Examining the Nexus between Explainability of AI Systems and User's Trust: A Preliminary Scoping Review

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Abstract

EXplainable AI (XAI) systems are designed to provide clear explanations of how the system arrived at a decision or prediction, which increases users' trust. However, the factors that promote trust among XAI users, the different dimensions of trust, and how they affect the human-AI relationship are still under exploration. Through a preliminary literature review, this paper aims to collect the most recent empirical evidence (n=13) that investigates the nexus between XAI and users' trust, highlighting the most salient factors shaping this relationship. The studies measured XAI, including understandability, informativeness, and system design factors. Different scales were used, such as Likert scales and pre-experimental surveys, as well as more nuanced approaches like image classification AI and focus groups. Trust in AI was evaluated through criteria like trustworthiness and scales for agreement with statements about trust, even if some studies adopted methods like latent trust evaluations, observational measures, and usability tests. The studies collectively suggest that various factors such as clear explanations, perceived understanding of AI, transparency, reliability, fairness, user-centeredness, emotional responses, and design elements of the system influence trust in AI. Low-fidelity explanations, feelings of fear or discomfort, and low perceived usefulness can decrease trust, with systems displaying medium accuracy or utilizing visual explanations not adversely affecting user trust. Explainability methods like PDP and LIME appear effective at increasing user trust, while SHAP explanations perform less well. To foster trust, AI developers should prioritize designs considering both cognitive and affective trust-building aspects.t.

Keywords

Artificial Intelligence, Explainability; Trust; XAI

1. Introduction

The spread of Artificial Intelligence (AI) systems across diverse domains has emphasized trust's significance in influencing user acceptance and utilization [1]. Yet, the "black-box" problem—AI algorithms' inability to elucidate their decision-making processes and functions to users—hampers trust-building. The resulting transparency and interpretability deficits may cause inadequate user comprehension, reducing trust in these systems. Confronting this issue, developers are formulating eXplainable AI (XAI) systems. XAIs offer users comprehensible explications of decision-making mechanisms, bolstering transparency and approval [2]. The increasing attention towards XAI systems is evidenced by the European Commission's High-level Group on Trustworthy AI and the numerous EU-funded projects in this field. Notably, the European project TUPLES [3] aims to build trusted planning and scheduling systems that are safe, robust, explainable, and efficient. TUPLES concentrates on elements fostering explainability and trustworthiness in these systems, cultivating user trust and facilitating improved human-AI interactions. Scholarly work suggests that XAI systems can elevate human trust in AI by fostering an understanding of their operations [1][4]. However, the intricacies of the connection between

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AI explainability and user trust remain ambiguous. Therefore, this study aims to analyze the most significant empirical studies investigating the relationship between AI explainability and users' trust to identify the key factors.

1.1. User's Trust in XAI Systems: The Psychological Perspective

Trust is pivotal in human-technology interactions and denotes a user's readiness to depend on an automated system for goal attainment [4]. In the AI era, user trust is integral for effective system utilization. Insufficient trust can precipitate disengagement, while excess trust can engender overreliance and frustration [5]. Consequently, AI should foster calibrated trust—generated by an alignment between expectations and system competence—to optimize user engagement [6]nand to avoid misuse, abuse, or disuse of the technology [7]. From a psychological standpoint, trust in human-AI interactions features cognitive and affective forms [8]. Cognitive trust emerges from rational assessments of system capabilities and performance, whereas affective trust derives from emotional components such as comfort and familiarity [8]. Both variants influence user behavior and decision-making with different antecedents and repercussions. As Gillath et al. [9] indicated, AI has a more substantial impact on cognitive trust, which typically establishes initial user trust. Over time, affective components gain prominence for maintaining long-term AI system relationships. The literature also highlights latent trust, offering a method to study user trust in AI through observed behavior and emotional responses [10]. This concept unveils implicit trust elements and yields insights into the emotional facet of trust, thereby facilitating system design enhancements. Thus, latent trust can potentially improve user interactions with AI systems. The multifaceted nature of trust enhances our understanding of human-AI interactions. Each aspect provides a distinct perspective on user behavior and decision-making concerning XAI. Yet, further exploration of these dimensions remains an active research area. In this context, our study aspires to enrich the nuanced comprehension of trust dynamics in the evolving AI landscape.

2. Method

We conducted a scoping literature review in three stages to identify critical factors influencing the relationship between XAI systems and user trust. Initially, we used databases like Scopus, Web of Science, and Google Scholar, employing keywords like Trust, Artificial Intelligence, Explainable AI, XAI, Transparen*, and Explainab*, resulting in 41 records. Next, our team utilized Ryann.ai [11], an AI-powered tool aiding remote collaboration for literature reviews. This software streamlined the selection process with features such as tagging, inclusion/exclusion functions, and selection rationale recording. Four researchers screened the sources during this stage based on title, abstract, keywords, content, relevance, research outcomes, and recency (considering the past five years). Lastly, additional authors examined the selected sources for research methodology and quality, ensuring no pertinent experimental studies were omitted. This procedure resulted in 13 sources included in our review, offering a comprehensive exploration of the relationship between XAI systems and user trust.

3. Results

The 13 selected studies summarized in Table 1, reveal recurrent themes within the experimental design, data collection, and outcomes of AI system evaluation. Trust measurement techniques frequently involve self-reported questionnaires that assess system features such as accuracy, reliability, transparency, and usability. Two studies also considered latent trust [12][13], examining user engagement, trust, and emotional responses to AI systems. The AI systems scrutinized vary widely yet display comparable patterns. Different methodologies are employed to measure explainability; in each study, users are asked to comprehend the predictions of AI or express their agreement with the system's internal functioning. The findings from 13 studies indicate that user trust in AI positively correlates with their perceived understanding of the algorithm influenced by factors like transparency, reliability, fairness, and the system's user-centeredness [14]. The results underscore the delicate balance necessary in providing explanations. Low-fidelity explanations [15], perceptions of low usefulness [16] and feelings of fear or discomfort can diminish trust [13]. Conversely, certain factors do not adversely affect trust, such as medium-accuracy systems [15] or those utilizing visual explanations [17][18]. Visual explanations can, in fact, help users achieve calibrated trust by providing additional information that can be trusted without over-trusting the system [19]. Furthermore, explanation methods like Partial Dependence Plot (PDP) and Local Interpretable Model-agnostic Explanations (LIME) garnered elevated levels of concurrence among participants, suggesting an enhancement in trust. Conversely, Shapley Additive Explanations (SHAP) elicited participant responses marked by neutrality and disagreement, demonstrating less effectiveness in fostering trust [20]. Hence, the usefulness of the XAI framework emerges as a clear theme in bolstering user trust. Despite initial difficulties users may have in interpreting AI results, clear explanations of AI functionality and decision-making processes increase user trust [21][22][23]. Additionally, anthropomorphic design can positively impact user acceptance and trust in XAI conditions [24]. This design approach generates affective trust, enhancing the user's and AI's emotional responses.

4. Conclusions

This scoping review's primary objective was to discern the key factors that shape the relationship between AI explainability and users' trust. According to the findings from the 13 selected studies, users are more likely to perceive AI systems as fair, dependable, and user-oriented when they can comprehend the rationale and logic underpinning these systems' decisions [14]. Conversely, factors such as low-fidelity explanations [15], perceived limited utility [16], and emotions of fear or discomfort [13] can rust trust. The role of the XAI in augmenting user trust is confirmed as a prominent theme that emerges from these observations. Even though users may initially face difficulties in interpreting AI outcomes, supplying clear explanations about AI functionality and decision-making processes bolsters user trust [21][22][23]. Even amid perceptions of unsatisfactory system performance, the XAI interface can aid in achieving an appropriate calibration of trust [23]. These findings pave the way for subsequent work and suggest several initial recommendations for developers aiming to enhance users' trust in XAI systems. As a first step, it is advisable for developers to prioritize the design and development of AI models that are intrinsically explainable. Incorporating interpretability features into the system architecture and decision-making processes facilitates comprehension and cognitive trust. Tools such as rule-based systems, decision trees, and model-agnostic explanations (e.g., PDP, LIME) can provide users with meaningful explanations [19]. Furthermore, it is vital to ensure that the explanations provided by AI systems are unambiguous, concise, and easily comprehensible to non-experts. One challenge would be to balance overly technical explanations, which may confuse users, and low-fidelity explanations, which may limit users' ability to make informed judgments about system outputs. Both communication strategies can lead to perceptions of limited usefulness. Medium-accuracy systems and visual aids may enhance user engagement without significantly impacting affective trust. Lastly, user feedback is crucial in refining XAI systems and fine-tuning trust calibration. User input can help pinpoint areas where explanations are inadequate or fail to address specific concerns. Continuous evaluation and iterative improvements of system explanation mechanisms maintain the "human-in-the-loop." Ultimately, developers can tailor XAI systems to optimize trust calibration processes and system performance. As AI becomes further entrenched in our daily lives, user-centric explainability will assume a critical role in leveraging the full potential of AI technologies while mitigating societal apprehensions. Even though this scoping review represents preliminary work, it provides a foundation for future research to discover additional strategies to fortify the link between AI explainability and users' trust.

Table 1
Included studies and results overview

Author(s), year	Research design, aim	System's type and aim	Provided explanations	XAI measurement	Trust measurement	Key findings
Aechtner et al., 2022	Experimental design (N= 60). Aim: compare users' perceptions of explanations generated by LIME, SHAP, and PDP.	LIME, SHAP and PDP aimed at perform the admission process of students for graduate schools.	SHAP: how features influence admission outcomes. LIME: how AI processes students' data. PDP: how variable changes impact predictions.	2 Items: "Does the user understand how the model decides?" "Does the explanation provide sufficient information on how the model decides?"	Single item: "Does the explanation increase the user's trust in the model?"	Trust in PDP (M=4.84) and in LIME (M=4.74) explanations are higher than trust in SHAP explanations (M= 3.85).
Bernardo and Seva, 2022	Synchronous between-subjects experimental design (N = 378). Aim: investigate user emotions and perceptions of AI-generated explanations.	AI system aimed at image classification.	Explanation of decisions showing the proportion of similar images in its dataset and their classification.	GoogleLens logic flow used to develop a XAI "*effective design*".	Trust assessment scale by Frazier et al. (2013). Example: "I trust the system even if I have little knowledge of it".	Latent trust increases with confidence and decreases with fear or discomfort. Perceived system usefulness positively affects trust.
Bernardo and Seva, 2023	Asynchronous virtual experiment (N = 143) Aim: explore users' emotions and trust toward XAI	Controlled AI system aimed at classifying different animal and plant species.	Explanations and recommendations for classifying various species of animals and plants.	The pre-experimental survey chose image classification for XAI design, confirmed by a UX expert focus group.	Latent trust measured by 3 emotional items (from (Bernardo & Seva, 2022).	Surprise towards XAI bolster trust in its functionality. Latent trust improves in those who felt confident.
Branley-Bell et al., 2020	Experimental design (N = 70). Aim: compare users' evaluation of AIs' explanations.	AI-based clinical decision support systems aimed at providing diagnostic explanations for breast cancer.	Diagnostic justifications generated by three XAI visualizations: decision tree, logistic regression, neural network models.	Single item: "How well do you understand the AI system's predictions and explanations?" 7-point Likert scale.	Single item: "How much do you trust the AI system?" -point Likert scale.	Users' understanding of AI showed moderate positive correlations with trust in its decisions (ps<.001)
Diprose et al., 2020	Cross-sectional study (N = 1322). Aim: evaluating the explainability of three ML outcomes	ML risk calculator aimed at support physicians' decisions in the diagnosis of pulmonary embolism.	Two global XAI methods: Variable importance, Individual Conditional expectation plots. Two local XAI methods: LIME, SHAP.	2 items. Example: "To what degree does the software's decision make sense to you?" 4-Point Likert scale.	Single item: "Would you follow the software's recommendation?" (Yes/No).	Significant correlations (ps < .001) between understanding and explainability, understanding and trust, explainability and trust.
Druce et al., 2021	Experimental design (N = 60). Aim: exploring AI system trustworthiness.	AI system aimed at recreational gaming, equipped with an automatic agent playing a video game.	3-fold explanation: AI performance graphics, agent proficiency in similar settings, narrative graphic information.	Group 1: XAI interface and 15-minute training session on how to use the system; Group 2: more straightforward interface and no additional training.	8 items. Example: "I understand how the Automated Game Player works – its goals, actions and output".	XAI framework boosts user trust. Group 1 shows more satisfaction, usability, usefulness than Group 2.
Ewerz et al., 2021	Mixed method design: survey and semi-structured interview (N = 20). Aim: evaluate users' perception of XAI dimensions and trust.	AI calculator aimed at processing users' data to calculate the risk of infection and mortality regarding COVID-19.	Explanations of how AI calculates assessment risk by highlighting the most influential variables.	12 items related to clarity, comprehensibility, and usefulness of the system-provided explanations.	6 items assessing four aspects of trust in XAI: reliability, transparency, fairness, and user-centeredness.	Transparency, reliability, fairness, and user-centeredness affect trust. Some users find AI results hard to understand.
Leichtmann et al., 2022	Experimental design (N = 410). Aim: Compare user trust in XAI versus non-XAI interfaces. Conditions: simple interface (Group 1) and XAI interface (Group 2).	AI system aimed at categorizing a mushroom image into one of 18 species and indicates its edibility.	Both interfaces show a mushroom image, edibility, and similar poisonous types. The XAI interface explains predictions and provides matching species images.	1 single item for each mushroom evaluation: "I understand how the AI arrives at this mushroom classification"(5-point Likert scale).	1 single item for each AI decision: "I trust this mushroom identification of the AI"(5-point Likert scale).	Group 2 trusts and AI classification less. Visual explanations prevent over-trust, fostering trust calibration.
Ochmann et al., 2020	Two-factorial, between-subject study (N = 120). Aim: explore acceptance and trust in anthropomorphic, non-anthropomorphic, XAI, no-XAI AI system.	AI job recommender system for HR management aimed at suggesting suitable job types for users.	AI suggests jobs, each rated on eight dimensions. In two scenarios, participants learn about AI's data processing.	Researchers defined AI explainability pre-study. XAI scenarios: explainable text vignettes and interfaces showing explanations.	Single item: "To what extent do you trust the opinion of AI in making decisions?"(7-point Likert scale).	Anthropomorphic design has a positive effect on acceptance, and on trust in XAI conditions. Trust do not affect acceptance.
Papenmeier et al., 2019	Experimental design (N = 327) Aim: Test if the level of explainability impact on trust.	ML system aimed at identifying offensive texts on social media.	Input features (single words) highlight the texts' most decisive words by color.	3 levels of explanation fidelity (high-fidelity, low, no explanation) and 3 levels of explanation accuracy (high, medium, low).	Subjective trust: Items from Korber (2018). Example: "I trust the system". Latent trust: observational measure.	Explainability level affects trust. Medium accuracy do not harm user trust. Low-fidelity explanation decreases trust.
Rainey et al., 2022	Experimental design by survey (N = 411) Aim: To explore users' trust and perceptions of XAI systems in healthcare.	AI systems commonly used by UK radiographers aimed at support image-based diagnosis decisions.	Visual explanations; indicators of the overall XAI performance.	Single item: "I understand how an AI system reaches its decisions" (7-point Liker scale).	Single item: "On a scale of 0 e 10, how trustworthy do you consider AI systems for use in image interpretation decision support?".	Mean level of trust is 5.28 (SE = 0.28). System performance indications and visual explanations are crucial features inspire trust.
Wanner et al., 2021	Mixed design (between- and within-subject) (N = 204). Aim: compare users' goodness perception of explainability on six ML algorithms.	Six ML algorithms aimed at performing statistical analyses on 4 different datasets.	Six ML XAI techniques: Linear regression, Decision tree, Graphical model, Support vector, Ensemble, ANN.	4 items. Example: "How understandable do you find the above explanation?"	Single item: "How trustworthy do you perceive the algorithm to be?"	Trustworthiness influences overall perceived explainability.
Weitz et al., 2019	Experimental design (N = 30). Two user groups interacting with AI. Group A: visual explanations; Group B: virtual agent.	A neural network model rained on a vocabulary speech dataset aimed at keyword classification.	Visual and textual explanations. A virtual agent giving feedback on Group A's interactions and system predictions.	5 items helpfulness, understanding, trustworthy, interactions, and likeableness. User's feedback collection.	Trust in Automation Questionnaire (Jian et al., 2000). 12 items Example: "The system is deceptive" (7-point Likert scale).	Users are less suspicious when explanations are provided. Group B shows more trust than Group A.
Aechtner et al., 2022	Experimental design (N= 60). Aim: compare users' perceptions of explanations generated by LIME, SHAP, and PDP.	LIME, SHAP and PDP aimed at performing the admission process of students for graduate schools.	SHAP, LIME and PDP visual explanations.	2 Items: "Do you understand how the model decides?" "Does the explanation provide sufficient information?"	Single item: "Does the explanation increase the user's trust in the model?"	Trust in PDP (M=4.84) and in LIME (M=4.74) explanations are higher than trust in SHAP explanations (M= 3.85).
Bernardo and Seva, 2022	Synchronous between-subjects experimental design (N = 378). Aim: investigate user emotions and perceptions of AI-generated explanations.	AI system aimed at image classification.	Explanation of decisions showing the proportion of similar images in its dataset and their classification	GoogleLens logic flow is used to develop an "effective design" XAI system	Trust assessment scale by Frazier et al. (2013). Example: "I trust the system even if I have little knowledge of it"	Latent trust increases with confidence and decreases with fear or discomfort. Perceived system usefulness positively affects trust.

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