The UX of AI
Literature Gaps in Human-Centred Design for Interactive AI

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Abstract

Artificial intelligence (AI) is a powerful tool for intelligent decision-making; however, there is an urgent need for a better understanding of how AI can be developed with a focus on user experience. This literature review aims to identify gaps within user experience research regarding AI, highlight current discussions in interactive AI design, discuss principles for designing trustworthy and human-centred AI, and link existing design heuristics to interactive AI design.

1 Introduction

'People from Western Europe see the development of AI as more likely harmful as beneficial' - Neudert, Knuutila, and Howard (2020)

In a review of global attitudes towards AI [67], it was found that 43% of Europeans think AI will be harmful while 38% believe it will be helpful. Positive views of AI require trust in the systems [8, 33, 85], with explainable [79] and high-quality [63] interfaces required to build this trust; yet, there are many gaps in research within the area of usability heuristics [83] and user experience [16] for AI, with Brand et al. [16] finding that user experience does not yet play a significant role in the field of AI. Alongside the research gaps, it has been identified that AI developers do not truly focus on user needs when developing 'human-centred' AI [14]. This literature review aims to identify gaps within user experience research regarding AI, discuss principles for designing trustworthy and human-centred AI, consider how artificial intelligence can be developed with a user experience focus, and link existing design heuristics to interactive artificial intelligence design principles.

The outcomes of AI systems impact the user experience similarly to trust and usability [14, 43, 90]; as such, managing user expectations is crucial to a good user experience [17]. Leveraging Norman's principles of design [69], along with Nielsen's design heuristics [64], will assist both in user experience design and expectation management. Further design principles referenced within this literature review are Lockwood's principles of user interface design [22] and Mace's principles of universal design [92]. Accessibility within user experience will not be a focal point of this literature review; however, Bergman and Johnson's seminal paper on accessible human-computer interaction [13] serves as suitable background reading for this area.

While discussions around AI systems within this research will focus on their explainability, interfaces, and outputs, Flach's book on machine learning algorithms [24] provides a fundamental understanding of the methods which form the systems discussed. For background reading regarding explainable AI, Samek et al.'s book on this topic [82] is recommended.

1.1 Key Terms

Throughout this literature review, the terms interactive AI, trust, and usability will be referenced; as these terms have several interpretations, their usage in this research refers to the following definitions:

- **Interactive AI** refers to Artificial Intelligence that enables interactive exploration and manipulation in real-time [86].
- **Trust** refers to the psychological mechanism for reducing uncertainty with an entity or within an environment [56].
- **Usability** refers to the extent to which users can use a system to achieve specified goals with effectiveness, efficiency, and satisfaction [35].

2 Human-in-the-Loop Focus

2.1 User-Centred Design

Human-Centred Design [26] and User-Centre Design [1] are design concepts based on principles related to user practices controlling system development and design [29]; traditionally, this refers to the development of systems and interfaces with a focus on user needs and interactions, but within AI this also refers to the development and design of algorithms [81]. Rantavuo [81] discusses how user-centred design practices are required for inclusive and ethical AI.

User experience design practices enable the design of trustworthy and ethical AI [12, 89]. User stories are one method for developing trustworthy and ethical AI [12, 30] as they consider all system aspects that add value to the user. Use case scenarios [74] and, to a further extent, the misuse case scenarios [4] enable the ethical development of AI [11] by identifying users' goals for a system and their methods of interaction; these scenarios can be adapted to identify areas of an interactive AI system that require explainability or simplified outputs [82]. Heuristic analysis of interactive AI was found to identify key flaws regarding trust and usability within interactive AI systems [48, 83].

While the aforementioned studies identify how user experience design practices can be implemented to design trustworthy and ethical AI, HCI research within AI is limited [14, 34]. Li and Lu [50] found that there is a mismatch between the ethical AI development guidelines[3] and the guidelines for human-AI interaction [6]; as such, there is a clear need for standardised guidelines and methodologies, regarding the user experience and ethical design of AI, to enable user-centred, trustworthy and ethical AI as the industry standard [65].

2.2 Keeping the User in Control

User control is crucial for trust in computing systems [21], which is especially true for AI systems that inform decision-making [10]. While some AI systems allow users to modify the parameters as a form of user control [5], the main method of providing users with control over the impacts of an AI system is by allowing them to understand how the decisions were made [47]. The ways to enable user control can be seen as setting suitable capability expectations and communicating outputs effectively[43]; these two areas will be discussed individually in later sections.

2.3 Designing AI for the Layman

Tullio et al. [95] reiterate the findings regarding user trust in AI systems [10] but also identify the importance of understanding how users perceive a system; in their study, Tullio et al. [95] found that using levels of feedback appropriate to the technical level of a user enabled users to understand the concepts of machine learning within the system, building trust. Simplicity builds trust within AI systems [79, 96] and will be discussed later as a design principle and heuristic.

3 The Expectations of AI

3.1 Expectation Management

Kocielnik, Amershi, and Bennett [43] found user acceptance and satisfaction of AI systems was a result of user expectations; this builds on existing research within user experience that found unmet and inflated expectations result in reduced user satisfaction [31, 36] and distrust [49]. Expectation management is crucial within AI [17] due to the exaggerated expectations for AI systems caused by the media [66], policymakers [18], marketing tactics [99], and respected contrarians [18, 42]. Cave et al. [18] discuss how, throughout history, the narratives of breakthrough technology are disconnected from reality; these narratives cause inflated expectations, as commonly seen with AI [25].

Grimes, Schuetzler, and Giboney [28] found that violating user expectations for a system had a greater impact on user acceptance than meeting an expectation and suggested that AI systems should set low expectations; in this research, it was also found that the expectations of an AI system impacted user acceptance more than the quality of the system [28]. Kocielnik, Amershi, and Bennett [43] had similar findings, as adjusting user expectations to accept imperfections in a system significantly improved user acceptance. Kocielnik, Amershi, and Bennett [43] also discovered that refocusing the output of an AI system to match user expectations improved user acceptance and trust. Users require clear expectations of the capabilities of an AI system for it to be accepted [39], as such methods for managing these expectations are necessary [17, 28]. Within user experience design, user expectations can be primed using the concept of affordances [69, 72].

3.2 Affordances in AI Expectation Management

Norman [69] defined an object's affordances as its possible interactions, with signifiers being design properties that announce these affordances [70]; Norman [72] states that affordances connect artefact development and user-centred design. By analysing the affordances of an AI system and implementing suitable signifiers, user expectations can be managed through interactions [72]. Constraints, defined as restrictions on user interactions [69], allow the user to understand what the system cannot do [71]; implementing constraints alongside affordances allows for a system to depict the scope of its capabilities clearly to users [76].

Identifying suitable affordances within interactive AI systems is often difficult [104], as many AI systems have capabilities that exceed their use cases. Enforcing constraints on the algorithm implemented and potential user interactions may mitigate issues regarding affordance identification [51], but this does not resolve the issue. Shin, Zhong, and Biocca [88] found that user understanding of algorithmic affordances impacts user trust; Shin, Zhong, and Biocca [88] also identified that there is little research into how users perceive algorithmic affordances. Further research into methods that depict algorithmic affordances and how context and interfaces impact algorithm acceptance is needed [88, 104].

4 Communicating with the User

4.1 Why communication matters

Within user-centred design, communication is the basis of many widely used principles and heuristics; communication through feedback can be seen in Lockwood's feedback principle [22], Norman's feedback principle [69], and Nielsen's 'visibility of system status' heuristic [64], while ensuring clarity of communication can be seen in Nielsen's 'match between system and the real world' heuristic [64] and Mace's Perceptible Information principle [92]. McKay [59] states that a well-defined user interface (UI) is simply a method for natural, understandable, and efficient communication with users and proposes that a UI should explain all tasks clearly and concisely; understanding effective UI design is important, as positive user experience is reliant on effective user interfaces [7].

Effective UI design is challenging within interactive AI due to the complexity of system outputs and the uncertainty of AI features [105]. Yang et al. [105] discuss how AI capabilities and limitations are not well researched, reiterating the findings of the affordances discussion, which results in difficulty mapping the affordances to interfaces; this is not a blanket statement for all interactive AI systems, as Yang et al. [105] created a complexity map depicting the levels of output complexity and capability uncertainty for different AI categories. When the affordances of a system are unclear, explainability and confidence can enhance user experience [37]. Jiang, Kahai, and Yang [37] found that explaining the outputs of models enhances user experience when user and algorithmic uncertainty is high [37], while simplified outputs and confidence scores increase user experience and trust when output complexity is high [37].

4.2 Explainability as Feedback

The explainability of an AI system is how interpretable the system is, intrinsically or through complementary explanations [58]; explainable interfaces [79] are interfaces that output the interpretable explanations to the user in a natural format. Generating explainable interfaces in itself is a vast research area, as there are differing formal definitions of what makes a system explainable [19, 102] and how to output the explanations for these systems [98]. To enable effective communication that builds trust within interactive AI, new regulations and industry standards regarding explainability methods are required [98] alongside tools that assist in the implementation and validation of these methods [19].

4.3 Confidence as Feedback

Confidence scores of system results enhance user trust in AI systems [106] and are a requirement for Trustworthy AI [2] Karran et al. [41] found visualisation design choices regarding confidence impacts user confidence in a system, with users preferring confidence outputs adjacent to the AI's outputs; Karran et al. [41] also identified a need for further research into human interpretable outputs.

5 Designing for Trust

5.1 Defining Designing for Trust in AI

Liao and Sundar [52] defined designing AI for trust as designing for trustworthiness cues within user interfaces; trustworthiness cues are methods for communicating trust within interfaces [101] by validating the efficiency, fairness, transparency, robustness, privacy, or security of the system [52]. Current AI trustworthiness frameworks focus on the results of AI systems rather than the interfaces [52]; as such, it is necessary to design for trust explicitly. Liao and Sundar [52] stated that the current focus on trustworthiness ignores how users judge trust and how interfaces can influence these judgements; these findings can also be seen in the misaligned interests of trustworthiness frameworks and human-AI interaction guidelines [50]. Liao and Sundar [52] proposed the MATCH model to refocus design for trust, separating AI system design into model design, system affordance design, and trustworthiness cue design; system affordance design was discussed within the 'Expectations of AI' section of this review.

5.2 Designing Models for Trust

Liao and Sundar's [52] discussion on the current focus of designing for trust highlights that trustworthiness in models is the current priority; therefore, designing models for trust can be achieved through following trustworthy AI guidelines, such as the EU's assessment list for trustworthy artificial intelligence [2]. Radclyffe, Ribeiro, and Wortham's review of the EU assessment list [80] found the current guidelines appropriate for AI ethics and sufficiently broad.

5.3 Designing AI Interfaces with Trustworthiness Cues

Designing interfaces for trust requires suitable affordance selection and efficient implementation of signifiers [52], known as trustworthiness cues. Norman [70] discussed how signifiers are clues for users that enable the understanding of entity usage without prior knowledge, which means that trustworthiness cues must prompt the user on potential AI functionality without assuming system knowledge. To enhance user understanding of cues and increase user trust, Nielsen's usability heuristics should be adhered to [64]. Lindley et al. [54] found that implementing signifiers and icons enhances user legibility and understanding of AI systems, but recommended further research into embedding signifiers within AI design methodologies.

While signifiers are effective in improving user understanding of AI systems [54], which increases user trust [95], suitable development of signifiers relies on the correct identification of algorithmic and model affordances [70]; due to this, issues that impact affordance identification within AI [104] also impact signifiers. Future developments in interactive AI should include design-led research [54] that identifies affordances and embeds signifiers to enhance the legibility of AI.

6 Design Heuristics for AI

6.1 The Need for AI Design Heuristics

The European Commission's 'Assessment List for Trustworthy Artificial Intelligence' [2] identifies that Universal Design principles should be considered during the planning and development of AI but does not define these principles. Höök discussed the need for more efficient development methods and enhanced usability principles for AI [32]. Usability heuristics and principles enable a user-focused design approach [27] that can be easily evaluated and reviewed [38].

6.2 Reviewing Existing Design Heuristics

Jimenez, Lozada, and Rosas [38] identified that Nielsen's usability heuristics [64] are a suitable basis for specialised usability heuristics due to their breadth; AI design heuristics should build upon Nielsen's usability heuristics [64] to ensure generalised usability as a basis [38]. Current proposed AI usability heuristics [6] omit Nielsen's usability heuristics [64], resulting in interface usability principles being ignored; for example, Amershi et al.'s proposed AI usability heuristics [6] do not reference documentation and error recovery, which are key usability principles [68]. Nielsen's usability heuristics [64] are reviewed to identify the need for each heuristic before usability gaps are identified regarding AI.

6.3 Reviewing Nielsen's Usability Heuristics

6.3.1 Visibility of system status

Jiang, Kahai, and Yang [37] discussed how explaining the output of an AI system can enhance user trust; however, due to the potentially slow computational speed of AI systems, users should also be informed when the system performs calculations [64]. Users require visibility of AI systems in the form of transparency and explainability of outputs [79], as discussed previously, and through interfaces that identify when the system processes requests; therefore, AI usability heuristics should separate visibility into processing and outputs.

6.3.2 Match between system and the real world

Interfaces that use natural and user-friendly formats are desirable within AI [79]. Interfaces and explainable outputs must match the user's language and mental models to be user-understandable [87]. Grimes, Schuetzler, and Giboney [28] found that user trust is negatively impacted when AI breaks a user's mental model by not matching user expectations or social norms. Merry, Riddle, and Warren [61] state that the explainability of AI models is the result of mental models and context of the user, rather than the outputs and models themselves; context-sensitive choices are based on actions that agree with norms [45]. A match between the system and the real world is necessary for interface usability [68] and interpretable, explainable outputs [79] within interactive AI systems.

6.3.3 User control and freedom

Constantine [21] discussed how user control is required for system trust, with Bader and Kaiser [10] reiterating the importance of control within AI. User freedom refers to the ability to undo, cancel, or terminate actions within a system [64]; however, the ability to undo actions is not always present within AI systems. LLMs do not have an inherent ability to undo actions, instead requiring manipulation of the chat history[40]. ChatGPT[1] does not allow users to undo actions but does allow previous messages to be edited. User freedom within AI is an area with little literature, yet it is crucial for usability.

6.3.4 Consistency and standards

Adhering to industry standards improves usability [64], as users do not primarily use a single system for all tasks [100], and standardisation between systems reduces the cognitive load of the user [60]. Vermesan et al. [97] discuss the need for standardisation within the AI industry to build user trust; Vermesan et al. [97] also discuss the challenges of standardisation within AI, which includes current standards being developed with a lack of stakeholder diversity. Current guidelines and standards also contain oversights within trust [52] and user-centred design [50]. Consistency and standards are required within AI, but suitable standards must first be developed [50, 52, 97]

6.3.5 Error prevention

Error prevention is crucial in AI due to the potential effects of miscalculations; for example, Coker et al.'s AI [20] that predicts the necessary drugs to provide lung cancer patients takes between 12 to 48 hours to produce a prediction, meaning an error causes a large loss of time and potential harm to patients. Outside of usability, errors are environmentally costly [103] due to the wasted electricity. Within AI, error prevention also prevents the system from producing errors; Philipp Brauner and Ziefle [78] found that AI errors reduce user trust, acceptance, and usability. To prevent user errors, AI systems must be designed with an understanding of desired and correct user actions, alongside verification methods [107].

6.3.6 Recognition rather than recall

As users have limited short-term memory [9], they rely on recognition rather than recall of information [68]. This heuristic refers solely to system interfaces rather than the systems themselves and relies on industry standards for AI system interfaces being developed. Oviatt [75] discussed how effective user-centred design relies on minimising a user's cognitive load through recognisable interfaces, with Lieberman [53] stating that AI interfaces would benefit from utilising this approach.

[1] https://chat.openai.com/

6.3.7 Flexibility and efficiency of use

Flexibility refers to personalisation and customisation, while use efficiency is implemented through shortcuts and accelerators [68]. This heuristic can take many forms within AI systems, as interfaces and AI models can be personalised [15]. Miraz, Ali, and Excell [62] discuss how AI systems rely on user interface plasticity; plasticity is the ability of an interface to allow changes in the system, such as the underlying model, and changes in the environment, such as user personalisation, while ensuring usability and functionality [84]. Creating interfaces using plasticity design methods ensures flexibility and efficiency, enabling AI system adaptation for diverse users [62].

6.3.8 Aesthetic and minimalist design

As identified previously, simplicity builds trust within AI systems [79, 96]. Maeda defines simplicity as subtracting the obvious and adding the meaningful [57]; however, simplicity also has negative connotations [57] so within UX the term minimalistic is often used instead [91]. Minimalistic systems do not refer to systems with low capabilities but to systems that implement simplistic and minimalist design principles for user interaction [96]. Obendorf [73] identifies how simplicity can increase user efficiency, trust, and conformity with user expectations. Simplicity can be achieved within AI systems by implementing Obendorf's notions of minimalism [73]; however, these notions rely on understanding systems' affordances and potential signifiers. It is important to note that while simplistic user interfaces can build user trust [79], oversimplification negatively impacts trust [46]. Minimalistic design is key to enhancing user understanding and user experience [73, 79, 96].

Within AI, minimalism can also take a secondary form. Minimalistic model design is a key principle of sustainable AI [103], as inefficient and resource-intensive models have larger carbon footprints. From a usability point of view, a minimalistic model design that enables faster output is preferable for users [93]. Minimalism applying to both model and interface design highlights a need for specified minimalism heuristics.

6.3.9 Help users recognise, diagnose, and recover from errors

Error messages should be easily understood so users can recover from errors [68]. Kocielnik, Amershi, and Bennett [43] found that error framing enhanced the acceptance of AI systems, with Linxiang Lv and Yang [55] finding that framing errors within LLMs to show gratitude and provide a resolution promoted user acceptance, over apologising for errors.

6.3.10 Help and documentations

Königstorfer and Thalmann [44] state that traditional software development documentation is unsuitable for AI and that AI systems must have documentation that includes capability analysis and explanation of outputs.

6.3.11 Summary

Through the analysis of AI using Nielsen's usability heuristics [64], key issues within AI usability were discussed; this analysis reiterated findings from previous literature and enabled the exploration of further literature gaps. Nielsen's usability heuristics [64] are required within AI systems, but they require further specificity or fine-tuning for AI applications. Nielsen's heuristics [64] are a suitable basis for future AI usability heuristics [38].

6.4 Current Heuristic Gaps

From the review of Nielsen's heuristics [64], it can be found that Amershi et al.'s proposed AI usability heuristics [6] focus on the AI model and ignore user interface implications; this aligns with Li and Lu [50] findings that AI guidelines do not pay attention to usability. Future usability heuristics for interactive AI should build upon Nielsen's [64] and Amershi et al.'s [6] heuristics to provide a holistic approach to AI usability.

7 Designing Responsible AI

7.1 Defining Responsible AI

Peters et al. [77] define responsible AI as intelligent systems that follow ethical guidelines and integrate ethical analysis into their development. The EU's 'Ethical Guidelines for Trustworthy AI' [3] is a framework that assists developers in creating responsible AI. Dignum [23] discussed how responsible AI is trustworthy; hence, responsible AI is an extension of trustworthy AI. Responsible AI ensures fairness, trust, and transparency [3, 77]; however, as previously identified, current ethics guidelines for responsible and ethical AI do not align with user-focused guidelines [50]. Understanding current AI ethics enables a discussion on current ethical guideline oversights.

7.2 AI Ethics

Current views on AI ethics can be found by analysis of the EU's 'Ethical Guidelines for Trustworthy AI' [3], which states that trustworthy AI should also be lawful, ethical, and robust. The EU Guidelines state that ethical AI is needed due to the creation speed of laws not matching technological development speeds [3]. AI is a field of applied ethics that focuses on how AI can improve individual quality of life, provide human autonomy, and enable a democratic society [3]. The EU's ethics are formalised within the 'Fundamental rights in the EU' [94], divided into respect for human dignity, freedom of the individual, respect for democracy, equality, and citizen's rights. The EU's AI ethics are based on the 'Fundamental rights in the EU' [94], using the principles of respect for human autonomy, fairness, applicability, and prevention of harm [3]. AI ethics are an extension of ethical norms for the context in which a system is developed [89].

7.3 Ethical Guidelines Usability Oversights

Li and Lu [50] discussed how Microsoft's guidelines for human-AI interaction [6] and the EU'S AI development guidelines[3] do not fully align but can be combined to enable suitable AI solutions. The findings of Li and Lu's research [50] identified a need for holistic guidelines that consider the trustworthiness, ethics, usability, and human-AI implications of AI systems. Combining current ethics and usability guidelines will allow for better analysis of potential gaps within them [50]; this will also enable the development of holistic guidelines with a suitable basis.

8 Conclusion

8.1 Summary

The literature on human-computer interaction, user experience design, and artificial intelligence was reviewed to identify current research gaps. Through analysis of current AI design methods, it was found that current research focuses primarily on the design of algorithms and models rather than the human-AI interactions; this focus leads to oversights in trustworthiness guidelines, lack of suitable AI usability heuristics, and gaps in UX methodologies for AI. The review took a breadth-first approach to finding literature gaps by examining further studies suggested by researchers and identifying where additional research overlapped. Understanding algorithmic and model affordances was an area of further research identified throughout this review.

As this literature review only covered the key principles of UX for AI, many areas are yet to be discussed. Further literature gaps may exist within HCI fields, such as cognitive psychology for AI users, ubiquitous AI design, UX design for AI in extended reality, and perceptual interfaces for AI.

8.2 Literature gaps

The following literature gaps have been highlighted within this review:

- Guidelines for trustworthy interactive AI
- Expectation management in AI and algorithmic affordances
- Explainability methods and tools for AI
- Efficient design of AI signifiers
- Interface plasticity design methods for AI
- User freedom in AI
- Usability Heuristics for Interactive AI
- Ethical AI guidelines that consider user experience

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