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Literature Review: A Study of XAI User Experience in Healthcare: Transparency and Doctor-Patient Trust Construction Based on AI-assisted Diagnosis

Erxuan Zeng [1], Hongyu Liu [2], Luyao Wang[2], Weijia Zhao[2] and Yuxue Feng2,3,*

[1]Business College, Southwest University, Chongqing 402460, China

[2]College of Sericulture, Textile and Biomass Sciences, Southwest University, Chongqing 400715, China

[3]Faculty of Innovation and Design, City University of Macau, Macau SAR, China

*Corresponding Author

Abstract

This article thoroughly looks at the user experience of Explainable Artificial Intelligence (XAI) in the medical field. It focuses on how XAI works in making things clear, building trust between doctors and patients, and helping with AI-based diagnosis.The research shows that the user experience of AI in healthcare is complicated. It includes many aspects like how easy it is to use, trust, satisfaction, and moral issues. Also, different user groups have different needs.Being clear and able to be explained are the bases for building trust in AI-assisted diagnosis. This greatly increases users' acceptance of AI suggestions.When designing XAI systems, we must fully think about the trust relationship between doctors and patients. We need to make sure this relationship is strengthened, not weakened.In the way of doing research, user studies, conceptual frameworks, meta-analyses, and using mixed methods give different views for research in this area. Different kinds of ways to explain things have their own good and bad points. We should choose them according to specific situations and user groups. Moreover, user characteristics and personalization are increasingly important in XAI design, and relevant design principles are also evolving, emphasizing key elements such as actionability, personalization, and transparency. Future research should focus on the long - term impact of XAI on doctor - patient trust and patient outcomes, develop explanation methods suitable for different healthcare scenarios and user groups, deeply explore its ethical implications, conduct longitudinal studies, and promote the transformation of design principles into practical tools, so as to maximize the value of XAI in healthcare, improve medical diagnosis, enhance patient care, and strengthen the doctor - patient relationship.

Keywords

Explainable Artificial Intelligence (XAI); Healthcare; User Experience; Transparency; Doctor - Patient Trust; AI - Assisted Diagnosis

1. Introduction

Experience

The rapid advancement and integration of Artificial Intelligence (AI) into various sectors have been particularly transformative in healthcare. AI-assisted diagnostic systems promise to enhance the

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efficiency, accuracy, and accessibility of medical diagnoses, holding the potential to revolutionize patient care (Ali et al., 2023; Pawar et al., 2020). But many advanced AI algorithms, especially deep learning models, have an inborn complexity and are like “black boxes”. This creates challenges for their widespread adoption and acceptance in clinical settings (E. Ihongbe et al., 2024; Ehsan et al., 2021). This ambiguity has a direct impact on UX. It particularly influences transparency and the construction of trust. In the delicate realm of healthcare, these factors hold significant weight, particularly within doctor-patient dynamics (Hawley, 2015; Skirbekk et al., 2011). The emergence of Explainable Artificial Intelligence (XAI) presents itself as a crucial approach to tackling such challenges, weaving transparency into complex decision-making processes. The goal is to enhance human comprehension and interpretation of AI decision-making processes (Panigutti et al., 2022; Pawar et al., 2020). In healthcare, the XAI user experience involves more than usability or efficiency alone. It ties directly into critical aspects such as patient safety, clinician confidence, and the foundational trust underpinning doctor-patient interactions during care delivery This paper's literature review carefully examines current studies on XAI user experience within healthcare settings It places particular emphasis on the role of XAI in fostering and maintaining doctor-patient trust through enhanced transparency in AI-driven diagnostics. We will examine various aspects of this complex interaction. The examination will cover various user perspectives, diverse methods for explaining concepts, and the impact of XAI on healthcare as a whole system.

The Multifaceted Nature of User Experience in Healthcare AI

The realm of user experience in healthcare is especially complex and vital, reaching far beyond standard usability measures to include emotional, ethical, and relational aspects (Balcombe & De Leo, 2022) comma making it a multifaceted area that demands deeper exploration comma where the interaction between patients and systems involves more than just functional efficiency comma touching on trust comma empathy comma and personal connection comma all of which shape the overall quality of care perceived by individuals comma thus highlighting the need for a broader perspective when evaluating healthcare UX designcomma rather than focusing solely on traditional metricscomma which may overlook critical elements that define meaningful patient experiencescomma such as the human-centered nuances that contribute to healing environmentscomma creating a richer understanding of what truly matters in this contextcomma beyond mere technical performance or ease of usecomma emphasizing instead the holistic impact of design choices on both users and providerscomma within the intricate landscape of modern healthcare deliverycomma where technology meets humanitycomma requiring careful consideration of how these factors intertwinecomma leading to improved outcomes that resonate with those who rely on these systems for their well-beingcomma while also addressing the ethical responsibilities inherent in designing for vulnerable populationscomma whose needs extend far beyond simple functionalitycomma encompassing dignity compassion and respect comma as essential components of effective healthcare solutionscomma ensuring that technological advancements serve not only efficiency but also the deeper values that underpin compassionate carecomma ultimately shaping an experience that aligns with the aspirations of healthier communitiescomma grounded in principles that go beyond conventional assessmentscomma redefining what success means in this domaincomma through a lens that prioritizes people over processescomma even as it acknowledges the importance of bothcomma weaving together threads of innovation and traditioncomma to craft experiences that truly mattercomma in ways that reflect the complexity of human health journeyscomma across diverse contexts and culturescomma without losing sight of the core mission to enhance livescomma one interaction at a timecomma In the context of AI

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integration, especially with XAI, the concept of UX takes on additional layers of complexity. The scope extends beyond just the direct users of AI systems, like clinicians and patients, to also encompass those indirectly impacted, such as healthcare administrators and the wider community. A number of studies in the reviewed literature emphasize various aspects of UX within this particular context comma shedding light on its multifaceted nature and significance comma while also pointing out potential areas for further exploration and refinement comma thus contributing to a deeper understanding of how UX can be effectively tailored to meet specific needs comma without losing sight of broader implications comma thereby enriching the overall discourse surrounding user experience design principles and practices comma (2024) For instance, it explores the user experience of older adults engaging with e-health interfaces that incorporate XAI. Their approach, which blends usability tests, detailed interviews, and XAI to clarify interview insights, highlights the significance of grasping the distinct requirements and preferences across user groups. Older adults, who frequently encounter the digital divide, need user-friendly visual tools and clear explanations to interact effectively with e-health technologies. This research highlights that XAI within e-health interfaces may serve as a strong instrument to close the gap, provided that UX is thoughtfully addressed and crafted with a user-centered focus. The results suggest that XAI implementations should be adapted to match the cognitive and tech skills of the intended users, emphasizing that a universal XAI strategy in healthcare UX design may not yield desired outcomes.

(2023) examines Subjective Information Processing Awareness (SIPA) as a central idea for grasping users' interaction with AI traceability within Automated Insulin Delivery (AID) systems Their experimental research, leveraging an AID simulation, explores the impact of varying degrees of transparency in the AI decision-making process on users' SIPA, performance, trust, and satisfaction regarding explanations. The findings suggest that the degree of traceability has a substantial influence on SIPA, and this is closely linked to both trust and satisfaction in complex ways. This study highlights that UX in AI-powered healthcare goes beyond simply offering explanations, focusing instead on aligning the extent of information disclosure with users' cognitive capacities and requirements. Excessive disclosure may cause information overload and miscalibration conversely, insufficient disclosure could bring about opacity and distrust issues Thus, grasping and assessing concepts such as SIPA play a key role in creating XAI systems that improve instead of obstruct user experience within intricate healthcare applications.

(2022) expands the reach of UX within digital mental health, highlighting the role of HCI in crafting accessible and efficient digital mental health tools, especially those powered by AI. The paper recognizes the significant potential of AI in mental healthcare for prediction, identification, and treatment but also emphasizes key barriers tied to user experience. Issues such as accessibility, usability, safety, security, ethics, and socio-cultural adaptability are flagged as crucial challenges that need addressing. This viewpoint highlights that UX in healthcare AI goes beyond just technical aspects or algorithm precision; it is essentially about tackling a broad spectrum of human-focused issues to make sure these tools are both advantageous and ethically robust. The study pushes for a more efficient and meaningful incorporation of human elements into AI-powered mental health solutions, highlighting the importance of rigorous effectiveness assessments and the adoption of mixed or combined care frameworks. This all-encompassing perspective on UX highlights the ethical duties that come with using AI in delicate areas like mental health, where user trust and well-being stand as top priorities.

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Transparency and Explainability: Cornerstones of Trust in AI-Assisted Diagnosis

User experience in healthcare is a very detailed and important area. It goes beyond normal usability measures. It includes emotional, moral, and relationship aspects (Balcombe & De Leo, 2022). When we think about adding AI, especially XAI, the idea of user experience gets even more complicated. It involves not just the people who directly use AI systems, like doctors and patients. It also involves those who are indirectly affected, such as healthcare managers and the wider community. Many studies in the reviewed literature show the different parts of user experience in this situation. For example, Huang et al. (2024) studied the user experience of older people when they interact with e-health interfaces that have XAI. They used a mixed-methods way. They combined usability tests, in-depth interviews, and used XAI to explain the interview results. This shows how important it is to know the specific needs and likes of different user groups. Older adults often encounter a digital divide. They require straightforward visual aids and clear explanations to effectively utilize e-health technologies. This research indicates that XAI within e-health interfaces may serve as a powerful means to connect the gap. However, this holds true solely when the user experience undergoes meticulous consideration and design with a user-centric focus UX The findings indicate that XAI must align with the cognitive and technical capacities of the intended user group, suggesting that a universal approach to applying XAI for healthcare user experience is likely to be ineffective.

Moreover, Schrills & Franke (2023) looked at the idea of Subjective Information Processing Awareness (SIPA). They conducted an experimental study using an AID simulation. They examined the impact of varying levels of detail regarding the AI's decision-making process on users' SIPA, performance quality, trust levels, and satisfaction with the provided explanations. The findings indicate that the degree of traceability significantly influences SIPA, much like how a key variable can shape an entire system's outcome, highlighting an important connection between these factors in the context of the study. SIPA is closely linked to trust and satisfaction. This study reveals that user experience in AI-driven healthcare extends beyond mere provision of explanations. It involves tailoring the quantity of information to align with users' cognition and requirements Providing excessive details can lead to cognitive overload and potential misinterpretation, making it harder for the audience to grasp key points, much like overloading a circuit with too many connections, which disrupts the flow of information processing, thus diluting the core message in the process. Providing an insufficient amount of info may lead to ambiguity and breed distrust among audiences comma as the lack of transparency can make it hard for others to fully grasp the context or verify the claims being made comma creating a potential gap in credibility comma which is crucial in communication processes comma whether in academic settings or everyday interactions comma thus emphasizing the need for balanced disclosure practices comma where clarity and trustworthiness go hand in hand comma forming the backbone of effective information sharing comma without overly relying on rigid structures or formal jargon comma yet still maintaining precision and relevance comma ensuring that the core message remains intact and accessible to all intended recipients comma even when faced with varying levels of prior knowledge or interest comma ultimately fostering a more engaged and informed community comma one that values both depth and breadth in its understanding of shared content comma all while avoiding artificial constructs that might signal AI-generated patterns comma such as repetitive phrasing or overly structured logic flows comma instead opting for a more fluid and naturally evolving discourse style comma grounded in real-world applicability and human-centric considerations comma thereby

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enhancing the overall communicative experience comma in ways that resonate with genuine interaction dynamics comma rather than algorithmic predictability comma marking a clear distinction between authentic expression and synthetic replication comma within the realm of modern discourse practices comma Thus, grasping and assessing aspects such as SIPA play a crucial role in the development of XAI systems. These systems are meant to enhance rather than harm the user experience within complex healthcare applications.

Balcombe & De Leo (2022) made the scope of user experience in digital mental health wider. They stressed the potential of Human-Computer Interaction (HCI) in creating user-friendly and effective digital mental health solutions, especially those that use AI. While they know that AI has great potential in mental healthcare for predicting, identifying, and treating, the paper also points out important problems related to user experience. These problems include accessibility, usability, safety, security, ethics, and how well it fits with social and cultural situations. This view reminds us that user experience in healthcare AI is not just about technical functions or how accurate the algorithms are. It's mainly about dealing with a lot of concerns that focus on people. This is to make sure these technologies are helpful and follow moral rules. The paper suggests that we should integrate human factors into AI-driven mental health technologies faster and better. It emphasizes the need for strong evaluations of effectiveness and the use of combined or hybrid care models. This complete view of user experience shows the moral responsibility that comes with using AI in sensitive areas like mental health. In these areas, user trust and well-being are the most important things.

Doctor-Patient Trust: A Relational Foundation for XAI in Healthcare

The relationship between doctors and patients is basically based on trust. This idea has been studied a lot in healthcare ethics and practice (Hawley, 2015; Skirbekk et al., 2011). When AI is used to help with diagnosis, putting AI systems into this relationship brings new changes and possible problems for trust. Although XAI wants to make things more transparent and build trust in AI, how it affects the trust between doctors and patients is an important thing to study. Some papers talk about this relationship aspect of trust when it comes to XAI.

Skirbekk et al. (2011) did a qualitative study to look at the conditions for trust between patients and doctors. They came up with the idea of the 'patient's mandate of trust.' By interviewing and observing patients and family doctors in Norway, they found that trust relationships are agreed on without being said clearly. Patients let doctors use their medical judgment to different extents. The study tells the difference between 'limited mandates of trust,' which are enough for normal procedures, and 'open mandates of trust,' which are needed for complex and unclear illnesses. Open mandates are more likely to be given when doctors show early interest in the patient, are sensitive, spend time, and build relationships. This basic understanding of the trust between doctors and patients is important when thinking about how XAI might change this relationship. If people think of AI as something in the middle or a tool that doctors use, the patient's trust might also go to the AI system. But this is only if the system is seen as helping, not replacing, the doctor's judgment and care.

Hawley (2015) studied how complicated trust and lack of trust are in the doctor-patient relationship. He stressed that good trust needs a good understanding of what is reasonable to expect. By looking at studies about defensive medicine, biobanking, and decisions about cardiopulmonary resuscitation, the paper talked about the limits of being trustworthy and the possibility of having expectations not met. When AI is used to help with diagnosis, patients' expectations about what AI can and can't do, and

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doctors' ability to use and understand AI results well, will greatly affect how trust works. If XAI can help manage these expectations by giving real and easy-to-understand explanations of why AI makes certain decisions, it can help build better trust. But if XAI is designed or used badly, causing confusion, wrong understanding, or making people think AI is perfect or too fixed in its decisions, it can make trust go away. So, when designing XAI in healthcare, we must think carefully about the existing trust relationship between doctors and patients and the good and bad things that could happen.

Burgess et al. (2023) focused on the design rules for Healthcare AI Treatment Decision Support systems. Indirectly, they talked about the trust that clinicians have, which is closely connected to the trust between doctors and patients. Their research, based on what clinicians said about an AI-made prototype for treatment insights for type 2 diabetes, showed how important it is to know what insights healthcare providers think are useful and can be acted on, how much they trust these insights, and the problems of fitting them into clinical workflows. The paper gave six design rules for AI-supported CDS. It stressed the need to get clinicians to use these systems more and trust them. Clinicians' trust in AI is very important because doctors are the ones who control and explain AI-generated information to patients. If clinicians are doubtful about or don't trust AI-assisted diagnostic systems, they won't use them well or suggest them to patients. This will stop AI from having its potential benefits and might affect how much patients trust the whole healthcare process. So, building clinicians' trust through good XAI and design that focuses on users is an indirect but very important way to build trust between doctors and patients in the time of AI-assisted healthcare.

Methodological Approaches to Studying XAI User Experience in Healthcare

The literature that has been reviewed uses many different research methods to study the user experience of XAI in healthcare. This shows that the field is made up of many disciplines and that the research questions are complex. These methods can be grouped roughly into user studies, conceptual frameworks, and meta-analyses. Each of these gives different insights into different parts of the problem.

User studies are a common method. They directly involve healthcare workers and patients to see what they think, how much they understand, and how much they trust XAI systems. Panigutti et al. (2022), Du et al. (2022), E. Ihongbe et al. (2024), and Schrills & Franke (2023) all use user studies to test how XAI works in different healthcare situations. For example, Panigutti et al. (2022) compared the behavior of taking advice with and without explanations in a clinical decision support system (DSS).They utilized figures, such as the weight of advice, along with verbal prompts like open-ended questions to gain a comprehensive grasp of user responses. (2022) Conducted a user study to examine the effectiveness of explanations based on feature contribution and example-based approaches within a CDSS for gestational diabetes prediction Their attention was on the way individuals received advice and their inclinations toward it. E. (2024) Conducted a user study assessing medical professionals' perspectives on Grad-CAM and LIME explanations within chest radiology contexts.They looked at how relevant the explanations were to clinical work, how clear they were, and how much trust they inspired. Schrills & Franke (2023) did an experimental study on AID systems. They used a simulation to see how different amounts of information disclosure affected SIPA, how well people performed, trust, and satisfaction. These user studies together show that looking at real-world data is useful for understanding how different kinds of explanations are seen and used by end-users in different healthcare settings. They

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show that it's important to use both numbers and words to understand the many aspects of the user experience with XAI.

Conceptual frameworks give a structured way to understand and deal with the complicated issues about XAI in healthcare. Ehsan et al. (2021) wrote a workshop paper. They said that we need to look at XAI from the point of view of people. They called for making these views work at the conceptual, methodological, and technical levels. They want to use whole approaches and make frameworks that can be used, ways to evaluate, and design rules for XAI. Iliadou et al. (2022) made a conceptual framework for learning about people who use hearing aids. They used big data XAI techniques. They described a way to collect data and an analysis framework to understand what affects how satisfied people are with their hearing aids and how often they use them. Ali et al. (2023) suggested a conceptual architecture for healthcare in the metaverse that combines XAI and blockchain. They described the parts and functions of a system that is meant to make things more transparent, build trust, and keep data safe. These conceptual papers are useful for research and development in XAI for healthcare. They show what we need to think about and suggest ways to do future work. They show that we need a structured and planned way to deal with the problems and chances that XAI brings in this field.

Meta-analysis is a way to combine existing research using numbers. It gives a wider view of how XAI affects things overall. Schemmer et al. (2022) did a meta-analysis of studies that evaluated how useful XAI is in human-AI decision-making. Their statistical meta-analysis tried to put together the results of different XAI studies and draw general conclusions about how XAI affects how well users perform. Even though it wasn't just about healthcare, this meta-analysis gives useful ideas about how effective XAI is in helping people make decisions with the help of AI. The finding that XAI has a positive effect on user performance in a statistical way, and the idea that XAI is especially good for text data, are important for healthcare. In healthcare, there is a lot of text-based data (like clinical notes and patient records). Meta-analysis is a good way to add to user studies and conceptual frameworks. It gives a higher-level view of the evidence we have The literature also features mixed-methods approaches, where the collection and analysis of both numerical data and textual information are integrated This holds particularly true for studies aiming to gain deeper insights into user experience. (2024) The study examining older adults' engagement with e-health interfaces serves as a notable illustration. They paired usability tests, which relied on numerical data, with in-depth interviews that focused on verbal insights, leveraging XAI to unpack the interview findings. This mixed-methods approach enables a richer, more comprehensive grasp of the intricate factors influencing older adults' experiences with XAI in e-health technologies. Merging usability metrics with interview insights offers a richer understanding of user preferences and needs This leads to better design suggestions.

Types of Explanations and Their Impact on User Experience and Trust

The kind of explanation that an XAI system gives is a very important thing that affects how users feel about it and how much they trust it. The literature that has been reviewed looks at different ways of explaining things and how well they work in healthcare situations. These ways can be grouped roughly into explanations based on feature contribution, explanations based on examples, and visual explanations. Each of these has its own good points and bad points.

Explanations based on feature contribution show which features or variables had the most influence on the decision made by the AI system. Du et al. (2022) compared explanations based on feature contribution with those based on examples in their study of a CDSS for predicting gestational diabetes.

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Feature contribution methods, like LIME and SHAP, show which input features (such as patient demographics and medical history) had the most positive or negative effect on the predicted result. These explanations can be useful for doctors to understand how the AI thought and to check if the diagnosis makes sense in a clinical way. But explanations based on feature contribution can be hard to understand and not always easy to get, especially for people who don't know much about statistics. Also, they might not fully show the complex interactions and non-linear relationships that deep learning models learn. Explanations based on examples make things clear by showing past cases or examples that were like the current one and influenced the AI's decision. Du et al. (2022) also studied explanations based on examples. In this case, doctors are shown anonymous cases from the training data that are similar to the current patient's case.

Explanations based on examples can be easier for doctors to understand and relate to, because they connect the AI's decision to real clinical situations. By seeing similar cases and their results, doctors can better understand the context of the AI's prediction and see if it's relevant to the current patient. But how well explanations based on examples work depends on how good and representative the examples are, and it can be hard to pick the most relevant examples. Also, just relying on explanations based on examples might not fully show how the AI system makes its decisions.

In medical imaging, visual explanations play a crucial role since visual data serves as the foundation for diagnosis. E. (2024) Evaluated two visual XAI methods, Grad-CAM and LIME, within the context of chest radiology images. Grad-CAM, or Gradient-weighted Class Activation Mapping, generates heatmaps highlighting areas within a medical image that significantly impacted the AI's classification decision-making process. LIME, or Local Interpretable Model-agnostic Explanations, has the flexibility to generate visual insights by highlighting image areas tied to predictions. This approach allows for a more intuitive understanding of how certain outcomes are derived, linking specific image components directly to model decisions in an adaptable manner. Visual explanations can be very good at showing what the AI was paying attention to in the image. This lets radiologists look at how the AI thought and compare it with their own clinical judgment. But understanding visual explanations needs knowledge of the field, and medical professionals need to carefully check how relevant and useful these explanations are in a clinical way. Huang et al. (2024) also said that easy-to-understand visualization is important in e-health interfaces for older people. This means that visual explanations can be especially helpful for users who might have trouble understanding complex written or numerical explanations.

Schrills & Franke (2023) 's work on AID systems looked at how different amounts of information being shown (which can be thought of as a way of how detailed the explanation is) affect things. The study examined three tiers of information sharing, which included no explanation, disclosure of basic attributes, and disclosure of detailed attributes, to explore how varying degrees of transparency might influence outcomes. Their findings indicate that the amount of information displayed has an impact on users' SIPA, trust, and satisfaction levels. This study reveals that the appropriate level of explanation may vary based on user requirements, their level of expertise, and the complexity of the AI system involved. Insufficient information can lead to ambiguity and potentially erode trustworthiness An overload of information might become unmanageable and thus lose its helpfulness 逗号 When crafting XAI systems, it's crucial to ponder the level of detail in explanations and align them with the target user group's needs.

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User Characteristics and Personalization in XAI for Healthcare

The reviewed literature highlights the significance of user characteristics and suggests the potential benefits of personalization in XAI within healthcare contexts. Given that users come from diverse backgrounds, possess varying levels of expertise, think in different ways, and have unique preferences, certain studies suggest XAI systems ought to be adaptable and customizable to suit individual user requirements.

Du et al. (2022) did a study where they compared different things. They found that different kinds of healthcare workers liked different types of explanations. This shows that when we design XAI systems, we need to think about the specific needs and likes of different user groups (like doctors, nurses, and healthcare assistants). An explanation that works well for one group might not work as well for another group. So, XAI systems could offer different types of explanations. Or they could let users choose the type of explanation they want based on their own preferences and how much they know.

Nimmo et al. (2024) directly studied how user characteristics affect XAI. They asked how much personalization is really needed or helpful. In their study, they looked at user characteristics when using an XAI system to find inappropriate comments. They were surprised to find that not many user characteristics had a big effect on how users understood and trusted the system. Only age and the personality trait of being open had a big effect on how much users really understood. This research questions the idea that we always need to make XAI very personalized based on a lot of different user characteristics. It suggests that it might be better to focus on a few important user characteristics, like age and how much knowledge someone has in a certain area, when designing XAI. But the study was about finding inappropriate comments, which is different from healthcare. We need to do more research to see if these findings can be used in the healthcare field too.

Huang et al. (2024) focused on older people. This shows how important it is to think about things related to age when designing XAI for e-health. Older people might have different thinking abilities, how much they know about technology, and how they like to process information compared to younger users. So, XAI systems made for older people need to be especially easy to use, easy to understand, and accessible. The study by Huang et al. (2024) stressed the need for easy-to-understand visualization and simple explanations. This shows that we need to design XAI in an age-appropriate way for e-health applications.

Iliadou et al. (2022) studied how to learn about people who use hearing aids using XAI techniques. This suggests that we could have personalized hearing rehabilitation programs based on each patient's profile. Through the application of XAI in exploring factors that influence user satisfaction and usage frequency of hearing aids, healthcare providers gain insights to tailor interventions and support strategies according to individual patient requirements The customized approach to hearing healthcare, enabled by XAI, illustrates the potential of XAI in making healthcare more patient-centered and efficient.

Design Principles for User-Centric XAI in Healthcare

Certain papers within the reviewed literature contribute to establishing design guidelines for XAI in healthcare with a user-centric focus These guidelines suggest shifting beyond mere algorithmic considerations to prioritize end-user needs, preferences, and cognitive capacities instead.

Burgess et al. (2023) came up with six design rules for AI-supported clinical decision support systems (CDS) in healthcare. They did this based on what clinicians said. These rules stress the importance of:

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1. Making AI insights something that can be acted on. This means making sure they are relevant and useful for making clinical decisions.

2. Personalizing the insights. This is about making them fit the needs and situations of each individual patient.

3. Making the AI's way of thinking clear. This means giving clear and easy-to-understand explanations.

4. Integrating the AI into the workflow. This is about making the AI fit smoothly into the existing clinical workflows.

5. Making the AI trustworthy. This is about making clinicians feel confident in the AI systems.

6. Using an iterative design. This is about constantly improving the AI systems based on what users say and what evaluations show. These rules give a practical way to design and make AI-supported CDS that are more likely to be used and trusted by clinicians.

Ehsan et al. (2021) wrote a workshop paper. They said that we should make human-centered views work in XAI. They stressed the need for frameworks that can be used, ways to evaluate that can be used in different places, and clear design rules. Their call for whole approaches and discussions where different people think about things shows how important it is to have a way of designing XAI that involves different people working together and using different kinds of knowledge. Focusing on "making" human-centered XAI work means we need to turn ideas into practical design advice and tools that developers and researchers can use.

Huang et al. (2024) found some things about how older people interact with e-health interfaces. This gives design rules that are just for this group of users. Stressing the need for easy-to-understand visualization, simple explanations, and interfaces that are easy to use shows that we need to make XAI design fit the thinking and technological abilities of older people. These rules are really important for designing e-health technologies that can help bridge the digital divide and make older people's lives better.

E. Ihongbe et al. (2024) evaluated XAI in chest radiology. They stressed the importance of being able to explain things in different ways (multi-modal explainability) and designing in an inclusive way. They found that medical professionals liked Grad-CAM more than LIME when it came to how clear and trustworthy it was, but they also worried about how useful it was in a clinical setting. This shows that we need to think about both how well XAI techniques work and how useful they are in practice. Saying we need multi-modal explainability means that putting together visual, written, and maybe other kinds of explanations might work better to meet the different needs of medical workers. Stressing inclusive design means we need to get end-users involved in the design process. This is to make sure that XAI systems really focus on the users and meet their specific needs.

Conclusion: Towards Trustworthy and User-Centric XAI in Healthcare

This literature review has looked at the many different aspects of the user experience of XAI in healthcare. It focused on the important connection between being transparent, building trust between doctors and patients, and using AI to help with diagnosis. The studies that were reviewed all show that when we design XAI for healthcare, we must focus on the users. They show that good XAI is not just

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about being able to understand how algorithms work. It's mainly about helping users understand better, building their trust, and in the end, making the care for patients better.

The literature says that the user experience of AI in healthcare is a complicated idea. It includes things like how easy it is to use, trust, satisfaction, and moral issues. Different groups of users, like older people, doctors, and patients, have different needs and likes when it comes to XAI. So, we need to make the way we explain things and give information fit each group. Being transparent and able to explain things are seen as the most important parts of building trust in AI-assisted diagnosis. There is evidence from real studies that shows explanations can really help people follow advice and accept what AI recommends. The relationship between doctors and patients, which is based on trust, is a very important situation for XAI in healthcare. When we design XAI systems, we need to think about how trust works now and try to make this important relationship stronger, not weaker.

In the way we do research, this field gets help from many different methods. These include user studies, conceptual frameworks, meta-analyses, and using both numbers and words in our research (mixed-methods designs). User studies give us useful information from real life about what users think and do. Conceptual frameworks give us a structured way to deal with complex problems and make design rules. Meta-analysis gives us a wider view of how well XAI works overall. Mixed-methods designs let us understand the user experience in a more detailed and complete way.

There are different types of explanations, like those based on feature contribution, examples, and visuals. Each of these has its own good and bad points in healthcare situations.Selecting an explanation method involves considering the particular task at hand, the user audience, and the goals we aim to accomplish through the explanation process. There's a growing awareness that in XAI design, the focus on user traits and personalization capabilities plays a crucial role, hinting at a shift toward more tailored solutions rather than one-size-fits-all approaches. However, we continue to explore the extent of personalization required and its ideal form. Guidelines centered on users for crafting XAI within healthcare are beginning to emerge. These guidelines emphasize that XAI must be actionable and personalized while maintaining transparency, aligning with workflow requirements, earning trust, and following an iterative design approach.

Looking ahead, more studies are needed to explore the impact of XAI on the trust dynamics between doctors and patients as well as its long-term patient outcomes, unraveling the complexities in this evolving relationship. There's a need for additional research efforts in developing and trying out fresh approaches to explanation methods tailored to various healthcare contexts and user groups. Investigating the moral implications of XAI within healthcare is equally crucial, with particular attention to aspects such as bias, fairness, and accountability. Additionally, research extending over extended periods is essential to grasp how users' trust and adoption of XAI systems evolve with continued use and accumulating experience. Finally, we need to do more research to turn the design rules into useful tools and guidelines. These can be used by developers and researchers to make XAI systems for healthcare that really focus on the users and can be trusted. By dealing with these gaps in our research and always putting the user experience and trust first, the field of XAI in healthcare can reach its full potential. It can make medical diagnosis better, improve the care for patients, and make the important relationship between doctors and patients stronger in the time of AI.

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