BRIDGING EFFICIENCY AND INTERPRETABILITY: EXPLAINABLE EDGE AI FOR CLINICAL DECISION-MAKING IN MEDICAL TELEMETRY

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Abstract. *The increasing adoption of medical telemetry and remote patient monitoring has transformed healthcare by enabling continuous observation of physiological signals in real-world environments. In this context, Edge Artificial Intelligence (Edge AI) has emerged as a promising approach for processing data locally, reducing latency and dependence on cloud infrastructures, particularly in resource-constrained settings. However, most edge-based models operate as black boxes, limiting their transparency and hindering clinical adoption. This study presents a systematic review, following PRISMA guidelines, of Explainable Artificial Intelligence (XAI) methods applied to Edge AI systems in medical telemetry. The analysis highlights a persistent trade-off between computational efficiency and interpretability, with most approaches favoring performance over explainability. From a clinical perspective, the findings emphasize that telemetry data alone is insufficient to support medical decision-making, requiring integration with clinical reasoning and contextual patient information. Additionally, the study discusses the risks associated with algorithmic and cognitive biases, as well as the challenges posed by limited infrastructure and professional training, particularly in developing healthcare systems. The results reveal a critical gap in the development of integrated, lightweight, and interpretable models suitable for real-world deployment. Addressing this gap is essential for advancing trustworthy, scalable, and clinically relevant artificial intelligence in healthcare.*

Keywords: *Edge AI. Explainable AI. Medical Telemetry. Patient Monitoring. Clinical Decision Support*

1. INTRODUCTION

The increasing adoption of remote patient monitoring systems has transformed modern healthcare by enabling continuous observation of physiological signals outside traditional clinical environments [1, 2]. Advances in wearable devices and medical telemetry have made it possible to collect real-time data such as heart rate, oxygen saturation, and electrocardiographic signals, supporting early detection of clinical deterioration and chronic disease management [2, 3].

Despite these advances, the growing volume and velocity of medical data pose significant challenges for timely and efficient analysis. Cloud-based solutions, although powerful, introduce concerns related to latency, data privacy, and connectivity limitations. In this context, Edge Artificial Intelligence (Edge AI) has emerged as a promising paradigm, enabling data processing directly on local devices with reduced latency and improved data security [4]. However, most machine learning and deep learning models deployed at the edge are inherently complex and operate as “black boxes,” limiting their transparency and interpretability [5]. In clinical settings, this lack of explainability represents a critical barrier to adoption, as healthcare professionals require clear and reliable justifications for algorithmic decisions that may impact patient outcomes [6].

Explainable Artificial Intelligence (XAI) has been proposed as a solution to address this limitation by providing insights into model behavior and decision-making processes [7]. Techniques such as Local Interpretable Model-agnostic Explanations (LIME) and SHapley Additive exPlanations (SHAP) have gained prominence in the literature, particularly in healthcare applications [7, 8, 9]. Nevertheless, these methods are often computationally expensive and may not be suitable for deployment in resource-constrained environments such as wearable devices and embedded systems. This creates a fundamental tension between two key requirements in medical telemetry systems: computational efficiency and model interpretability. While Edge AI prioritizes low-resource consumption and real-time processing, XAI methods frequently introduce additional computational overhead, making their integration challenging in practical scenarios [10].

Furthermore, there is a notable lack of studies that systematically investigate the intersection of Edge AI and XAI within the context of medical telemetry, particularly in applications related to continuous patient monitoring. Several papers tends to address these domains independently, without considering their combined implications for clinical usability and system design [1 – 6, 33, 35 – 36].

In this context, this study aims to systematically review the literature on explainable artificial intelligence models designed for low-resource environments in medical telemetry. The focus is on identifying current approaches, evaluating their applicability to patient monitoring, and highlighting existing research gaps. By bridging the fields of Edge AI and XAI, this review seeks to contribute to the development of trustworthy, efficient, and clinically relevant AI systems for next-generation healthcare.

2.BACKGROUND

Medical telemetry has evolved from a supportive technological component to a structural pillar of contemporary healthcare systems, enabling continuous, high-resolution monitoring of physiological signals across heterogeneous care settings [5, 9, 11]. The proliferation of wearable devices and advanced biosensors has substantially increased the granularity and temporal resolution of patient data, fostering a paradigm shift from episodic to continuous care [12]. This transition is particularly relevant in the management of chronic diseases and in the early detection of acute clinical deterioration, where subtle physiological variations may precede critical events. However, the increasing ubiquity of telemetry systems has introduced a paradox: while data availability has expanded exponentially, the capacity to transform such data into actionable clinical knowledge remains constrained [13]. The high-frequency, multimodal nature of telemetry data imposes significant computational and operational challenges, particularly in terms of real-time processing, data transmission, and clinical interpretability. In this context, reliance on centralized cloud-based infrastructures may be suboptimal due to latency, bandwidth limitations, and concerns related to data governance and privacy [14, 15].

In this way, Edge AI emerges as a strategic response to these limitations by decentralizing computational processes and enabling inference directly at the point of data acquisition. This paradigm not only reduces latency and network dependency but also supports context-aware and time-sensitive clinical decision-making [16]. From a clinical standpoint, the ability to detect anomalies in near real time, such as arrhythmogenic patterns, respiratory instability, or neurological deviations, represents a critical advancement in patient monitoring, particularly in high-risk and resource-constrained environments [17]. Notwithstanding these advantages, the clinical integration of Edge AI remains hindered by the epistemological opacity of most machine learning models. The predominance of black-box architectures conflicts with fundamental principles of clinical practice, which require transparency, traceability, and justification of decisions [16, 18]. In high-stakes environments such as healthcare, predictive accuracy alone is insufficient; interpretability becomes a prerequisite for trust, accountability, and safe adoption [19, 20, 21, 22].

Thus, XAI has been proposed as a means to reconcile model complexity with clinical interpretability. Nevertheless, existing XAI approaches are often misaligned with the operational constraints of edge environments. Post-hoc explanation techniques, while methodologically versatile, tend to introduce additional computational overhead and may lack stability across different input conditions. Conversely, intrinsically interpretable models, although computationally attractive, may not capture the complexity inherent to physiological data, potentially limiting their clinical utility [8, 10, 11, 23, 24].

This tension reveals a fundamental methodological gap: current approaches treat efficiency and interpretability as competing goals, rather than as co-dependent requirements. In the context of medical telemetry, such a dichotomy is particularly problematic, as both dimensions are essential for enabling real-time, reliable, and clinically actionable insights [8. 10, 23, 25]. Therefore, advancing the field requires a paradigm shift toward the co-design of models that are simultaneously computationally efficient and inherently interpretable [26]. From a clinical perspective, the successful integration of explainable edge-based systems has the potential to redefine patient monitoring by enabling continuous, transparent, and context-aware decision support. Such systems could not only enhance early detection and intervention but also contribute to reducing cognitive burden on healthcare professionals, standardizing clinical reasoning processes, and improving overall quality and safety of care [22, 24, 27, 28].

3.METHODS

3.1 STUDY DESIGN

This study was conducted as a systematic literature review following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [29]. The objective was to identify, analyze, and synthesize existing research on explainable artificial intelligence (XAI) applied to edge-based systems in medical telemetry, with a particular focus on patient monitoring in resource-constrained environments [30].

3.2 WORKFLOW OVERVIEW

The systematic review followed a structured workflow based on PRISMA guidelines, encompassing search, selection, extraction, and synthesis stages. A comprehensive search was conducted across IEEE, PubMed, Scopus, and Web of Science using predefined search strings combining terms related to Edge AI, XAI, and medical telemetry.

Retrieved records were initially screened by title and abstract to exclude irrelevant studies, followed by full-text assessment according to predefined inclusion and exclusion criteria. Duplicate entries were identified and removed prior to screening. Studies were included if they addressed the application of edge-based artificial intelligence and explainability techniques within healthcare contexts, particularly in patient monitoring and medical telemetry.

Data extraction was performed using a structured protocol, collecting information on study characteristics, methodological approaches, explainability techniques, computational strategies, and clinical applicability. The selected studies were then qualitatively synthesized, focusing on identifying patterns, methodological trends, and trade-offs between interpretability, computational efficiency, and clinical relevance.

Potential sources of bias include publication bias and heterogeneity across study designs, which may limit generalizability.

4. DISCUSSION

The findings of this review highlight a critical intersection between technological advancement and clinical applicability in the context of medical telemetry. While Edge AI and XAI have evolved as promising paradigms, their integration into real-world healthcare settings remains limited by both technical and clinical constraints [5, 22, 23, 31].

From a clinical perspective, Edge AI represents a significant advancement by enabling real-time processing of physiological data directly at the point of care. This capability is particularly relevant in environments characterized by limited infrastructure. In such scenarios, the absence of high-performance computational resources, such as GPUs or reliable cloud connectivity, necessitates the use of lightweight, efficient models capable of operating on legacy hardware and low-power devices [2, 4, 11, 12, 15, 32]. However, the requirement for computational efficiency often leads to simplified models, which may compromise either predictive performance or interpretability [33].

In the Brazilian healthcare context, these challenges are further exacerbated by systemic constraints, including overcrowded hospitals, limited diagnostic infrastructure, and prolonged waiting times for examinations and specialist evaluations [34]. Emergency departments frequently operate beyond capacity, while delays in access to imaging and laboratory results can significantly impact the timeliness and accuracy of clinical decision-making [35]. Even when diagnostic reports are available, discrepancies between reported findings and feasible clinical conduct may arise due to resource limitations, availability of treatments, or institutional constraints. In this setting, Edge AI systems have the potential to partially mitigate operational bottlenecks by enabling decentralized, real-time analysis of patient data, thereby supporting triage, prioritization, and early detection of critical conditions. However, if not carefully designed, such systems may inadvertently reinforce existing inequalities or introduce additional risks, particularly when deployed in environments with heterogeneous data quality and limited clinical validation [5, 17, 31, 32, 33]. Therefore, the adoption of lightweight and explainable AI models in Brazil must be aligned not only with computational constraints but also with the practical realities of clinical workflows, ensuring that technological support translates into actionable, context-aware, and resource-sensitive decision-making [5, 6, 9, 23, 26].

Simultaneously, the growing adoption of telemetry systems has introduced new challenges for healthcare professionals [2, 7, 20, 31]. Although continuous monitoring provides a richer and more granular representation of patient status, it also increases the cognitive burden associated with data interpretation [22]. Clinicians are required to process large volumes of high-frequency, and often noisy, physiological data, which may not be readily translatable into actionable clinical insights. In this context, artificial intelligence systems are expected to function not merely as predictive tools, but as decision-support systems capable of contextualizing and summarizing relevant patterns [36]. However, the predominance of black-box models in Edge AI applications limits their clinical utility. Without transparent reasoning, such systems may generate predictions that are difficult to interpret, validate, or trust [24, 37]. This lack of explainability becomes particularly problematic in high-stakes clinical environments, where decisions directly impact patient outcomes. XAI techniques aim to address this limitation by providing interpretable outputs, yet their integration into edge-based systems remains challenging due to computational constraints [5, 10].

Moreover, even when telemetry data is accurately captured and processed, it is insufficient as a standalone basis for clinical decision-making [16, 20, 22, 36]. Medical decisions inherently depend on a combination of factors, including patient history, physical examination, contextual variables, and clinical judgment [38]. Telemetry data, while valuable, represents only a partial view of the patient's condition. Overreliance on algorithmic outputs derived from such data may lead to incomplete or biased interpretations [20, 26, 38]. This concern is further compounded by the presence of bias in both data and decision-making processes. Machine learning models trained on limited or non-representative datasets may encode systematic biases, which can propagate into clinical recommendations. Additionally, clinicians themselves are subject to cognitive biases, such as confirmation bias or automation bias, where undue trust is placed in algorithmic outputs. The interaction between algorithmic bias and human bias creates a complex risk landscape, potentially increasing the likelihood of diagnostic errors. [39]

Furthermore, the predominance of black-box models in clinical environments introduces an additional layer of complexity when considered alongside pre-existing biases inherent to medical practice [37, 38, 39]. Algorithmic opacity limits the clinician's ability to interrogate how specific variables influence predictions, potentially masking embedded biases originating from non-representative training data or historical inequalities in healthcare delivery. When such systems are deployed without adequate transparency, there is a risk that biased patterns (related to factors such as socioeconomic status, ethnicity, age, or comorbidities) may be perpetuated or even amplified [39]. This issue is particularly concerning when aligned with cognitive biases already present in clinical decision-making, including anchoring bias, confirmation bias, and automation bias. In practice, clinicians may consciously or unconsciously rely on prior assumptions about patient profiles, which, when combined with opaque algorithmic outputs, can reinforce skewed interpretations and lead to suboptimal or inequitable care. The lack of explainability thus not only undermines trust in AI systems but also restricts the clinician's ability to critically assess whether a recommendation is clinically appropriate or potentially biased [22, 23].

In this context, the integration of explainability becomes essential to mitigate both algorithmic and human biases [38, 40]. Transparent models can provide insight into the relative contribution of clinical variables, enabling practitioners to identify inconsistencies, question unexpected outputs, and align algorithmic suggestions with individualized patient assessment [41, 42]. Ultimately, addressing the black-box nature of AI systems is not solely a technical challenge, but a necessary step toward promoting fairness, accountability, and ethical integrity in medical decision-making [40].

So, XAI assumes a central role not only as a technical feature, but as a clinical necessity. By providing transparent and interpretable justifications, explainable systems can support clinicians in critically evaluating algorithmic outputs, rather than passively accepting them. This is particularly important in resource-constrained environments, where diagnostic support tools may compensate for limited access to specialized expertise [23, 33]. Despite its recognized importance, the adoption of XAI in clinical practice remains limited and uneven across healthcare systems. In many real-world scenarios, AI solutions are deployed prioritizing predictive performance and operational efficiency, while explainability is treated as a secondary or optional feature [37, 42]. This gap reflects not only technical challenges but also institutional and cultural barriers, including lack of standardized frameworks, insufficient training of healthcare professionals, and limited regulatory enforcement regarding interpretability requirements [38]. As a result, clinicians are often required to interact with systems that provide outputs without adequate justification, which may hinder trust, reduce usability, and compromise safe integration into clinical workflows [43]. Bridging this gap requires a shift in perspective, where explainability is incorporated as a fundamental design principle rather than an auxiliary component, ensuring that AI systems are aligned with the epistemological and ethical demands of medical practice [22, 23].

Furthermore, the integration of Edge AI and XAI has the potential to enhance clinical workflows by enabling real-time, context-aware decision support while maintaining transparency. Such systems could reduce cognitive overload by filtering and prioritizing relevant information, while simultaneously preserving the clinician's role as the final decision-maker. Importantly, this approach aligns with a human-centered model of artificial intelligence, in which technology augments, rather than replaces, clinical reasoning. Nevertheless, achieving this integration requires addressing the inherent trade-offs between computational efficiency, interpretability, and predictive performance. Future developments must focus on designing models that are not only lightweight and deployable in constrained environments, but also capable of producing clinically meaningful explanations. Without this balance, the gap between technological capability and clinical adoption is likely to persist.

To provide a structured overview of the current landscape, the Table 1 presents a comparative synthesis of representative studies addressing the intersection of Edge AI, XAI, and clinical applications in medical telemetry. The selected studies were analyzed according to key dimensions, including clinical application domain, computational approach, explainability technique, resource constraints, level of clinical integration, and identified limitations. This comparative framework aims to highlight not only the diversity of methodological approaches but also the persistent challenges in aligning computational efficiency with interpretability and real-world clinical applicability.

Table 1. Comparative Analysis of Edge AI and Explainable AI Approaches in Clinical Telemetry Systems

Study	Clinical Application	Edge-AI Approach	XAI Approach	Resource Context	Clinical Integration	Limitations
44	Cardiac monitoring	Embedded CNN	Grad-CAM	Wearable device	Low	Superficial explanations and high computational cost
45	Arrhythmia detection	TinyML	SHAP	Limited Hardware	Moderate	SHAP not feasible in real-time
46	Diagnostic support	---------	Grad-CAM	Hospital Environment	Moderate	Lack of clinical validation

By the authors (2026).

The analysis of the selected studies, summarized in the table, reveals a fragmented landscape in the integration of Edge AI, Explainable Artificial Intelligence (XAI), and clinical practice. Most approaches prioritize computational efficiency through edge-based deployment strategies, such as embedded convolutional neural networks (CNN) and TinyML architectures, particularly in wearable and resource-constrained environments [44, 45]. However, these solutions frequently lack interpretability, as evidenced by the limited adoption of XAI techniques across studies. When explainability is incorporated, it is predominantly achieved through post-hoc methods such as SHAP, LIME, and Grad-CAM, which often introduce additional computational overhead and are not consistently feasible in real-time or low-resource settings [44, 45, 46].

From a clinical perspective, the level of integration remains heterogeneous. While some studies demonstrate moderate to high applicability in controlled environments, particularly in hospital-based systems, most approaches show limited alignment with real-world clinical workflows [46]. In particular, systems deployed in wearable or remote monitoring contexts tend to offer low clinical integration, reflecting challenges related to interpretability, usability, and validation. Additionally, the reliance on black-box models in several studies further constrains clinical adoption, as these approaches fail to provide transparent and actionable insights required for decision-making [44, 46].

A recurring limitation across the literature is the trade-off between model performance, computational efficiency, and interpretability [16, 20, 22, 46]. Furthermore, few studies address the need for clinical validation or consider the complexity of real-world healthcare environments, including data heterogeneity and infrastructure constraints [32]. These findings reinforce the existence of a critical gap in the development of integrated solutions that simultaneously address technical feasibility and clinical applicability [22, 23, 44, 45, 46].]

In parallel, the effective incorporation of such technologies into clinical practice is contingent upon continuous professional training and capacity building. Clinicians must be adequately prepared not only to operate AI-enabled devices and interpret their outputs, but also to critically appraise the limitations and uncertainties associated with algorithmic predictions [22, 26, 27, 39]. This includes understanding how models are trained, recognizing potential sources of bias, and identifying situations in which automated recommendations may be unreliable [38]. Importantly, clinical decision-making should not be reduced to the interpretation of quantitative metrics alone; it must remain grounded in comprehensive patient assessment, including physical examination, clinical history, and contextual factors [5, 38, 39].

An additional point of concern lies in the progressive reduction of the patient to isolated quantitative metrics, particularly in environments increasingly mediated by data-driven systems [17, 19, 26]. While telemetry and AI-based models provide valuable numerical indicators, there is a risk that clinical reasoning becomes overly anchored in these measurements, to the detriment of holistic patient assessment [1, 3, 37]. In practice, this may lead to situations in which subtle but clinically significant signs (such as pain patterns, behavioral changes, or contextual risk factors) are overlooked because they are not adequately captured by sensors or model inputs. This phenomenon is especially critical in acute conditions, where early clinical signs may precede measurable deviations in monitored variables, and delayed recognition can result in severe outcomes, such as the progression to myocardial infarction [37]. From a computational perspective, this highlights a fundamental limitation of current systems: the inability to fully represent the complexity of clinical reality through structured data alone [1]. Consequently, there is a pressing need to design AI systems that explicitly acknowledge these limitations, reinforcing their role as decision-support tools rather than decision-making substitutes, and encouraging clinicians to integrate algorithmic outputs with comprehensive clinical evaluation [5, 9, 23].

In summary, while Edge AI and XAI offer substantial potential to improve patient monitoring and clinical decision-making, their effective implementation depends on a nuanced understanding of both technological limitations and clinical realities [39]. Bridging this gap is essential to ensure that advances in artificial intelligence translate into safer, more reliable, and contextually informed healthcare practices [22, 23].

5. CONCLUSION

This paper systematically analyzed the intersection between Edge AI and Explainable XAI within the context of medical telemetry, highlighting both their potential and current limitations in real-world healthcare scenarios. The findings indicate that, although Edge AI enables efficient, low-latency processing of physiological data in resource-constrained environments, its widespread adoption is hindered by the lack of interpretability inherent to most deployed models. From a computational perspective, the literature reveals a persistent methodological gap, in which efficiency and explainability are often treated as competing objectives rather than complementary requirements [22, 23]. This limitation is particularly critical in clinical environments, where transparency, traceability, and reliability are essential for safe decision-making [26, 27, 39]. The absence of explainable mechanisms not only reduces trust in AI systems but also increases the risk of propagating hidden biases, especially when combined with existing cognitive biases in medical practice [38].

Furthermore, this review emphasizes that telemetry data, while valuable, is inherently insufficient as a standalone basis for clinical decision-making [1, 3]. The reduction of complex patient conditions to isolated metrics may lead to incomplete or misleading interpretations, particularly in acute scenarios [14]. In this sense, AI systems must be explicitly designed as decision-support tools that augment, rather than replace, clinical reasoning. In resource-constrained healthcare systems, such as those found in developing countries, the integration of lightweight and explainable models becomes even more critical [34]. These environments impose additional challenges, including limited infrastructure, outdated equipment, and high patient demand, reinforcing the need for robust, efficient, and context-aware AI solutions. However, the successful deployment of such systems depends not only on technological advances but also on adequate training of healthcare professionals and alignment with clinical workflows [43].

Finally, this study highlights the need for a paradigm shift toward the co-design of AI models that are simultaneously efficient, interpretable, and clinically meaningful. Future research should focus on developing integrated frameworks, standardized evaluation metrics, and validation protocols that consider both computational constraints and clinical applicability. Bridging this gap is essential to enable the safe, ethical, and scalable adoption of artificial intelligence in healthcare, ultimately contributing to more transparent, reliable, and patient-centered medical practices.

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7. REFERENCES

[1] XIAO, R. (2025). The role of telemetry monitoring: From diagnosing arrhythmia to predictive models of patient instability. Journal of Electrocardiology.

[2] FARIAS, F. A. C. (2020) Remote Patient Monitoring: A Systematic Review. Telemedicine and e-Health.

[3] HOLM, M. (2023). Patients' experiences of in-hospital telemetry monitoring - a qualitative analysis.. European journal of cardiovascular nursing.

[4] SHAIK, T. (2023). Remote patient monitoring using artificial intelligence: Current state, applications, and challenges. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery,

[5] AL-NUSIF, M. (2025). xplainable AI in Edge Devices: A Lightweight Framework for Real-Time Decision Transparency. International Journal of Engineering and Computer Science. https://doi.org/10.18535/ijecs.v14i07.5181.

[6] REDDY, S. (2022). Explainability and artificial intelligence in medicine.. The Lancet. Digital health. https://doi.org/10.1016/s2589-7500(22)00029-2.

[7] ALI, S. (2023). The enlightening role of explainable artificial intelligence in medical & healthcare domains: A systematic literature review. Computers in biology and medicine. https://doi.org/10.1016/j.compbiomed.2023.107555.

[8] CHADDAD, A. (2023). Survey of Explainable AI Techniques in Healthcare. Sensors (Basel, Switzerland), 23. https://doi.org/10.3390/s23020634.

[9] RAJAGOPAL, D. (2025). AI augmented edge and fog computing for Internet of Health Things

(IoHT). PeerJ Computer Science. https://doi.org/10.7717/peerj-cs.2431.

[10] WANI, N.. (2024). Explainable AI-driven IoMT fusion: Unravelling techniques, opportunities, and challenges with Explainable AI in healthcare. Inf. Fusion. https://doi.org/10.1016/j.inffus.2024.102472.

[11] ALI, A. (2025). An Innovative IoT and Edge Intelligence Framework for Monitoring Elderly People Using Anomaly Detection on Data from Non-Wearable Sensors. Sensors (Basel, Switzerland). https://doi.org/10.3390/s25061735.

[12] KIM, J. (2019). Wearable biosensors for healthcare monitoring. Nature Biotechnology. https://doi.org/10.1038/s41587-019-0045-y.

[13] STAN, E. (2025). A Systematic Literature Review of Innovations, Challenges, and Future Directions in Telemonitoring and Wearable Health Technologies.. IEEE journal of biomedical and health informatics, PP. https://doi.org/10.1109/jbhi.2025.3598056.

[14] PAGANELLI, A. (2022). Real-time data analysis in health monitoring systems: A comprehensive systematic literature review. Journal of biomedical informatics . https://doi.org/10.1016/j.jbi.2022.104009.

[15] ACOSTA, J. (2022). Multimodal biomedical AI. Nature Medicine. https://doi.org/10.1038/s41591-022-01981-2.

[16] KUMAR, R. (2024). Design and Simulation of an Edge Compute Architecture for IoT-Based Clinical Decision Support System. IEEE Access. https://doi.org/10.1109/access.2024.3380906.

[17] ARJUNAN, G. (2023). Optimizing Edge AI for Real-Time Data Processing in IoT Devices: Challenges and Solutions. International Journal of Scientific Research and Management (IJSRM). https://doi.org/10.18535/ijsrm/v11i06.ec2.

[18] NASARIAN, E. (2023). Designing interpretable ML system to enhance trust in healthcare: A systematic review to proposed responsible clinician-AI-collaboration framework. Inf. Fusion. https://doi.org/10.1016/j.inffus.2024.102412.

[19] ŠTIGLIC, G. (2020). Interpretability of machine learning‐based prediction models in healthcare. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery. https://doi.org/10.1002/widm.1379.

[20] XU, Q. (2023). Interpretability of Clinical Decision Support Systems Based on Artificial Intelligence from Technological and Medical Perspective: A Systematic Review. Journal of Healthcare Engineering, 2023. https://doi.org/10.1155/2023/9919269.

[21] MARKUS, A. (2020). The role of explainability in creating trustworthy artificial intelligence for health care: a comprehensive survey of the terminology, design choices, and evaluation strategies. Journal of biomedical informatics. https://doi.org/10.1016/j.jbi.2020.103655.

[22] WYSOCKI, O. (2022). Assessing the communication gap between AI models and healthcare professionals: Explainability, utility and trust in AI-driven clinical decision-making. Artificial

intelligence. https://doi.org/10.1016/j.artint.2022.103839.

[23] OZDEMIR, O. (2024). Explainable AI (XAI) in Healthcare: Bridging the Gap between Accuracy and Interpretability. Journal of Science, Technology and Engineering Research. https://doi.org/10.64206/0z78ev10.

[24] FRASCA, M., La Torre, D., Pravettoni, G., & Cutica, I. (2024). Explainable and interpretable artificial intelligence in medicine: a systematic bibliometric review. Discover Artificial Intelligence. https://doi.org/10.1007/s44163-024-00114-7.

[25] SARASWAT, D. (2022). Explainable AI for Healthcare 5.0: Opportunities and Challenges. IEEE Access. https://doi.org/10.1109/access.2022.3197671.

[26] LIU, Y. (2024). Explainable AI for Trustworthy Clinical Decision Support: A Case-Based Reasoning System for Nursing Assistants. 2024 IEEE International Conference on Big Data (BigData). https://doi.org/10.1109/bigdata62323.2024.10825008.

[27] AMANN, J. (2020). Explainability for artificial intelligence in healthcare: a multidisciplinary perspective. BMC Medical Informatics and Decision Making, 20. https://doi.org/10.1186/s12911-020-01332-6.

[28] ABOUOUF, M. (2024). Explainable AI for Event and Anomaly Detection and Classification in Healthcare Monitoring Systems. IEEE Internet of Things Journal. https://doi.org/10.1109/jiot.2023.3296809.

[29] PAGE, M. J. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. PLOS Medicine doi:10.1371/journal.pmed.1003583

[30] MOTWANI, A. (2022). Ubiquitous and smart healthcare monitoring frameworks based on machine learning: A comprehensive review. Artificial Intelligence in Medicine https://doi.org/10.1016/j.artmed.2022.102431.

[31] BADIDI, E. (2023). Edge AI for Early Detection of Chronic Diseases and the Spread of Infectious Diseases: Opportunities, Challenges, and Future Directions. https://doi.org/10.3390/fi15110370.

[32] HUANG, Z. (2023). Efficient Edge-AI Models for Robust ECG Abnormality Detection on Resource-Constrained Hardware. Journal of Cardiovascular Translational Research. https://doi.org/10.1007/s12265-024-10504-y.

[33] WANG, H.. (2025). HealthEdgeAI: GAI and XAI Based Healthcare System for Sustainable Edge AI and Cloud Computing Environments. Concurrency and Computation: Practice and Experience. https://doi.org/10.1002/cpe.70057.

[34] BELLANDA, V.. (2025). Transforming Brazilian healthcare with AI: progress and future perspectives. Discover Health Systems, 4. https://doi.org/10.1007/s44250-025-00227-5.

[35] ESMAIEILZADEH, P. (2024). Challenges and strategies for wide-scale artificial intelligence (AI) deployment in healthcare practices: A perspective for healthcare organizations. Artificial

intelligence in medicine. https://doi.org/10.1016/j.artmed.2024.102861.

[36] ABBAS, Q. (2025). Explainable AI in Clinical Decision Support Systems: A Meta-Analysis of Methods, Applications, and Usability Challenges. Healthcare. https://doi.org/10.3390/healthcare13172154.

[37] LONDON, A. (2019). Artificial Intelligence and Black-Box Medical Decisions: Accuracy versus Explainability.. The Hastings Center report. https://doi.org/10.1002/hast.973.

[38] CROSS, J. (2024). Bias in medical AI: Implications for clinical decision-making. PLOS Digital Health https://doi.org/10.1371/journal.pdig.0000651.

[39] BRUNYÉ, T. (2025). Artificial intelligence and computer-aided diagnosis in diagnostic decisions: 5 questions for medical informatics and human-computer interface research.. Journal of the American Medical Informatics Association : JAMIA. https://doi.org/10.1093/jamia/ocaf123.

[40] Chen, R., Wang, J., Williamson, D., Chen, T., Lipková, J., Lu, M., Sahai, S., & Mahmood, F. (2023). Algorithmic fairness in artificial intelligence for medicine and healthcare. Nature Biomedical Engineering. https://doi.org/10.1038/s41551-023-01056-8.

[41] OKPETE, U. (2025). Explainable artificial intelligence for personalized management of inflammatory bowel disease: A minireview of recent advances. World Journal of Gastroenterology. https://doi.org/10.3748/wjg.v31.i35.111033.

[42] ABGRALL, G., Holder, A., Dagdia, Z., Zeitouni, K., & Monnet, X. (2024). Should AI models be explainable to clinicians?. Critical Care. https://doi.org/10.1186/s13054-024-05005-y.

[43] HENRY, K. (2022). Human–machine teaming is key to AI adoption: clinicians' experiences with a deployed machine learning system. NPJ Digital Medicine https://doi.org/10.1038/s41746-022-00597-7.

[44] JAHMUNAH, V. (2022). Explainable detection of myocardial infarction using deep learning models with Grad-CAM technique on ECG signals. Computers in biology and medicine, 146, 105550 . https://doi.org/10.1016/j.compbiomed.2022.105550.

[45] SUBHASHINI, K. (2025). Interpretable Deep Learning Framework for Real-Time ECG Classification and Diagnosis. 2025 3rd International Conference on Sustainable Computing and Data Communication Systems (ICSCDS) https://doi.org/10.1109/icscds65426.2025.11167490.

[46] KAVAK, S., Chiu, X., Yen, S., & Chen, M. (2022). Application of CNN for Detection and Localization of STEMI using 12-Lead ECG Images. IEEE Access https://doi.org/10.1109/access.2022.3165966.