: A review of its causes, strains, inhibitors, and impacts. *Journal of Decision Systems*, *29*(sup1), 243–258. https://doi.org/10.1080/12460125.2020.1796286

O'Donovan, P., Agarwala, A., & Hertzmann, A. (2015). DesignScape: Design with Interactive Layout Suggestions. *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, 1221–1224. https://doi.org/10.1145/2702123.2702149

Oh, C., Song, J., Choi, J., Kim, S., Lee, S., & Suh, B. (2018). I Lead, You Help but Only with Enough Details: Understanding User Experience of Co-Creation with Artificial Intelligence. *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, 1–13. https://doi.org/10.1145/3173574.3174223

Oulasvirta, A., Dayama, N. R., Shiripour, M., John, M., & Karrenbauer, A. (2020). Combinatorial Optimization of Graphical User Interface Designs. *Proceedings of the IEEE*, *108*(3), 434–464. https://doi.org/10.1109/JPROC.2020.2969687

Pandian, V. P. S., & Suleri, S. (2020). *BlackBox Toolkit: Intelligent Assistance to UI Design* (arXiv:2004.01949). arXiv. https://doi.org/10.48550/arXiv.2004.01949

Park, J., Han, S. H., Kim, H. K., Cho, Y., & Park, W. (2013). Developing Elements of User Experience for Mobile Phones and Services: Survey, Interview, and Observation Approaches. *Human Factors and Ergonomics in Manufacturing & Service Industries*, *23*(4), 279–293. https://doi.org/10.1002/hfm.20316

Preece, J., Sharp, H., & Rogers, Y. (2015). *Interaction Design: Beyond Human-Computer Interaction* (4th edition). John Wiley.

Salminen, J., Sengün, S., Jung, S., & Jansen, B. J. (2019). Design Issues in Automatically Generated Persona Profiles: A Qualitative Analysis from 38 Think-Aloud Transcripts. *Proceedings of the 2019 Conference on Human Information Interaction and Retrieval*, 225–229. https://doi.org/10.1145/3295750.3298942

Sanders, E. B.-N., & Stappers, P. J. (2008). Co-creation and the new landscapes of design. *CoDesign*, *4*(1), 5–18. https://doi.org/10.1080/15710880701875068

Schmidt, A., & Etches, A. (2014). *Useful, Usable, Desirable: Applying User Experience Design to Your Library*. ALA Editions.

Sermuga Pandian, V. P., Suleri, S., Beecks, C., & Jarke, M. (2020). MetaMorph: AI Assistance to Transform Lo-Fi Sketches to Higher Fidelities. *32nd Australian Conference on Human-Computer Interaction*, 403–412. https://doi.org/10.1145/3441000.3441030

Silva-Rodríguez, V., Nava-Muñoz, S. E., Castro, L. A., Martínez-Pérez, F. E., Pérez-González, H. G., & Torres-Reyes, F. (2020). Classifying design-level requirements using machine learning for a recommender of interaction design patterns. *IET Software*, *14*(5), 544–552. https://doi.org/10.1049/iet-sen.2019.0291

Souza Baulé, D. de, Wangenheim, C. G. von, Wangenheim, A., & Hauck, J. C. R. (2020). Recent Progress in Automated Code Generation from GUI Images Using Machine Learning Techniques. *JUCS - Journal of Universal Computer Science*, *26*(9), 1095–1127. https://doi.org/10.3897/jucs.2020.058

Suleri, S., Sermuga Pandian, V. P., Shishkovets, S., & Jarke, M. (2019). Eve: A Sketch-based Software Prototyping Workbench. *Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems*, 1–6. https://doi.org/10.1145/3290607.3312994

Sun, L., Zhou, Z., Wu, W., Zhang, Y., Zhang, R., & Xiang, W. (2020). Developing a Toolkit for Prototyping Machine Learning-Empowered Products: *International Journal of Design*, *14*(2), 16.

Swearngin, A., & Li, Y. (2019). Modeling Mobile Interface Tappability Using Crowdsourcing and Deep Learning. *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, 1–11. https://doi.org/10.1145/3290605.3300305

Tian, H., Lu, W., Li, T. O., Tang, X., Cheung, S. C., Klein, J., & Bissyandé, T. F. (2023). Is ChatGPT the Ultimate Programming Assistant--How far is it?. arXiv preprint arXiv:2304.11938.

Todi, K., Weir, D., & Oulasvirta, A. (2016). Sketchplore: Sketch and Explore with a Layout Optimiser. *Proceedings of the 2016 ACM Conference on Designing Interactive Systems*, 543–555. https://doi.org/10.1145/2901790.2901817

Tokkonen, H., & Saariluoma, P. (2013). How user experience is understood? *2013 Science and Information Conference*, 791–795.

Tranfield, D., Denyer, D., & Smart, P. (2003a). Towards a Methodology for Developing Evidence-Informed Management Knowledge by Means of Systematic Review. *British Journal of Management*, *14*(3), 207–222. https://doi.org/10.1111/1467-8551.00375

Tranfield, D., Denyer, D., & Smart, P. (2003b). Towards a Methodology for Developing Evidence-Informed Management Knowledge by Means of Systematic Review. *British Journal of Management*, *14*(3), 207–222. https://doi.org/10.1111/1467-8551.00375

Verganti, R., Vendraminelli, L., & Iansiti, M. (2020). Innovation and Design in the Age of Artificial Intelligence. *Journal of Product Innovation Management*, *37*(3), 212–227. https://doi.org/10.1111/jpim.12523

Wallach, D., Flohr, L., & Kaltenhauser, A. (2020). Beyond the Buzzwords: On the Perspective of AI in UX and Vice Versa. *International Conference on Human-Computer Interaction*, 146–166. https://doi.org/10.1007/978-3-030-50334-5_10

Wilson, C. (2013). *Interview Techniques for UX Practitioners: A User-Centered Design Method*. Newnes.

Yang, B., Wei, L., & Pu, Z. (2020). Measuring and Improving User Experience Through Artificial Intelligence-Aided Design. *Frontiers in Psychology*, *11*, 595374.

Yang, Q. (2017). *The Role of Design in Creating Machine-Learning-Enhanced User Experience* (Technical Report SS-17-04; 2017 AAAI Spring Symposium Series, p. 6). Association for the Advancement of Artificial Intelligence. https://www.aaai.org/ocs/index.php/SSS/SSS17/paper/viewFile/15363/14575

Yasin, A., Fatima, R., Wen, L., Afzal, W., Azhar, M., & Torkar, R. (2020). On Using Grey Literature and Google Scholar in Systematic Literature Reviews in Software Engineering. *IEEE Access*, *8*, 36226–36243. https://doi.org/10.1109/ACCESS.2020.2971712

Yuan, T. (2023). User Portrait Based on Artificial Intelligence. In J. C. Hung, N. Y. Yen, & J.-W. Chang (Eds.), *Frontier Computing* (pp. 359–366). Springer Nature. https://doi.org/10.1007/978-981-99-1428-9_44

Zhou, C., Chai, C., Liao, J., Chen, Z., & Shi, J. (2020). Artificial intelligence augmented design iteration support. *2020 13th International Symposium on Computational Intelligence and Design (ISCID)*, 354–358. https://doi.org/10.1109/ISCID51228.2020.00086

Zhou, J., Tang, Z., Zhao, M., Ge, X., Zhuang, F., Zhou, M., Zou, L., Yang, C., & Xiong, H. (2020). Intelligent Exploration for User Interface Modules of Mobile App with Collective Learning. *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, 3346–3355. https://doi.org/10.1145/3394486.3403387

Zimmermann, G., Ableitner, T., & Strobbe, C. (2017). User Needs and Wishes in Smart Homes: What Can Artificial Intelligence Contribute? *2017 14th International Symposium on Pervasive Systems, Algorithms and Networks & 2017 11th International Conference on Frontier of Computer Science and Technology & 2017 Third International Symposium of Creative Computing (ISPAN-FCST-ISCC)*, 449–453. https://doi.org/10.1109/ISPAN-FCST-ISCC.2017.66