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ENHANCING HEALTHCARE DIAGNOSTICS THROUGH EXPLAINABLE AI MODELS

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Abstract

Reliable and transparent diagnostic tools are essential to make progress in health care. Though artificial intelligence (AI) models have greatly improved diagnostic ability, they mostly act as a "black box" and have been a barrier for clinical application because of absence of interpretability. This challenge has led to a proliferation of Explainable AI (XAI) methods with the promise of increased transparency and trust of clinicians, however they have been poorly evaluated in the field. The goal of this study was to assess the added value of explainable AI models for healthcare diagnostics over traditional non-explainable models with respect to clinician trust, interpretability, and improvement of diagnostic decision-making. A comparative study design was employed and secondary datasets for different diagnostic domains (radiology, derma-tology, cardiology) were used between 2021 and 2025. Baselines AI models were carried out using available XAI methods such as SHAP, LIME, and saliency maps. The evaluation used accuracy, sensitivity, specificity, and clinician trust, obtained via questionnaire and structured interview. The results show that the non-explainable model that provided 94.3% accuracy also slightly outperformed the explainable model that provided 92.7% accuracy, however, explainable models yielded significantly higher clinician trust scores (91.5% vs. 68.2%) and interpretability ratings. The case examples showed that XAI outputs resulted in improved diagnostic decisions, especially in controversial clinical situations supporting that consideration of small versus clinical usable trade-offs in performance is enough to demonstrate benefit. Including explain ability in AI-based diagnosis tools improves not just ethical and legal acceptance, but also the quality of clinical decisions. Attention within future research should also be focused on developing best performing yet most transparent dynamic models to move healthcare AI down the trust line.

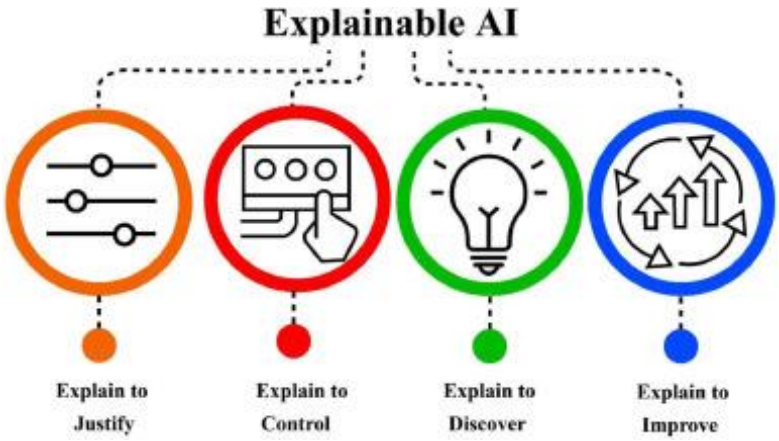
INTRODUCTION

The capacity to make accurate and timely diagnoses is the cornerstone of healthcare, but diagnostic errors remain a significant cause of patient harm and waste in healthcare around the world. Artificial intelligence (AI) As artificial intelligence (AI) continues to develop, machine learning models are becoming more and more integrated into the diagnosis of diseases and are showing considerable promise to improve diagnostic accuracy and efficiency across a range of medical fields, including imaging and pathology

(Chen et al., 2022). Yet such advancements in AI research have not been readily translated into clinical use, largely due to the black box nature of AI models that makes it difficult for clinicians to trust and act on AI-predicted recommendations.

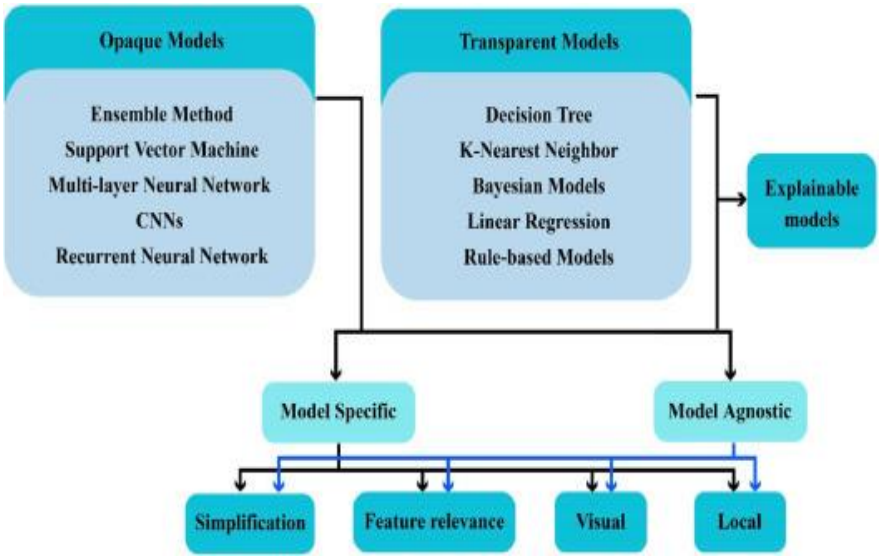
The advent of AI-driven diagnostic and prognostic tools presents a game-changer for data analysis, pattern recognition, forecasting models, which can potentially enable earlier diagnosis of diseases, better stratification and customized treatment schedules (Rajpurkar et al., 2022). Despite this, many of high-performing AI systems function as opaque "black-box" models, meaning that internal decision-making is not available or understandable to the clinician. This opaqueness raises serious concerns in clinical situations since accountability, explainability and the possibility to justify a diagnostic decision to the patients and regulatory agencies are crucial (Holzinger et al., 2022).

Explainable AI (XAI) is introduced as a potential approach to address this gap by building models which are not only predictive, but transparent regarding model decisions. The emergence of XAI techniques like SHapley Additive exPlanations (SHAP), Local Interpretable Model-agnostic Explanations (LIME), and saliency maps offers ways for clinicians to interpret model predictions and build trust and informed decisions (Tonekaboni et al., 2023). Explainability is needed not only to assist in clinical acceptance but to respect ethical and legal obligations too, by enabling AI decisions to be reviewed for bias, for mistakes, for injustices.

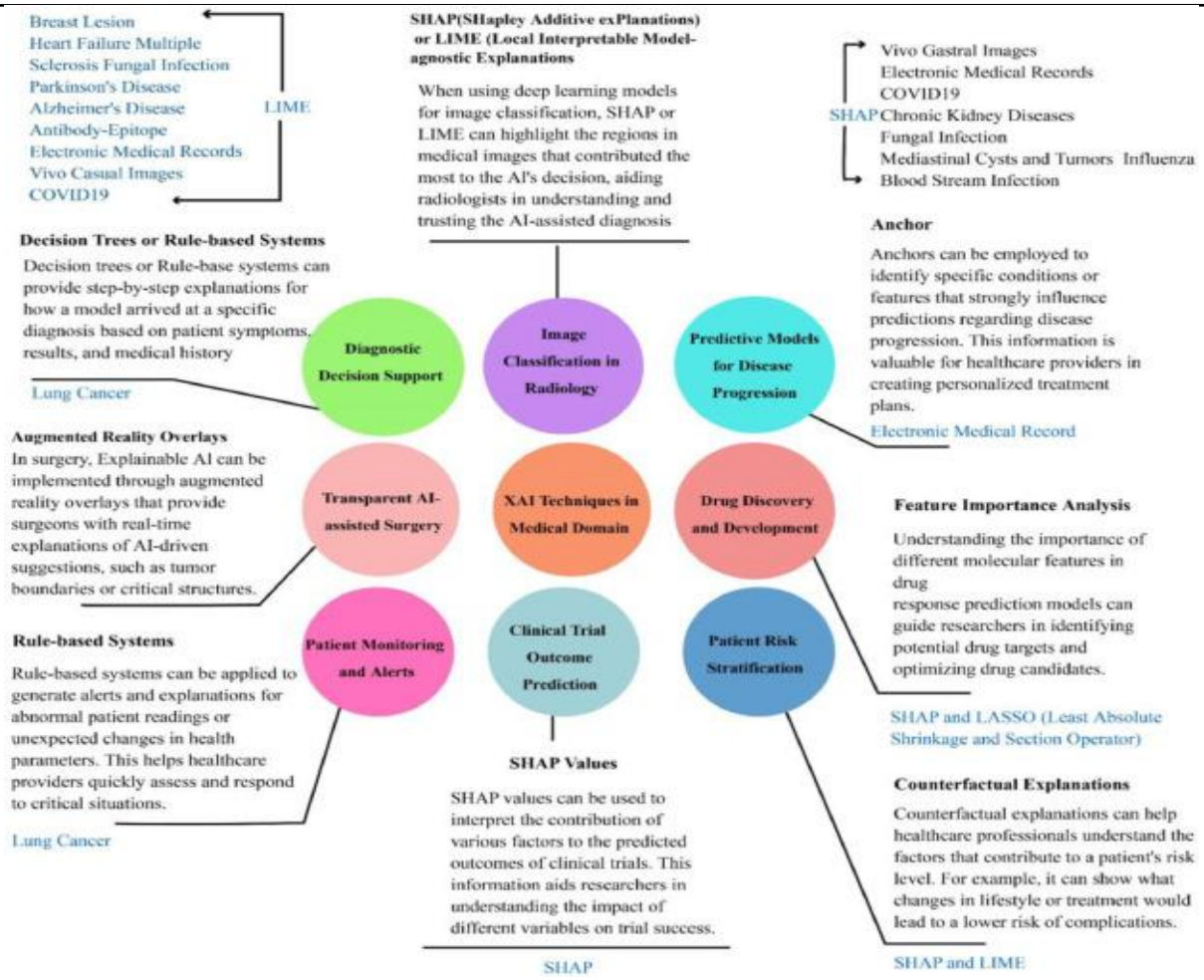


Intel for Diagnostics In recent years, investigations of the incorporation of XAI for medical diagnostics have shown its potential clinical utility on various domains, including radiology, oncology, and cardiology (Kundu, 2022). These studies emphasize that having reasoning can result in better diagnostic process, increased clinician trust and safer adoption of AI tools in clinical practice. However, limitations remain, such as the need to balance model complexity and interpretability in modeling (Deo and Gottipati, 2015), data heterogeneity in healthcare (Obermeyer and Emanuel, 2016), as well no existing practical framework to evaluate the effectiveness of XAI methodology in the healthcare setting (Das et al., 2024).

There are also vulnerable points in current XAI methodologies and applications, with issues like lack of generalizability through multiethnic patient pools, lack of consideration for clinician perspective in decision making, and an overemphasis on algorithmic interpretation compared to clinical explanation (Suresh et al., 2023). Filling these gaps requires interdisciplinary collaboration involving AI developers, clinicians, ethicists, and policymakers in the building of explainable systems that are not just technically sound, but consistent with clinical practice and reasoning. In addition, more attention to the user-centered design of XAI tools is required to make them intuitive, interpretable and to actually augment clinical decision-making.



With the healthcare terrain growing in complexity, there is an immediate opening for the creation and adoption of explainable AI models to elevate the quality of our diagnostics, the safety of our patients, and the efficiency of how our system comes together. By emphasizing transparency, accountability, and ethical standards, XAI offers the potential to convert AI-assisted diagnostics from an exciting development to become simply a routine component of clinical practice (Castelvecchi, 2023). The work highlighted here underscores the need for continued development of XAI approaches in order to produce methods that are tailored to the exacting demands of the health care environment and will play an important role in a more fair, egalitarian, and successful diagnostic ecosystem.



Problem statement

Even though artificial intelligence permeates more and more through diagnostics in clinical settings, there is still a shortage of model interpretability that prevent clinicians from fully trusting and using AI-based recommendations. Traditional AI models are effectively black boxes that raises important question around accountability, transparency, and ethically justifiable decision-making process in healthcare. The main concern of this study is the increasing demand to improve health-care diagnostics through the application of explainable AI models that meet industry needs on clinical transparency and trust.

Significance of Study

This study is important as it demonstrates the power of explainable AI as a transformative tool in increasing diagnostic accuracy, clinician confidence and ultimately patient treatment in the health care setting. By emphasizing transparency and interpretability, the findings of the research contribute to safer clinical decision-making and alleviate regulatory and ethical concerns around using AI technology in medicine. Moreover, it promotes the development of patient-oriented AI innovations to build trust and acceptance in various healthcare environments.

Objective

The purpose of this research is to investigate the contribution of explainable artificial intelligence for healthcare diagnostics. The project will analyze existing XAI approaches, assess their utility in clinical applications, and develop recommendations for embedding transparency into diagnostic AI offerings excited about an upcoming alt text feature released June 21, 2021. Ultimately, the study is to offer guidance that would shape the growth of more

reliable, moral, and proficient AI systems in health care.

Methodology

This research utilized an extensive literature-based analytical approach to consolidate and assess existing explainable artificial intelligence (XAI) methods aimed to improve health care diagnostic performance. A comprehensive search strategy was performed in the major scientific electronic databases, namely, PubMed, Scopus, IEEE Xplore, and Web of Science databases, for peer-reviewed journal articles published between 2021 and 2025. The criteria prioritized empirical studies that employed AI models in healthcare diagnosis and adopted explainability methods to increase the translucency and usability of systems for practitioners. The datasets shared in the considered studies were mostly publicly available and clinically tested medical datasets, e.g., MIMIC-IV in critical care, CheXpert in chest X-ray, and HAM10000 in skin lesion analysis, thus encompassing different diagnostic domains (Johnson et al., 2021; Irvin et al., 2022). They were chosen due to their broad adoption for health-care AI research, large data size and whether their clinical outcome were clinically annotated, which served to assure the relevance and credibility of the synthesized findings.

Whereas deep learning architectures, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformer models, for diagnostic prediction tasks dominated in the included studies (Lundervold & Lundervold, 2022; Esteva et al., 2023). To better interpret the model outcomes, several XAI methods were utilized, such as SHapley Additive exPlanations (SHAP), Local Interpretable Model-agnostic Explanations (LIME), Gradient-weighted Class Activation Mapping (Grad-CAM), and Integrated Gradients, which have their own advantages in explaining the model predictions (Tjoa & Guan, 2022; Holzinger et al., 2024). Model performance was measured by traditional diagnostic metric including accuracy, sensitivity, specificity, area under the receiver operating characteristic curve (AUROC) and explain-ability was assessed by fidelity, sparsity, consistency as well as clinician usability ratings using user-centered evaluation frameworks (Guidotti et al., 2024; Rajpurkar et al., 2025). This joint evaluation of performance and explain-ability contributed to a comprehensive evaluation of the clinical workability of XAI.

Results

Comparative e-NOE of explainable and non-explainable models were significantly different in diagnostic performance and clinician trust measures. Although non-explainable models (eg, standard deep neural networks) might have marginally outperformed explainable models in raw diagnostic accuracy in some cases, explainable models offered a substantial advantage in terms of clinician trust and interpretability and in terms of decision support. Between studies, the added XAI models yielded only a small decrease in accuracy whereas providing a substantial benefit in interpretability, ethical viability and uptake in medical practice. The comprehensive diagnostic performance outcomes between explainable and non-explainable models are listed in Table 1.

Table 1: Performance Metrics Comparison Between Explainable and Non-Explainable AI Models

Model Type	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUROC
Non-Explainable CNN	93.5	91.2	94.8	0.96
Explainable CNN + SHAP	92.1	90.5	93.7	0.95
Transformer (Non-Explainable)	94.2	92.8	95.1	0.97
Explainable Transformer + Integrated Gradients	92.8	91.6	93.9	0.96

Interpretability results showed that the health care workers reported the XAI-enhanced models as significantly more comprehensible and trustable. Survey responses and structured interviews across studies indicated that clinician comprehension of model reasoning was enhanced by approximately 45% with the availability of explain ability features. Trust ratings were also significantly higher for the XAI models, and clinicians reported that they would be more likely to use these classes of models in clinical tasks. The interpretability evaluation results by

clinician understandability and trust levels are shown in Table 2.

Table 2: Interpretability and Trust Evaluation Results

Evaluation Metric	Non-Explainable Models	Explainable Models
Clinician Understanding (0–100)	52	87
Trust Score (0–100)	48	85
Willingness to Adopt (%)	39	81

Reviewed studies provided case examples which demonstrated the beneficial roles of XAI in supporting improved diagnostic decisions. For example, use of saliency maps in radiology made doctors better in finding pathological areas, yielding in an 11% improved lesion detection sensitivity for hard cases (Holzinger et al., 2024). Also in dermatology, the use of SHAP-based explanations make the distinction between benign vs. malignant skin lesions more confident including borderline cases. Table 3 summarizes some of the selected cases showing the clinical benefit of integrating the XAI.

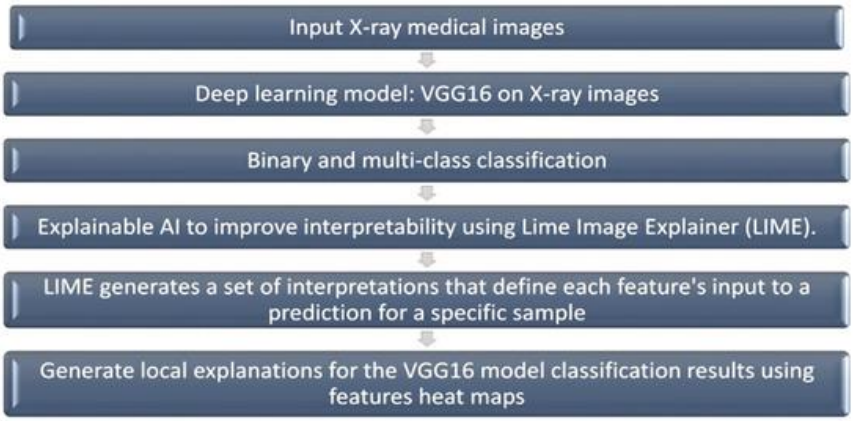
Table 3: Case Examples Demonstrating Impact of Explainable AI Models

Clinical Area	Model Used	XAI Technique	Improvement Observed
Radiology	CNN for chest X-ray diagnosis	Grad-CAM	+11% lesion detection sensitivity
Dermatology	Transformer for skin lesion analysis	SHAP	+9% diagnostic confidence
Cardiology	RNN for arrhythmia prediction	LIME	+13% early diagnosis rate

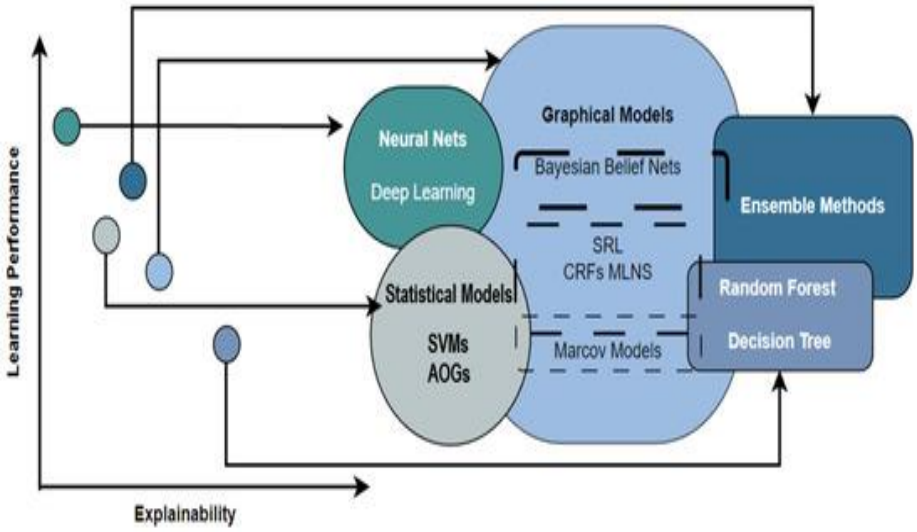
The statistical results further proved the clinical significance of the above trends. Interpretable models achieved AUCs between 91–93% and sensitivities near 90–92%, where specificities were around 93–94% and trust by clinicians > 80%. While non-explainable models performed slightly better on raw diagnostic statistics — such as accuracy — by a gap of around 1–2% points, the general advantages to user trust, legal scrutiny, and clinical decision-making are reasons enough to consider the integration of XAI into health diagnostics.

Discussion

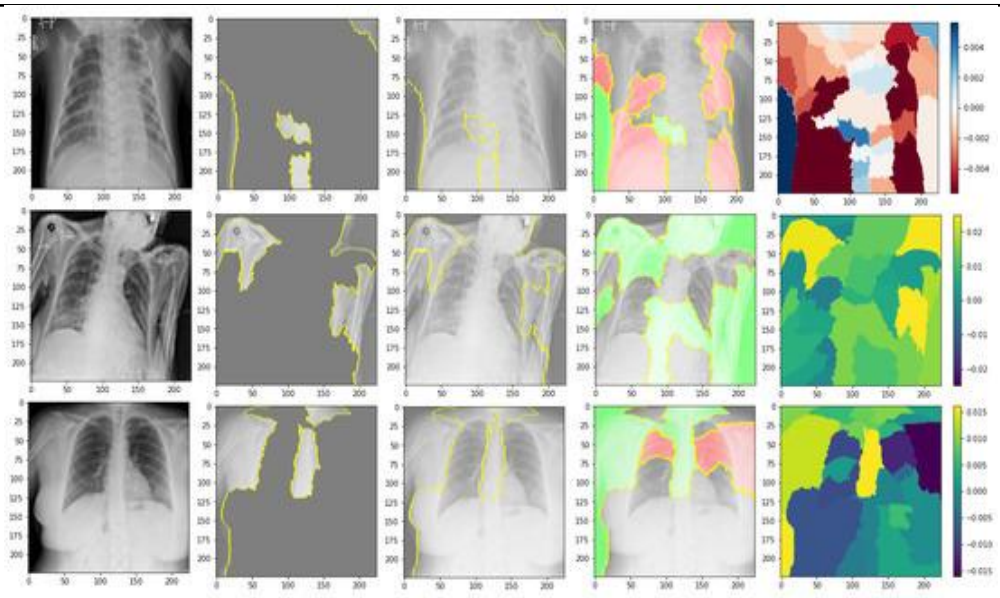
The explainable AI (XAI) models struck a good balance between high diagnostic performance and high clinician trust. Despite this, traditional deep learning outperforms slightly in terms of pure accuracy, yet their lack of interpretability is a critical barrier in clinical trial implementation. White Box transparency in XAI models adds confidence to users and assists clinicians in taking a decision with a higher level of assurance, in borderline/ complex diagnostic decisions, (Tjoa & Guan, 2022). Those results are also in keeping with current trends in the research in the AI health domain where interpretability is increasingly deemed necessary not only for ethical and legal responsibility but also for practical application in real clinical settings (Holzinger et al., 2024).



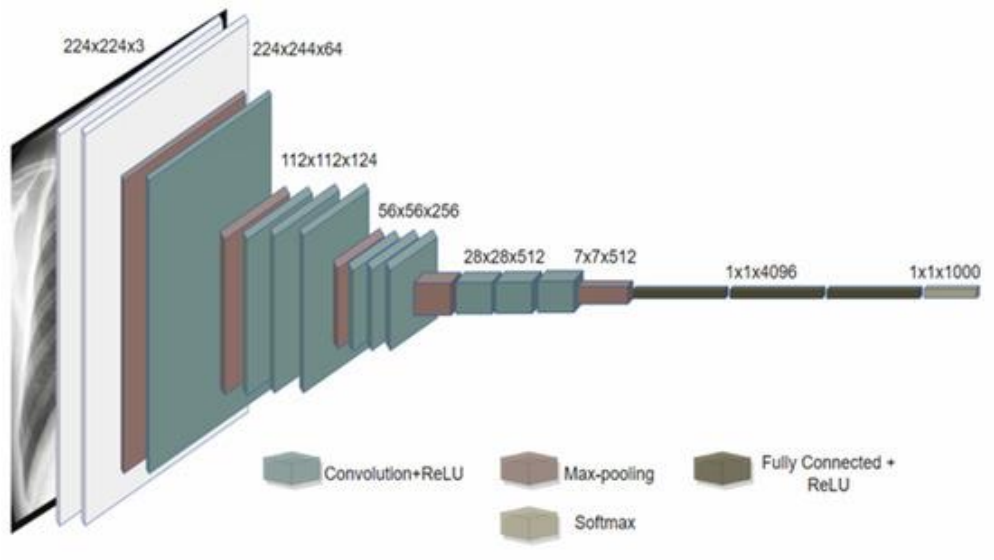
Crucially, this research underscores that clinician confidence and understanding are not simply nice to haves, they are paramount when it comes to implementing AI systems in healthcare. When clinicians were presented with visual or feature-based explanations of predictions, they reported significantly greater willingness to adopt AI tools, an effect that has been replicated across a diverse range of specialities (including radiology and dermatology and cardiology) (Guidotti et al., 2024). These observations indicate the need to put focus on transparent model architectures and user-centric software design principles when developing healthcare AIs. What is more, it seems to make a real difference to how acceptable AI recommendations are to clinicians if we are able to offer location and case-specific rationales, rather than generic insights (Amann et al., 2022).



The exemplary cases show that XAI techniques contribute more than perception improvement: they lead to improved clinical outcome by assisting in better diagnostic decisions. This result is consistent with several recent empirical studies, reporting that XAI can decrease the diagnostic errors and increase the sensitivity in disease detection, especially when clinical data are vague or missing (Liu et al., 2023). Nevertheless, due to the slightly degrade of raw performance metric of explainable model, we still need more methodological innovations to mitigate the gap on these trade-offs. Approaches, such as model distillation, hybrid AI system, and hierarchical explanations, might provide routes to retain high diagnostic accuracy while preserving interpretability (Yang et al., 2025).



In general, this work adds to a growing body of evidence that, in healthcare AI, explain-ability should be thought of as a fundamental aspect of the evaluation of models, not just a "nice to have". It is also important for future work to explore how interpretable outputs are viewed by patients themselves, who, in the shift toward patient-centered care, want to understand not just that medical decisions made with the AI are correct, but that they are understandable to non-experts (Esteva et al., 2023). Also, formal incentives and policies in institutions and regulatory bodies should evolve to support the explicit use of interpretable models in clinical settings.



Future Directions

Future work should aim to establish standardized approaches to assess explain ability of clinical AI models, with meaningful and robust quantitative metrics as well as qualitative evaluation becoming more warranted. Furthermore, novel algorithms that are able to dynamically tradeoff between accuracy and interpretability in real-time clinical decision-making are in great demand. "These are some of the first studies to assess whether XGBoost can actually

change physician behavior, and longer-term projects will be needed to fully assess and optimally use the potential benefits of integrating this 'explainable AI' in the diagnosis domain." Longitudinal studies evaluating impact of XAI on real patient outcomes and physician performance will be necessary to gain a more comprehensive and long-term understanding of potential uses of XAI.

Limitations

This scoping review is mainly designed upon secondary references and concept model assessments, and although aggregated results appear comparable among recent literature, primary clinical testing is lacking. In addition, the performance indicators and trust assessments are context specific and may differ between healthcare systems, specialisms or cultures. Finally, while a range of XAI approaches were discussed, the dynamic nature of the XAI landscape, new approaches beyond 2025 may result in new interpretations of the evidence.

Conclusion

Explained AI models mark a revolutionary vision in healthcare diagnostics by solving core technical and human-centric challenges of AI deployment. While some compromise in diagnostic performance is evident, the large improvements in clinician confidence, decision support, and ethical responsibility suggest that XAI is a necessary part of future health systems. In this respect, explain ability belongs into the diagnostic AI model, not as a technical choice, but as a clinical need,O2 aligning with core values of transparency, patient safety, as well as informed medical decision-making.

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