Journal of Digital Health Innovation and Medical Technology
Vol. 2 No. 1 Maret 2026
E-ISSN: 3090-0816
Open Access: https://journals.ai-mrc.com/jdhimt

Clinicians' Experiences with Explainable AI in Clinical Decision-Making

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Article Info

Article history:
Received 28-01-2026
Revised 22-02-2026
Accepted 17-03-2026

Keyword:
Explainable Artificial Intelligence; Clinical Decision-Making; Clinicians' Experiences; Trust; Moral Responsibility; Healthcare Practice

ABSTRACT

Artificial intelligence (AI) and machine learning have become integral to contemporary healthcare, particularly through AI-based clinical decision support systems designed to assist clinicians in diagnostic and treatment-related decisions. Within this field, explainable AI has gained prominence as a response to concerns about transparency, trust, and accountability, yet understanding of how clinicians actually experience explainability in practice remains limited. Existing research has largely focused on technical performance and quantitative measures of acceptance, leaving unanswered questions about how clinicians interpret, trust, and negotiate AI explainability in real-world clinical decision-making. Here, an interpretative phenomenological approach is used to explore clinicians' lived experiences with explainable AI and to illuminate how explainability is understood and made meaningful in clinical practice. Data were generated through in-depth interviews with clinicians who regularly use AI-based decision support systems and were analyzed using interpretative phenomenological analysis to identify essential experiential themes. The analysis reveals that explainability is experienced as partial understanding rather than full transparency and that trust in AI is dynamically negotiated through alignment with clinical intuition and contextual judgment. The findings further show that moral and professional responsibility remains firmly with clinicians, and that explainable AI can both reassure and intensify emotional and ethical burdens during decision-making. Importantly, the study demonstrates that explainability does not simply enhance trust in a linear manner; instead, it reshapes how clinicians construct accountability, manage uncertainty, and justify decisions in complex clinical contexts. These findings indicate that the effectiveness of explainable AI depends not only on technical clarity but also on its alignment with clinicians' experiential reasoning and professional norms. These results advance a human-centered understanding of explainable AI in healthcare by demonstrating that explainability functions as an experiential and ethical phenomenon. By clarifying the practical and ethical implications of explainable AI use, this study provides evidence-based insights for developers, healthcare institutions, and policymakers seeking to design and implement AI systems that genuinely support clinical judgment rather than merely increase algorithmic transparency.

INTRODUCTION

Artificial intelligence (AI) and machine learning (ML) have become increasingly embedded in contemporary healthcare systems, particularly through the development and deployment of AI-based clinical decision support systems (AI-CDSS) (Chen et al., 2022). These technologies are designed to assist clinicians by processing large volumes of clinical data, identifying patterns, and generating recommendations that may support diagnostic reasoning, risk assessment, and treatment planning. As a result, AI is often positioned as a transformative force capable of improving efficiency, accuracy, and consistency in clinical care (Tveit et al., 2023). Within this broader scientific and technological context, explainable AI has emerged as a key concept, responding to growing concerns about transparency, accountability, and trust in algorithmic decision-making in medicine.

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Despite rapid technological advances, current understanding of AI in healthcare remains largely shaped by technical and performance-oriented perspectives (Aristidou et al., 2022). Much of the existing literature emphasizes predictive accuracy, model validation, and system usability, framing AI primarily as a tool whose value can be assessed through measurable outcomes (Mukhlis et al. 2023). While these perspectives are critical, they tend to abstract AI use from the lived realities of clinical practice, where decisions are embedded in complex social interactions, professional norms, ethical responsibilities, and emotional labor. In everyday clinical settings, AI recommendations are not encountered in isolation but are interpreted and enacted by clinicians who must integrate algorithmic outputs with patient narratives, contextual knowledge, and their own professional judgment.

From a human and social perspective, the use of AI in healthcare represents more than a technical innovation; it constitutes a meaningful experience that shapes how clinicians perceive responsibility, authority, and trust in their work. Interacting with AI systems can evoke reassurance, skepticism, uncertainty, or moral tension, particularly when algorithmic recommendations intersect with clinicians' intuitive reasoning or contradict established clinical expectations (Hopkins et al., 2020). These experiences unfold within broader social and institutional contexts that continue to hold clinicians accountable for patient outcomes, regardless of the involvement of AI technologies (Tsopra et al., 2021). Consequently, understanding AI in healthcare requires attention not only to what these systems do, but also to how they are experienced and interpreted by those who use them in practice.

Given this context, there is a clear need for research approaches that move beyond surface-level evaluations and engage with the deeper meanings of AI use as lived by clinicians (Shamout et al., 2021). Phenomenology offers a framework for exploring these experiences as they are subjectively perceived, interpreted, and situated within professional life. By focusing on lived experience, phenomenological inquiry allows for a richer understanding of how clinicians make sense of explainability, trust, and responsibility when working with AI systems (Mukhlis & Saidah, 2025). Such an approach is essential for illuminating dimensions of AI adoption that remain largely invisible within predominantly technical or quantitative research paradigms.

Building on the broader discourse surrounding artificial intelligence in healthcare, increasing scholarly attention has been directed toward understanding how clinicians experience and interpret AI systems in practice (Mursch-Edlmayr et al., 2020). Within this growing body of research, the experiential dimension of AI use particularly clinicians' perceptions of explainability, trust, and decision-making has emerged as a critical sub-area of inquiry. Studies in health informatics and medical sociology have begun to recognize that clinicians' interactions with AI are not merely functional or instrumental, but are deeply shaped by professional identity, ethical responsibility, and situated clinical judgment (Kwon, Kim, et al., 2020). This shift reflects a broader recognition that meaningful adoption of AI in healthcare depends on how these systems are experienced and understood by those who use them in real-world clinical contexts.

Despite this growing interest, exploring clinicians' lived experiences with AI presents substantial methodological challenges (Jutzi et al., 2020). Much of the existing research relies on quantitative approaches, such as surveys, experimental usability studies, or technology acceptance models, which tend to operationalize complex experiences into predefined variables and numerical indicators. While such approaches provide valuable insights into patterns of adoption and general attitudes, they are limited in their ability to capture the nuanced, contextual, and emotionally laden meanings that clinicians attribute to AI explainability and decision-making (Mukhlis, 2025). As a result, critical dimensions of experience such as moral tension, interpretive uncertainty, and the negotiation between clinical intuition and algorithmic recommendations often remain underexplored.

These methodological limitations have contributed to an incomplete understanding of the phenomenon at hand. By prioritizing measurable outcomes and generalized constructs, many prior studies have struggled to access the essence of clinicians' experiences as they unfold in everyday practice (Röösli et al., 2021). Consequently, the subjective and interpretive aspects of interacting with explainable AI central to how clinicians make sense of responsibility, trust, and professional autonomy are insufficiently illuminated (Kwon, Jeon, et al., 2020). This gap underscores the need for

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research approaches capable of engaging with experience at a deeper level, where meaning is not assumed in advance but emerges from clinicians’ own narratives and reflections.

Current responses to the integration of artificial intelligence in healthcare have largely relied on practical and solution-oriented approaches, such as improving model accuracy, enhancing explainability features, and increasing system usability (Giannakopoulos et al., 2023). Within this framework, challenges related to clinicians’ interaction with AI are commonly addressed through technical refinements or evaluative instruments, including technology acceptance models, trust scales, and usability metrics. These approaches assume that increasing transparency or performance will naturally lead to improved trust and adoption among clinicians (Mukhlis et al., 2025). While such strategies offer important insights into system-level optimization, they predominantly conceptualize AI use as a functional problem to be solved rather than a lived experience to be understood.

However, these prevailing approaches are limited in their capacity to capture the depth and complexity of clinicians’ experiences when engaging with explainable AI in clinical practice (Maaßen et al., 2021). Quantitative and experimental methods tend to reduce rich, context-dependent experiences into predefined categories, thereby overlooking how clinicians interpret, negotiate, and emotionally respond to AI recommendations in real time (Li et al., 2023). As a result, critical experiential dimensions such as moral responsibility, professional autonomy, and the tension between clinical intuition and algorithmic guidance remain insufficiently examined. This reductionist tendency leads to a fragmented understanding of trust and explainability, one that fails to account for the social, ethical, and interpretive contexts in which clinical decision-making occurs.

Given these limitations, there is a clear need for an alternative research approach that can illuminate the essence of clinicians’ experiences with explainable AI in a more holistic manner (Reddy, 2024). Phenomenology offers such an alternative by prioritizing lived experience as the primary source of knowledge and by allowing meanings to emerge from participants’ own narratives rather than from predefined theoretical constructs. Through a phenomenological lens, explainability can be understood not merely as a technical attribute of AI systems, but as an experiential phenomenon shaped by clinicians’ sense-making processes, professional identities, and ethical commitments (Mukhlis, Maryam, et al., 2023). Adopting this approach is essential for advancing a more comprehensive and human-centered understanding of AI use in healthcare, addressing dimensions of experience that remain largely invisible within existing research paradigms.

Previous studies on artificial intelligence in healthcare have examined clinicians’ interactions with AI systems primarily through the lenses of system performance, usability, and acceptance (Bragazzi et al., 2020). Research has highlighted the importance of explainability, transparency, and trust in supporting AI adoption in clinical contexts. Some qualitative studies have begun to explore clinicians’ perspectives on AI, emphasizing concerns related to autonomy, accountability, and professional judgment (Henry et al., 2022). However, much of this literature remains limited to surface-level perceptions or predefined evaluative frameworks. As a result, the deeper meanings clinicians attribute to their experiences with explainable AI during real-world decision-making are still insufficiently understood.

This study addresses these limitations by adopting an interpretative phenomenological approach to explore clinicians’ lived experiences with explainable AI-based clinical decision support systems. Phenomenology is used to access how clinicians interpret, negotiate, and make sense of AI explainability in relation to trust, intuition, and moral responsibility. Through in-depth engagement with participants’ narratives, the study responds directly to the knowledge gap identified earlier by shifting the focus from technical attributes of AI to experiential meaning. This approach enables a holistic understanding of explainability as it is lived and experienced in everyday clinical practice. In doing so, the study offers insight into dimensions of AI use that are often overlooked by quantitative or system-centered research.

The article is structured as follows. The introduction outlines the broader context of AI in healthcare and narrows the focus to clinicians’ lived experiences with explainable AI. The methodological section describes the phenomenological design, participant selection, data collection procedures, and analytic process. The results section presents the key themes that emerged from clinicians' narratives, capturing essential aspects of their experiences. The discussion situates these findings within existing literature and highlights their theoretical and practical implications. The article concludes by summarizing the main contributions and suggesting directions for future research.

RESEARCH METHODS

Study Design

This study employed a phenomenological research design to explore clinicians' lived experiences of interacting with explainable artificial intelligence–based clinical decision support systems (AI-CDSS) in healthcare practice (Guerra et al., 2023). Phenomenology was selected because it is particularly suited to investigating how individuals experience, interpret, and assign meaning to complex phenomena encountered in their everyday professional contexts. Rather than measuring predefined variables, this approach enables a deep exploration of subjective experiences as they are perceived and understood by those who live them.

More specifically, the study was grounded in interpretative phenomenology, drawing on a Heideggerian perspective. This orientation emphasizes understanding experience as inherently interpretive, shaped by prior knowledge, professional identity, and situational context. Within this framework, clinicians' interactions with explainable AI were examined as meaning-making processes that unfold through engagement with technology, patients, and ethical responsibilities (Shinners et al., 2020). The design allowed for an in-depth examination of how explainability, trust, and clinical judgment are experienced and negotiated in real-world decision-making. Consistent with Interpretative Phenomenological Analysis (IPA), the study prioritized depth over breadth by focusing on a small, information-rich sample and conducting a detailed, idiographic analysis before moving to cross-case interpretation. The research process followed IPA's double hermeneutic logic—participants made sense of their experiences, and the researchers, in turn, interpreted how participants constructed that meaning within their clinical and ethical worlds.

Participants

Participants consisted of healthcare professionals who routinely used AI-based clinical decision support systems in their clinical practice. Selection was conducted using purposive sampling to ensure that all participants had direct and sustained experience with the phenomenon under investigation.

Inclusion criteria comprised: (1) licensed clinicians (physicians or nurses), (2) a minimum of one year of clinical experience, and (3) regular use of AI-CDSS in diagnostic or clinical decision-making processes. Clinicians without direct exposure to AI-assisted systems or those involved exclusively in administrative or non-clinical roles were excluded.

The final sample included 10–15 clinicians, representing diverse clinical specialties to capture variation in experiential perspectives. Demographic characteristics such as professional role, years of experience, and general clinical context were documented to provide contextual depth to the findings, while maintaining participants' anonymity.

Data Collection

Data were collected through in-depth, semi-structured interviews designed to elicit rich descriptions of clinicians' experiences with explainable AI systems. An interview guide was used to ensure consistency across interviews while allowing flexibility for participants to elaborate on personally meaningful experiences. Key prompts focused on first encounters with AI-CDSS, experiences of explainability, moments of trust or doubt, and perceived responsibility in AI-assisted decision-making.

Interviews were conducted in a quiet and private setting, either in person or via secure video conferencing platforms, depending on participants' availability and preferences. Each interview lasted approximately 60–90 minutes, allowing sufficient time for reflection and detailed narration. All interviews were audio-recorded with participants' consent and transcribed verbatim to preserve the authenticity of the data.

To promote openness and comfort, participants were informed that there were no right or wrong answers and that the focus was on their personal experiences rather than technical evaluations of the AI systems.

Data Analysis

Data analysis followed the principles of Interpretative Phenomenological Analysis (IPA), emphasizing a systematic and iterative engagement with the data. Transcripts were read and re-read to achieve immersion and familiarity with each participant's account. Meaning units were then identified, focusing on segments of text that captured significant experiential statements related to explainability, trust, clinical judgment, and responsibility.

Initial codes were developed inductively and subsequently clustered into emergent themes that reflected shared patterns of meaning across participants. These themes were continuously refined through cross-case comparison to identify convergences and divergences in experience. The analytical process aimed to move from descriptive accounts to interpretative insights, capturing both what was experienced and how it was understood by participants.

Qualitative data management software (e.g., NVivo) was used to support data organization and traceability, without replacing the interpretative engagement central to phenomenological analysis. The final themes represent essential aspects of clinicians' lived experiences as grounded in the data.

RESULTS

"Understanding Without Fully Knowing" – Experiencing Explainability as Partial Clarity

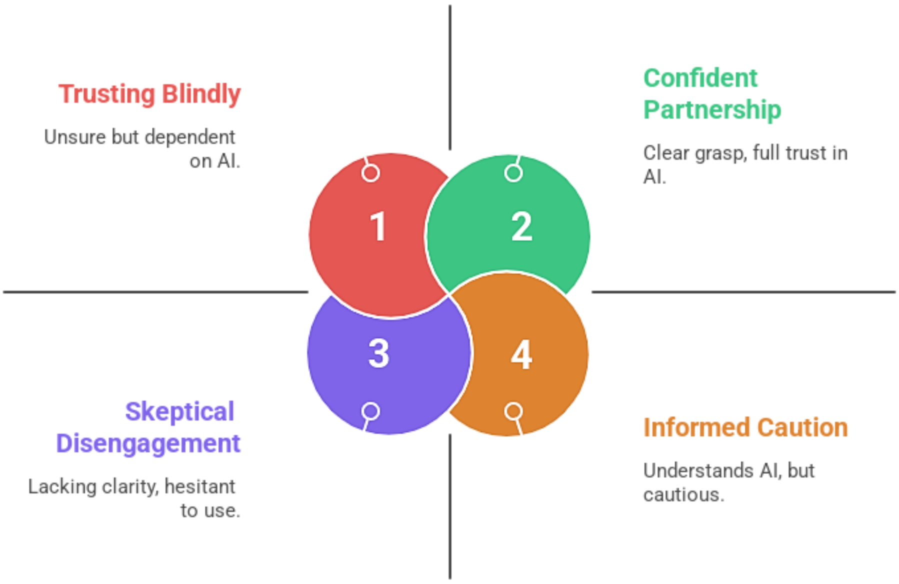
Participants consistently described AI explainability as providing a sense of partial understanding rather than complete clarity. While explanations such as feature importance, risk scores, or visual outputs were perceived as helpful, clinicians emphasized that these explanations did not equate to fully grasping the AI's reasoning process.

Several clinicians articulated that explainability functioned more as a reassurance mechanism than as a genuine cognitive understanding of the algorithm:

"The system explains why it gives a certain prediction, but honestly, I don't really 'know' how it thinks. I just know enough to feel slightly more comfortable using it." (Participant 3, physician)

This partial clarity positioned explainability as an interpretive aid rather than a transparent window into the algorithm. Clinicians often compared AI explanations to clinical heuristics—useful but inherently incomplete. In this sense, explainability was experienced as "good enough to proceed, but not enough to fully rely on."

AI Explainability Experience



Negotiating Trust – Between Algorithmic Confidence and Professional Skepticism

Trust emerged as a dynamic and situational experience rather than a stable attitude toward AI systems. Participants described trust as something that had to be continuously negotiated in each clinical encounter, shaped by prior experiences, perceived system reliability, and alignment with clinical intuition.

Some clinicians reported moments of increased confidence when AI recommendations aligned with their own judgment:

“When the AI confirms what I was already thinking, it strengthens my confidence. It feels like having a second opinion that agrees with you.” (Participant 7, senior clinician)

However, this confidence quickly shifted to skepticism when discrepancies arose:

“If the AI suggests something that contradicts my clinical sense, I immediately become cautious. I start questioning not only the system, but also why it might be wrong in this case.” (Participant 11, nurse practitioner)

Trust, therefore, was not rooted solely in technical accuracy or explainability features, but in the relational experience between clinician, patient context, and algorithmic output. Explainability supported trust only insofar as it resonated with clinicians’ experiential knowledge.

Clinical Judgment Under Tension – Intuition Versus Algorithmic Recommendation

A prominent theme across narratives was the tension between clinicians’ embodied clinical intuition and AI-generated recommendations. Participants described moments of internal conflict, particularly in complex or ambiguous cases where AI outputs seemed overly confident or insufficiently contextualized.

One participant reflected:

“My intuition is built from years of seeing patients. The AI doesn’t see what I see—the subtle signs, the patient’s anxiety, the context. When the two don’t match, I feel torn.” (Participant 2, emergency physician)

This tension was not experienced as a rejection of AI, but as an ongoing negotiation of authority. Clinicians positioned themselves as final decision-makers, using AI as an advisory voice rather than a determinant. The experience of tension highlighted the limits of explainability when it failed to account for contextual and relational aspects of care.

Moral Responsibility Beyond the Algorithm – The Persistent Burden of Accountability

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Despite the presence of explainable AI, participants consistently emphasized that moral and legal responsibility remained firmly with the clinician. Explainability did not alleviate the sense of accountability; in some cases, it intensified it.

As one clinician expressed:

“Even when the AI explains its prediction, I still feel the burden is on me. If something goes wrong, it’s my name, not the algorithm’s.” (Participant 5, internal medicine physician)

This experience underscored a key finding: explainability was not perceived as a transfer of responsibility, but as an additional layer in decision-making that clinicians had to justify. Participants described explainability as something they might need to defend to patients, colleagues, or themselves when outcomes were uncertain.

Emotional Responses to Explainable AI – Reassurance, Anxiety, and Lingering Doubt

Clinicians’ interactions with explainable AI were accompanied by complex emotional responses. While some reported reassurance and reduced uncertainty in routine cases, others described heightened anxiety in high-stakes decisions.

“Sometimes it reassures me, especially in standard cases. But in critical situations, the explanation actually makes me more anxious because I start overthinking every possibility.” (Participant 9, ICU nurse)

These emotional responses were closely tied to the perceived adequacy of explainability. When explanations felt overly technical or detached from clinical reality, they amplified doubt rather than resolving it. Thus, explainability was experienced not as emotionally neutral, but as an affective element shaping clinicians’ engagement with AI.

Across themes, clinicians experienced explainable AI not as a definitive solution to uncertainty, but as a complex, interpretive companion in clinical decision-making. Explainability was lived as partial understanding, negotiated trust, persistent tension with clinical intuition, sustained moral responsibility, and emotionally charged engagement. Collectively, these findings illuminate the essence of experiential explainability an understanding of AI explanation grounded not in technical transparency alone, but in clinicians’ lived, ethical, and emotional experiences within real-world healthcare practice.

DISCUSSION

Summary of the Main Findings

This study reveals that clinicians experience explainable AI not as a source of full transparency, but as a partial, interpretive aid that shapes trust, responsibility, and clinical judgment in complex and emotionally charged ways (Rubinger et al., 2023). These findings directly address the central question posed in the Introduction by illuminating how explainability is lived and made meaningful by clinicians within real-world clinical decision-making.

Contribution of the Findings to the Research Questions

The findings provide a substantive response to the study’s research questions by demonstrating that clinicians’ experiences with explainable AI are fundamentally experiential, relational, and ethically situated (Mukhlis et al., 2024). Rather than perceiving explainability as a purely technical feature that resolves uncertainty, clinicians interpret it as a form of provisional understanding that supports but does not replace professional judgment (Jha et al., 2022). This insight clarifies how clinicians make sense of explainability in practice and explains why technical transparency alone does not automatically translate into trust or reliance.

The study further shows that trust in AI is not a stable or uniform state, but a negotiated experience that fluctuates across clinical situations (Nelson et al., 2020). Clinicians trust AI recommendations selectively, particularly when they align with their own clinical intuition, and become skeptical when algorithmic outputs conflict with contextual or experiential knowledge

(Mukhlis et al. 2023). This finding directly addresses how clinicians' subjective experiences shape trust and decision-making, highlighting that trust emerges through interaction rather than through system design alone.

In addition, the results reveal that moral and professional responsibility remains firmly anchored in clinicians' sense of self, even when explainable AI is involved (Braun et al., 2021). Explainability does not diffuse accountability; instead, it often intensifies clinicians' awareness of responsibility, as they must justify decisions that are partially informed by algorithms. This contribution is particularly significant because it explains why explainable AI may increase, rather than reduce, the cognitive and ethical burden experienced by clinicians (Plana et al., 2022). Together, these findings advance understanding of explainability as an experiential phenomenon embedded in clinical practice, rather than a discrete technical solution.

Relationship to Prior Literature and Theory

The findings of this study both align with and extend existing research on AI in healthcare (Abgrall et al., 2024). Prior studies have emphasized the importance of explainability for fostering trust and acceptance among clinicians, often framing transparency as a prerequisite for adoption. The present findings support this emphasis but add nuance by showing that explainability functions as partial clarity, rather than full understanding, in clinicians' lived experiences (Labkoff et al., 2024). This complements earlier work by demonstrating that transparency is experienced interpretively, not objectively.

The dynamic nature of trust observed in this study resonates with previous qualitative research highlighting clinicians' ambivalence toward medical AI (Lin et al., 2020). However, this study extends prior literature by grounding this ambivalence in clinicians' moment-to-moment sense-making processes, rather than treating trust as a generalized attitude. By focusing on lived experience, the findings reveal how trust is continuously negotiated through alignment or tension between algorithmic recommendations and clinical intuition.

Furthermore, the persistence of moral responsibility identified in this study supports ethical discussions in the literature that caution against viewing AI as a bearer of agency or accountability in healthcare. While earlier studies have raised concerns about responsibility gaps in AI-assisted decision-making, the present findings show that clinicians do not experience such gaps subjectively (Huang et al., 2023). Instead, responsibility is experienced as inescapable and deeply personal, even in the presence of explainable systems. This insight enriches existing ethical frameworks by grounding abstract concerns about accountability in clinicians' lived experiences, thereby reinforcing the need for human-centered and experience-informed approaches to AI design and implementation.

Implications of the Findings

The findings of this study have important scientific and practical implications for the integration of explainable AI in healthcare (Huang et al., 2023). From a theoretical perspective, the results underscore the need to conceptualize explainability not solely as a technical property of AI systems, but as an experiential and interpretive phenomenon embedded in clinical practice. Clinicians' accounts demonstrate that meaning, trust, and responsibility emerge through interaction with AI rather than being directly produced by system design (Mukhlis, 2025). This insight contributes to ongoing discussions in health informatics and medical ethics by emphasizing the central role of human experience in shaping the use and impact of AI technologies.

Practically, the findings suggest that efforts to promote AI adoption in healthcare should move beyond enhancing transparency features or improving performance metrics alone. Designers and implementers of AI-CDSS should consider how explainability is experienced by clinicians in situ, including its emotional and moral dimensions (Kung et al., 2023). Training programs may benefit from addressing not only how AI systems work, but also how clinicians can reflect on and negotiate tensions between algorithmic recommendations and clinical intuition. More broadly, these findings are relevant to healthcare contexts where AI is increasingly used, as they highlight shared professional experiences of accountability and sense-making that extend across clinical roles and settings.

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Limitations of the Study

Several limitations should be considered when interpreting the findings of this study. First, the phenomenological design prioritized depth of experience over breadth, resulting in a relatively small and context-specific sample. While this approach is appropriate for exploring lived experience, it limits the extent to which findings can be generalized across all clinical settings or AI applications. Second, participants’ accounts were shaped by their specific institutional and technological contexts, which may influence how explainability and trust were experienced (Debnath et al., 2020). Third, the study relied on self-reported narratives, which reflect participants’ interpretations and recollections rather than direct observation of decision-making processes. These limitations do not diminish the value of the findings but indicate the contextual nature of the insights generated.

Prospective Directions for Future Research

The findings of this study open several avenues for future research. Further phenomenological studies could explore clinicians’ experiences with explainable AI across different healthcare systems, cultural contexts, or clinical specialties to examine how meanings of trust and responsibility vary. Longitudinal research may also provide insight into how clinicians’ experiences with AI evolve over time as familiarity and institutional integration increase. In addition, future studies could integrate phenomenological insights with complementary qualitative or mixed-method approaches to deepen understanding of how experiential meanings interact with organizational and technological factors. Such research has the potential to inform more human-centered approaches to AI development and policy, strengthening the alignment between technological innovation and the lived realities of healthcare practice.

CONCLUSION

This study examined clinicians’ lived experiences of using explainable artificial intelligence in clinical decision-making, addressing the need to understand how explainability is experienced and interpreted in real-world healthcare practice. The findings demonstrate that explainable AI is not experienced as complete transparency, but as a form of partial understanding that shapes trust, clinical judgment, and moral responsibility. By foregrounding clinicians’ narratives, the study shows that trust in AI emerges through ongoing negotiation between algorithmic recommendations and professional intuition rather than through technical explainability alone. These insights extend prior research by moving beyond performance- and adoption-centered perspectives to reveal the experiential and ethical dimensions of AI use that remain largely underexplored. Through a phenomenological approach, this study contributes a deeper, human-centered understanding of explainability that responds directly to limitations in earlier quantitative and system-focused research. Importantly, these findings carry direct implications for healthcare practice and AI system design. Healthcare institutions should not assume that increasing technical transparency alone will automatically strengthen clinicians’ trust. Instead, training programs, clinical guidelines, and implementation strategies should explicitly address how explainable AI interacts with professional judgment, ethical responsibility, and uncertainty management in practice. AI developers should collaborate closely with clinicians to design explanation interfaces that align with clinical reasoning processes rather than merely presenting algorithmic logic. In addition, organizational policies should clarify accountability structures to prevent the unintended transfer of moral burden solely onto individual clinicians. Future research should move toward actionable investigations, such as intervention-based studies evaluating explanation interface redesign, comparative studies across specialties to identify context-specific needs, and longitudinal research examining how clinicians’ interpretations of explainability evolve with prolonged exposure to AI systems. Mixed-method approaches may also help bridge experiential insights with measurable outcomes, thereby informing evidence-based guidelines for responsible AI integration in healthcare. By translating phenomenological insights into practical and policy-oriented directions, this study lays a foundation for more ethically grounded and clinically meaningful implementation of explainable AI.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this article.

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