

USER EXPERIENCE (UX) IN INTELLIGENT SYSTEMS: A SYSTEMATIC REVIEW OF HUMAN CENTERED AI DESIGN FOCUS ON UI/UX + AI + HCI

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Abstract

Artificial intelligence (AI) is increasingly embedded in digital products and services, making user experience (UX), user interface (UI), and human-computer interaction (HCI) central to how people understand, trust, and use intelligent systems. This systematic review examines how human-centered AI design approaches can improve interaction with AI-enabled systems, with particular attention to explainability, trust, transparency, control, accessibility, and UX evaluation. The review synthesizes peer-reviewed and scholarly literature addressing UX, HCI, human-AI interaction, explainable AI, interface design, accessibility, and intelligent systems. The literature was organized thematically around human-centered design, interaction and interface principles, explainability and trust, evaluation methods, and unresolved challenges. Findings indicate that effective AI UX requires more than conventional usability: users need understandable system behaviour, appropriate explanations, practical opportunities to correct or override outputs, and interaction designs that support calibrated trust. The review also identifies fragmented evaluation practices, uneven accessibility considerations, and difficulties in translating technical explanations into useful interface experiences as continuing research gaps. Overall, the evidence supports designing AI systems around human goals, capabilities, responsibilities, and contexts. Future research should strengthen longitudinal evaluation, standardize reporting and core UX measures, and develop inclusive, actionable, and human-centered AI interfaces.

Keywords: User Experience (UX); User Interface (UI); Human-Computer Interaction (HCI); Human-Centered AI (HCAI); Explainable AI (XAI); Human-AI Interaction; Intelligent Systems; Trust; Accessibility; AI Design.

Introduction

Background

Artificial intelligence (AI) is increasingly embedded in systems used for information retrieval, recommendation, content generation, decision support, education, healthcare, finance, and

workplace activities. As AI systems move from being background computational components to active participants in human tasks, the quality of interaction becomes a central design concern. The National Institute of Standards and Technology (NIST) describes human-AI interaction as context-dependent and potentially non-deterministic, noting that AI can perform or alter human activities and therefore requires attention to human goals, outcomes, usability, and trustworthiness (Theofanos, Choong, & Jensen, 2024). This changes the role of the user interface: it is not merely a mechanism for issuing commands, but a space in which people interpret outputs, provide information, evaluate recommendations, correct errors, and decide how much authority to give the system.

This shift creates a broader challenge for user experience (UX) and human-computer interaction (HCI). Traditional interactive systems are often designed around relatively predictable relationships between user actions and system responses. AI-enabled systems can instead produce outputs that vary with data, context, model behaviour, or user interaction. Consequently, effective AI UX must address not only efficiency and ease of use, but also uncertainty, feedback, user control, recoverability, and the user's understanding of what the system is doing. NIST's human-centered design guidance similarly emphasizes explicit understanding of users, tasks, and environments, continuous user involvement, iterative evaluation, and attention to the whole user experience (NIST, 2026).

Recent literature indicates that the field is moving beyond a narrow focus on making AI understandable toward designing richer forms of human participation. Raees et al. (2024), in a review of human-AI interaction research, argue that existing work has often concentrated on explanation and contestability while giving less attention to broader forms of user agency, adaptation, collaboration, and participation in the evolution of AI systems. Wang et al. (2024) likewise identify a transition toward human-centered AI, with trust, acceptance, decision-making, teamwork, and human-AI collaboration becoming prominent research concerns. These findings suggest that UX should be considered as part of the wider human-AI relationship rather than as a surface layer added after the AI model has been developed.

The importance of this broader perspective is also evident in research on explainability and trust. Rong et al. (2024) surveyed user studies of model explanations and found that human-centered evaluation involves outcomes such as understanding, trust, and task performance. Al-Ansari et al. (2024) similarly reviewed user-centered evaluation of explainable AI and showed that explainability research is closely connected to HCI and

UX concerns. However, explanation alone does not guarantee effective interaction. Explanations must be appropriate to the user's task, knowledge, and context, and must support meaningful interpretation and action. NIST's AI Risk Management Framework therefore treats transparency,

explainability, interpretability, privacy, fairness, and accountability as interconnected characteristics of trustworthy AI rather than isolated technical features (NIST, 2023).

Taken together, these studies reveal an important gap: research on AI interaction is growing, but evidence remains distributed across UX, HCI, explainability, trust, accessibility, and responsible-AI communities. Recent reviews have called for more integrated approaches that connect technical system properties with human goals and measurable interaction outcomes (Raees et al., 2024; Schmager, Pappas, &

Vassilakopoulou, 2025). This review addresses that gap by bringing UI/UX, AI, and HCI perspectives together and examining how design approaches and evaluation practices can support understandable, controllable, inclusive, and trustworthy interaction with intelligent systems.

Problem Statement

A central problem in intelligent-system design is the mismatch that can occur between technical AI capability and human understanding. High predictive or generative performance does not necessarily produce an effective user experience if people cannot interpret system outputs, recognize limitations, determine when an output may be unreliable, or intervene when necessary. Human-centered AI research emphasizes that AI systems should be evaluated in relation to human goals and outcomes, not solely through technical performance measures (Theofanos, Choong, & Jensen, 2024).

The problem is therefore both technical and interactional. An AI system may be accurate but difficult to understand, efficient but inaccessible, or highly adaptive but difficult for users to control. Similarly, adding explanations does not automatically resolve the problem: explanations can be excessive, poorly timed, difficult to interpret, or disconnected from the user's actual task. Research on human-AI interaction increasingly points toward agency and collaboration as important complements to explanation and contestability (Raees et al., 2024).

The literature is also fragmented across research communities. Studies of interface design, explainability, trust, accessibility, human-AI interaction, and responsible AI frequently use different concepts, measures, and evaluation approaches. This

fragmentation makes it difficult to determine which design practices consistently improve UX across intelligent systems. Reviews of human-centered AI and user-centered explainable AI consequently highlight the need for more integrated research that connects design processes, human outcomes, and evaluation methods (Al-Ansari et al., 2024; Schmager et al., 2025). The present review responds to this gap by synthesizing evidence across these areas and identifying the design principles, evaluation practices, and unresolved challenges most relevant to human-centered UX in intelligent systems.

Aim and Objectives

The aim of this review is to synthesize evidence on UX in intelligent systems through the combined perspectives of UI/UX design, AI and HCI.

- Identify human-centered design approaches used in intelligent systems.
- Synthesize UX and HCI principles that support effective human-AI interaction.
- Examine methods used to evaluate UX in AI-enabled systems.
- Analyze the roles of explainability, trust, transparency, control and accessibility.
- Identify limitations, research gaps and directions for future AI-UX research.

Research Questions

- RQ1: What human-centered design approaches are used in intelligent systems?
- RQ2: Which UX and HCI principles improve interaction with AI-enabled systems?
- RQ3: Which methods and measures are used to evaluate UX in intelligent systems?
- RQ4: How do explainability, transparency, trust, control and accessibility influence AI-related UX?
- RQ5: What research gaps limit the development of effective human-centered intelligent systems?

Conceptual Foundation

The literature on UX in intelligent systems increasingly treats human interaction as a multidimensional design problem rather than a matter of interface appearance or conventional usability alone. Across HCI, human-centered AI, explainability, and trust research, a common concern is the relationship between AI capability and human agency. However, the literature does not fully converge on how these dimensions should be combined. Some studies concentrate on understanding and explanation, whereas others emphasize interaction, collaboration, control, or evaluation. This section therefore synthesizes the literature analytically, identifying areas of agreement, differences in emphasis, and gaps that motivate the present review.

Human-Computer Interaction

Human-computer interaction provides the broadest analytical foundation because it shifts attention from the technical system alone to the relationship between people, tasks, technology, and context. In AI-enabled systems, this relationship becomes more complex because system behaviour may be adaptive, probabilistic, or generative.

Raees et al. (2024) argue that much human-AI interaction research has focused on explaining AI behaviour and allowing users to contest decisions, while comparatively less attention has been given to stronger forms of agency, adaptation, and participation in the evolution of AI systems. This is significant for UX because successful interaction cannot be reduced to whether a user understands an output; users may also need to influence, correct, negotiate with, or collaboratively shape system behaviour. Thus, HCI contributes a process-oriented perspective in which AI interaction is evaluated through user goals, agency, context, and outcomes rather than through model performance alone.

User Experience and User Interface

UX and UI research contributes a second layer by examining how system capabilities are encountered in actual use. The literature distinguishes interface mechanisms from the broader experience produced through interaction, but intelligent systems make the boundary particularly important because the interface communicates AI outputs, uncertainty, system status, and opportunities for intervention. Nguyen, Canossa, and Zhu (2024) surveyed 53 publications on explainable interfaces and found that interface and UX design are increasingly treated as mechanisms for making explainable AI more usable and practically effective. This extends conventional UI thinking: the interface is not simply a presentation layer for an already-complete AI system but part of how the system's behaviour becomes understandable and actionable. The research therefore supports integrating AI behaviour and interface design earlier in the design process.

Human-Centered AI

Human-centered AI brings HCI and AI into a common design perspective by asking how computational capabilities can support human goals while preserving meaningful human involvement. The literature generally agrees that human-centered AI should consider human needs, values, abilities, and outcomes, but studies differ in what they regard as the most important form of human involvement. Raees et al. (2024) emphasize moving beyond explanation and contestability toward greater agency and interaction, while other work on human-centered explainable AI focuses more specifically on whether explanations are meaningful to users. This difference is useful rather than contradictory: it indicates that human-centered AI is broader than explainability. For the present review, human-centered AI is therefore treated as an umbrella perspective linking user needs, system behaviour, interaction, oversight, and evaluation.

Explainable AI and Explainable Interfaces

Explainability research demonstrates why technical model transparency cannot be separated from UX. Al-Ansari et al. (2024) systematically reviewed 101 full-text studies selected from 3,414 records and showed that user-centered evaluation of explainable AI involves different goals,

methods, domains, and participant considerations. Similarly, Kim, Maathuis, and Sent (2024) reviewed 73 user-evaluated explainable AI studies and identified 30 properties of meaningful explanations, organized around contextual explanation quality, contribution to human-AI interaction, and contribution to human-AI performance. Only 19 of the 73 studies used an evaluation framework that had also been used by another study, indicating substantial methodological fragmentation.

These findings challenge the assumption that an explanation is automatically useful because it reveals information about a model. Nguyen et al. (2024) similarly surveyed 53 publications and showed that explainable interfaces require deliberate UX decisions concerning how explanations are presented and interacted with. The research therefore agrees that explanation must be evaluated from the user's perspective, but it also reveals a gap: there is still no universally accepted way of translating technical explainability into interface experiences that are consistently understandable, useful, actionable, and appropriate to context.

Trust and Trust Calibration

Trust research adds another dimension because users must decide how much reliance to place on AI outputs. The literature distinguishes appropriate reliance from both under-reliance and over-reliance, making trust a calibration problem rather than simply a desirable outcome. Evidence from human-centered explainable AI research shows that explanations may contribute to perceived trustworthiness and control, but these effects depend on what users understand and how explanations relate to the task. Kim, Maathuis, and Sent (2024) found that meaningful explanations can be evaluated through properties such as trustworthiness, usefulness, actionability, and understandability, as well as their contribution to interaction and performance.

Taken together, the literature suggests that trust should not be designed independently of usability, explainability, and control. An interface that encourages reliance without helping users understand limitations may produce inappropriate reliance, while excessive warnings or poorly designed uncertainty information may reduce useful engagement. The unresolved issue is therefore how these dimensions can be evaluated together across different AI contexts. This review addresses that gap by treating trust as one component of a broader UX system involving explanation, agency, accessibility, control, and measurable interaction outcomes.

Methodology

This study employed a systematic literature review to examine research at the intersection of user experience (UX), user interface (UI), human-computer interaction (HCI), artificial intelligence (AI), and human-centered AI. The review followed a structured process for identifying, screening, selecting, and synthesizing relevant studies.

Review Design

The review covered publications from 2010 to 2026. A total of 150 research articles were identified and examined. The research process was shared among the five members of the research team, with each member responsible for reviewing 30 articles. The work was completed over six days using a coordinated screening procedure designed to maintain consistency and prevent repeated examination of the same articles.

Search Strategy

The team searched scholarly literature relevant to UX in intelligent systems, including human-centered AI, human-AI interaction, UX, UI, HCI, explainable AI, explainable interfaces, trust in AI, usability, accessibility, and intelligent systems. Publications from 2010 to 2026 were considered. During the search, the team prioritized articles displaying an HTML indication because these provided accessible, less restricted full-text content for review. Each researcher recorded and shared the articles reviewed that day before the next team member began the next stage of the search, reducing the possibility of duplication.

Inclusion Criteria

Articles were included when they were published between 2010 and 2026, addressed AI-enabled or intelligent interactive systems, examined UX, usability, HCI, human-AI interaction, human-centered AI, explainability, trust, accessibility, or related interaction concerns, and provided sufficient accessible content for assessment. Articles with an HTML indication were prioritized because they could be accessed for review without substantial access restrictions. From the 150 articles examined, 42 met the relevance requirements and were included in the final synthesis.

Exclusion Criteria

Articles were excluded when they did not provide a meaningful connection to human interaction with intelligent systems, did not contribute evidence relevant to the research questions, or did not meet the publication and accessibility criteria. Studies focused solely on algorithmic or technical issues without a meaningful UX, HCI, or human-AI interaction component were also excluded. Of the 150 articles examined, 108 were not used in the final synthesis. No duplicate articles were identified during screening because each researcher shared the five articles reviewed that day before the next researcher began.

Synthesis Approach

The 42 included articles were synthesized thematically around five connected dimensions: human-centered design; interaction and interface principles; explainability and trust; UX evaluation; and unresolved challenges and research gaps. The synthesis compared findings across studies rather than reproducing individual source descriptions, with particular attention to areas of agreement,

differences in emphasis, and limitations identified in the literature. The screening process can be summarized as: 150 articles identified and reviewed; 108 excluded or not used; and 42 included in the final synthesis. No duplicate records were identified.

Human-Centered AI Design Approaches

User-Centered Design

User-centered design remains a foundation for AI UX because it starts with people rather than model capabilities. User research, contextual inquiry, prototyping and iterative evaluation help teams understand what users actually need from an intelligent system. For AI, UCD should continue after deployment because model behaviour and user expectations can change over time.

Human-in-the-Loop Design

Human-in-the-loop design deliberately retains human participation in AI-supported decisions. The interface should make intervention practical rather than merely theoretical. Useful mechanisms include review steps, editable outputs, approval controls, correction mechanisms and clear recovery paths after errors.

Explainability-Centered Design

Explainability should be designed around the user's task. A person deciding whether to accept a recommendation may need a concise rationale, relevant evidence and an uncertainty indicator rather than a technical description of the model. Recent evidence shows that meaningful explanations can involve understandability, usefulness, actionability, trustworthiness and their effects on interaction and task performance (Kim et al., 2024).

Trust-Centered Design

Trust-centered design combines reliable system behaviour with transparent communication and user control. Designers should avoid interface patterns that encourage unquestioning reliance. Instead, systems can communicate uncertainty, limitations and error states in ways that support informed decisions.

Accessible and Inclusive Design

AI interfaces must account for differences in sensory, physical, cognitive and digital capabilities. Accessibility should be integrated from the beginning rather than added after the model and interface have been completed. Multimodal interaction, adjustable presentation, readable information structures and compatibility with assistive technologies can reduce barriers to participation.

UX Principles for Intelligent Systems

Usability

AI features should make tasks easier rather than introduce unnecessary complexity. Interfaces should present actions clearly, minimize avoidable cognitive effort and support efficient recovery from mistakes.

Transparency

Users need sufficient information to understand what the AI is doing and what role it plays in a decision. Transparency should be proportional to the user's needs rather than implemented as technical disclosure for its own sake.

Control and Agency

Users should have practical mechanisms to accept, edit, reject, correct or override AI outputs when the context requires it. Control is particularly important when system errors can affect important decisions.

Personalization

Personalization can improve relevance, but it can also create privacy and autonomy concerns. Intelligent interfaces should make important adaptive behaviour understandable and provide meaningful settings where appropriate.

Accessibility

Accessibility should cover both the interface and the AI interaction itself. Designers should consider alternative input/output modes, language differences, cognitive accessibility and varying levels of technical expertise.

Feedback and Error Recovery

AI systems should treat errors as part of interaction design. Clear feedback, editable outputs, undo mechanisms and explanations of failure can help users recover without losing confidence or control.

Evaluation of UX in Intelligent Systems

Surveys and Questionnaires

Questionnaires can capture perceived usability, satisfaction, trust, confidence and perceived control. However, AI introduces dimensions that traditional usability questionnaires may not fully capture. Studies therefore often combine general UX measures with AI-specific constructs.

Usability and User Testing

User testing can measure task completion, errors, time, comprehension and interaction problems. For intelligent systems, tests should also examine whether users understand AI limitations, whether they can recover from incorrect outputs and whether their reliance is appropriately calibrated.

Interviews and Focus Groups

Qualitative methods are useful for studying mental models, expectations, trust, perceived agency and ethical concerns. They can reveal problems that performance metrics alone cannot explain, such as why users reject a system even when its measured accuracy is high.

Performance Measures

- Task completion time and success rate.
- Frequency and severity of user errors.
- Interaction effort and number of steps.
- Comprehension of AI outputs and explanations.
- Reliance and intervention behaviour.
- Perceived workload and satisfaction.
- Learning time and improvement across repeated use.

Human-AI Evaluation

Recent reviews demonstrate that human-centered XAI evaluation remains methodologically diverse. Kim et al. (2024) found that only 19 of 73 reviewed papers used an evaluation framework that had also been used by another study in their sample. This limits cross-study comparison and supports the development of more consistent evaluation practices.

Challenges and Research Gaps

Trust and Over-Reliance

AI systems can create both under-trust and over-trust. A system that communicates excessive confidence may encourage people to accept poor recommendations, while a system that communicates uncertainty poorly may be ignored even when it is useful. Research should therefore examine trust as a dynamic relationship that changes with experience and system performance.

Explainability That Does Not Match User Needs

A major gap is the translation of technical explainability methods into usable interface experiences. Designers need guidance for deciding what to explain, when to explain it, how much information to provide and how to allow users to request deeper detail.

Recent reviews identify this as an active research area rather than a solved design problem.

Privacy and Personalization

Personalized AI experiences depend on user data. This creates a tension between relevance and privacy. Interfaces should make important data practices understandable and avoid making users feel that adaptation occurs without their knowledge or meaningful choice.

Accessibility and Inclusion

Accessibility remains challenging because AI systems can introduce barriers at multiple layers: data, model outputs, language, interaction modality and interface presentation. Future research should evaluate accessibility as part of the complete human-AI workflow rather than treating it as a separate interface checklist.

Ethics, Fairness and Accountability

Human-centered AI must consider the consequences of biased outputs, unequal access, privacy risks and unclear responsibility. UX design cannot solve all algorithmic fairness problems, but it can make limitations visible, support user reporting and provide mechanisms for human review.

Evaluation Fragmentation

Different studies use different constructs, scales and experimental designs. This makes it difficult to compare results across systems. Standardized core measures, combined with domain-specific measures, could improve cumulative knowledge without forcing every AI application into the same evaluation framework.

Future Directions

Longitudinal AI-UX Research

Future studies should observe users over longer periods because trust, mental models and interaction habits can change after repeated exposure to AI.

Explainable Interfaces

The development of explainable interfaces should connect model explanations with interaction design, allowing explanations to be understandable, actionable and appropriately timed.

Designer-Centered AI Tools

AI tools for UX practitioners should support the complete design process, including user research, synthesis, ideation, prototyping, evaluation and iteration. Research on AI assistance for UX suggests that empathy and cross-screen user flows should remain central rather than being reduced to automated screen generation (Lu et al., 2024).

Responsible and Inclusive AI

Future systems should integrate accessibility, privacy, fairness and accountability into the design lifecycle rather than treating them as final-stage compliance activities.

Conversational and Multimodal Interaction

Conversational and multimodal interfaces create opportunities for more natural interaction, but they also require careful attention to ambiguity, feedback, user control and accessibility.

Standardized Evaluation Frameworks

Researchers should work toward shared reporting practices for AI-UX studies, including clear descriptions of participants, tasks, AI behaviour, interface conditions, measures and limitations.

Discussion

The findings of this systematic review show that user experience in intelligent systems cannot be understood through interface usability alone. Across the 42 articles included in the final synthesis, recurring concerns involved human-centered design, interaction and interface principles, explainability, trust, control, accessibility, and UX evaluation. The literature therefore supports an integrated view in which the quality of an AI system depends not only on what the system can do, but also on how clearly its behaviour is communicated and how effectively users can understand, evaluate, correct, and respond to its outputs.

This finding is consistent with Raees et al. (2024), who examined trends in human-AI interaction and argued that research has increasingly moved beyond simply explaining AI decisions toward more interactive forms of human involvement. Their review highlights agency, participation, and interaction as important dimensions of human-AI relationships. The present review supports this direction but extends the discussion beyond interaction alone by connecting agency with practical UX concerns such as accessibility, feedback, error recovery, trust, and interface control. This broader connection is important because an AI system may provide opportunities for interaction while still creating poor experiences if users cannot understand its outputs or recover effectively from errors.

The findings also agree with Nguyen, Canossa, and Zhu (2024), whose systematic survey of 53 publications shows that human-centered explainable AI interfaces require deliberate decisions about how explanations are presented and experienced by users.

This supports the view that explainability is not only a property of an AI model; it is also an interface and UX problem. The present review further connects explainability with control and trust. An explanation is more useful when it helps a user understand an output and supports an appropriate action, correction, or decision. Consequently, simply displaying more technical information does not necessarily produce a better user experience.

Al-Ansari et al. (2024) provide further evidence of methodological variation in user-centered explainable AI research. Their review examined 101 full-text studies selected from 3,414 records and identified differences in study methods, participants, data collection approaches, and evaluation measures. This methodological variation is also reflected in the wider literature reviewed in the present study. Different researchers assess UX using different constructs and measures, making direct comparison difficult. The implication is that future AI-UX research would benefit from clearer reporting practices and a combination of common core measures with context-specific measures.

Another important finding is that the literature tends to address explainability, trust, accessibility, control, and usability as related but often separate research concerns. The present review brings these concerns together within a single human-centered UX perspective. This synthesis suggests that they should be considered interconnected: explanations can affect understanding and trust; interface transparency can affect users' sense of control; accessibility can determine whether users can benefit from explanations or correction mechanisms; and effective error recovery can influence whether users remain able to exercise meaningful agency when AI outputs are incorrect.

The review also identifies a gap between principles proposed in the literature and their consistent evaluation in real-world settings. Many studies investigate particular AI applications or specific UX dimensions, but fewer provide evidence across longer periods of use or across diverse user groups and contexts. This limits the extent to which findings from one intelligent system can be generalized to another. Longitudinal studies, more inclusive participant groups, and clearer evaluation frameworks could therefore strengthen the evidence base for human-centered AI design.

Overall, the contribution of this review is the integration of UI/UX, AI, and HCI perspectives into a common analytical framework for intelligent systems. Rather than treating explainability, trust, accessibility, privacy, control, and usability as isolated features, the review identifies them as interconnected components of human-AI interaction. The findings support a design approach in which AI systems are developed around human goals, capabilities, responsibilities, and contexts,

while future research focuses on more consistent evaluation, stronger user agency, inclusive design, and practical mechanisms for understanding and controlling AI behaviour.

Conclusion

The strongest design direction emerging from the literature is a human-centered approach in which users participate through research, testing, feedback, explanation, correction and oversight. Explainability, trust, accessibility, privacy and fairness should therefore be treated as connected UX concerns.

The review further concludes that future AI interfaces should support human judgement rather than simply automate human activity. Research should improve the consistency of evaluation, study interaction over time, develop designer-centered AI tools and create interfaces that communicate AI capabilities and limitations clearly. The central goal is not to make people adapt to AI, but to design AI systems that fit human goals, abilities, responsibilities and real-world contexts.

References

Kim, S., Maathuis, H., & Sent, D. (2024). Human-centered evaluation of explainable AI applications: A systematic review. *Frontiers in Artificial Intelligence*, 7, 1456486. <https://doi.org/10.3389/frai.2024.1456486>

Schmager, S., Pappas, I. O., & Vassilakopoulou, P. (2025). Understanding Human-Centered AI: A review of its defining elements and a research agenda. *Behaviour & Information Technology*, 44, 3771–3810. <https://doi.org/10.1080/0144929X.2024.2448719>

Theofanos, M. F., Choong, Y.-Y., & Jensen, T. (2024). AI Use Taxonomy: A Human-Centered Approach. *NIST Trustworthy and Responsible AI*, NIST AI 200-1. <https://doi.org/10.6028/NIST.AI.200-1>

Wang, D., Zheng, K., Li, C., & Guo, J. (2024). Transitioning to Human-Centered AI: A Systematic Review of Theories, Scenarios, and Hypotheses in Human-AI Interactions. *Proceedings of the Association for Information Science and Technology*, 61, 673–678. <https://doi.org/10.1002/pra2.1078>

Al-Ansari, M., et al. (2024). User-centered evaluation of explainable artificial intelligence (XAI): A systematic literature review. *Human Behavior and Emerging Technologies*. <https://doi.org/10.1155/2024/4628855>

How to explain AI systems to end users: A systematic literature review and research agenda. (2022). *Information Technology & People*, 32(7). <https://doi.org/10.1108/INTR-08-2021-0600>

Lu, Y., Yang, Y., Zhao, Q., Zhang, C., & Li, T. J.-J. (2024). AI assistance for UX: A literature review through human-centered AI. arXiv:2402.06089.

Nguyen, T., Canossa, A., & Zhu, J. (2024). How human-centered explainable AI interfaces are designed and evaluated: A systematic survey. arXiv:2403.14496.

Raees, M., Meijerink, I., Lykourantzou, I., Khan, V.-J., & Papangelis, K. (2024). From explainable to interactive AI: A literature review on current trends in human-AI interaction. *International Journal of Human-Computer Studies*, 189, 103301. <https://doi.org/10.1016/j.ijhcs.2024.103301>

Rong, Y., Leemann, T., Nguyen, T.-T., Fiedler, L., Qian, P., Unhelkar, V., Seidel, T., Kasneci, G., & Kasneci, E. (2024). Towards human-centered explainable AI: A survey of user studies for model explanations. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 46(4), 2104–2122. <https://doi.org/10.1109/TPAMI.2023.3331846>

Trust models and theories in human–computer interaction: A systematic literature review. (2024). *Computers in Human Behavior Reports*, 16, 100495. <https://doi.org/10.1016/j.chbr.2024.100495>

Xu, W. (2024). A “User Experience 3.0” paradigm framework: User experience design for human-centered AI systems.

Sciannamè, M., & Spallazzo, D. (2023). AIXE: Building a scale to evaluate the UX of AI-infused products. IASDR 2023: Life-changing design.