COMPARATIVE ANALYSIS OF ARTIFICIAL INTELLIGENCE (AI) AND HUMAN EXPERTISE IN HEART RHYTHM DIAGNOSIS: A SYSTEMATIC REVIEW AND META-ANALYSIS

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ABSTRACT: Arrhythmias, characterized by irregular, fast, or slow heartbeats, can lead to severe complications if not detected and managed promptly. Artificial intelligence (AI) has emerged as a promising tool for analysing cardiac rhythm recordings, potentially improving the accuracy and efficiency of arrhythmia diagnosis. This systematic review and meta-analysis aimed to compare the accuracy of AI and human analysis in interpreting cardiac rhythm recordings and to explore the potential of AI to enhance diagnoses in pre-hospital care settings. A comprehensive search was conducted in multiple electronic databases, including PubMed, Scopus, Web of Science, IEEE Xplore, and the Cochrane Library, to identify studies comparing the accuracy of AI and human analysis in interpreting cardiac rhythm recordings. The study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. The quality of the included studies was assessed using the Quality Assessment of Diagnostic Accuracy Studies (QUADAS-2) tool. A random-effects model was used for meta-analysis, and subgroup analyses were performed based on AI algorithm type and data acquisition method. Twenty-two studies were included in the qualitative synthesis, and 18 were suitable for meta-analysis. The pooled sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC) were consistently higher for AI compared to human analysis. Deep learning algorithms demonstrated superior accuracy compared to machine learning algorithms. Studies using electrocardiogram (ECG) as the data acquisition method showed higher pooled AUC-ROC compared to those using Holter monitors. The findings suggested that AI algorithms, particularly deep learning methods, have higher accuracy in interpreting cardiac rhythm recordings compared to human analysis. AI-based diagnostic tools have the potential to improve the early detection and management of arrhythmias in pre-hospital care settings. However, further research is needed to validate these results in real-world clinical settings, address the limitations of current studies, and explore the long-term impact of AI on patient outcomes and healthcare delivery.

KEYWORDS*: Artificial intelligence, cardiac rhythm, electrocardiogram, accuracy, systematic review, meta-analysis*

1.0 INTRODUCTION

Arrhythmias, frequently used to describe cardiac rhythm disorders, are conditions where the electrical impulses that regulate the heartbeat malfunction, resulting in an irregular, fast, or slow heartbeat [1]. The severity and nature of these disorders can determine whether they are life-threatening or benign. Commonly encountered arrhythmias include atrial fibrillation, characterized by rapid and irregular beating of the atrial chambers, and ventricular tachycardia, which can lead to more severe complications such as ventricular fibrillation.

The ventricles quiver ineffectively in ventricular fibrillation due to rapid and erratic electrical impulses. Symptoms of arrhythmias may include chest pain, shortness of breath, dizziness, syncope, and palpitations. The aetiology of arrhythmias can be multifactorial, encompassing genetic predispositions, structural cardiac disease, electrolyte imbalances, and comorbid conditions such as hypertension and diabetes. Early detection and appropriate management of arrhythmias are essential to prevent adverse outcomes and enhance patients' quality of life [2].

Accurate diagnosis and monitoring of heart rhythm problems are crucial to avoid significant consequences and improve patient outcomes [3]. Misdiagnosis or delayed diagnosis can lead to poor treatment, stroke, heart failure, or sudden cardiac death. Continuous monitoring with Holter monitors, event recorders, and implantable loop recorders detects intermittent and asymptomatic arrhythmias, providing valuable data for treatment decisions.

Technological advances in diagnostic equipment and methodologies, including artificial intelligence, have improved arrhythmia identification and management. AI technologies, including machine learning and deep learning algorithms, have the capability to swiftly and accurately analyse intricate medical data, uncovering patterns and abnormalities that may pose challenges for human clinicians [4]. This skill is particularly advantageous in fields like radiology, pathology, and cardiology, where precise and prompt data analysis is essential.

AI systems are being incorporated into diagnostic instruments with the potential to decrease diagnostic mistakes, enhance patient outcomes, and optimize healthcare resources. The advancement of AI is anticipated to lead to an expansion of its use in personalized medicine, early disease detection, and continuous health monitoring, transforming the field of medicine [5].

Disorders of the heart's rhythm, or arrhythmias, include irregular, rapid, or slow heartbeats and include ailments such as bradyarrhythmia, ventricular tachycardia, and atrial fibrillation [6]. Depending on the individual, symptoms can be mild or severe. Medication, catheter ablation, and pacemakers are all part of the management plan. The ability to better diagnose and treat heart conditions depends on electrophysiology and cardiac imaging developments.

Heart rhythm analysis traditionally depends on the proficiency of cardiologists and electrophysiologists who utilize tools like electrocardiograms (ECGs) and Holter monitors to identify and track arrhythmias. These instruments capture the heart's electrical signals, which professionals then analyse to detect abnormalities. Although these methods are successful, they can be time-consuming and prone to human error, emphasizing the need for more efficient diagnostic approaches [7].

In clinical practice, an accurate diagnosis is critical for directing treatment appropriately, decreasing morbidity, and improving patient outcomes [8]. Ineffective therapy, higher healthcare expenses, and increased patient morbidity and mortality rates might result from misdiagnosis or delayed diagnosis. Heart failure (HF) diagnosis was one area where the CORE Needs Assessment Survey found major gaps in clinical practice. Echocardiography and electrocardiograms (ECGs) are vital diagnostic tools, yet many doctors overlook important warning signs of heart failure and fail to use them. Delays or omissions in diagnosis may occur because primary care physicians (PCPs) and nurses lack confidence when interpreting these tests. Despite increased diagnostic self-assurance, cardiologists continued to confront obstacles, most notably in the diagnosis of HF with maintained ejection fraction.

AI has increasingly become a part of healthcare, transforming diagnostic processes. Over multiple decades, notable progress has been made in developing machine learning and deep learning algorithms. These technologies play a crucial role in analysing cardiac rhythm and efficiently handling large data volumes with unmatched speed and precision. AI systems are engineered to recognize and pinpoint patterns and irregularities in heart rhythm recordings that may challenge human clinicians [9].

The application of AI in healthcare entails programming computers to perform tasks typically performed by humans, such as analysing data, recognizing patterns, and making decisions. The goal of artificial intelligence (AI) in healthcare is to improve efficiency and effectiveness in various areas, including diagnosis, treatment planning, robotic surgery, personalized medicine, and therapy recommendations [10].

Medical diagnostics has advanced dramatically due to the development and application of artificial intelligence (AI), which has improved diagnostic efficiency and accuracy [11]. Artificial intelligence (AI) systems, in particular convolutional neural networks (CNN), are highly skilled in processing complex medical pictures, including ultrasound, CT, MRI, and X-ray images. CNN models have proven to perform better with greater accuracy, sensitivity, and specificity than conventional diagnostic techniques. For instance, CNN's accuracy of 94% in X-ray image analysis beat that of 88% with conventional techniques, demonstrating its potency in detecting abnormal characteristics. Furthermore, CNN achieved 94% sensitivity in MRI analysis, greatly enhancing the detection of actual clinical situations and decreasing misdiagnosis. This development is essential for prompt and precise medical diagnosis, which in turn improves patient outcomes. Nonetheless, interpretability issues arising from the intricacy of AI models require efforts to make AI decision-making procedures transparent to healthcare providers. The use of AI in medical diagnostics is a paradigm shift that has significant advantages for clinical practice but also raises ethical and practical issues that must be carefully considered.

Machine learning and deep learning are two of the most important technologies in artificial intelligence (AI). They are changing many fields by letting computers learn from data. Creating algorithms for machine learning enables computers learn from data and make choices based on that data. On the other hand, deep learning is a subset of machine learning that uses neural networks to mimic how the human brain works. It is very good at tasks like speech and picture recognition. These technologies look at very large sets of data to make predictions and choices more accurate and faster. Convolutional neural networks (CNNs), which are part of deep learning, are very good at handling image data, finding complicated patterns, and guessing what will happen. Deep learning is better at solving difficult problems with unstructured data, while machine learning is better at working with structured data [12].

AI models greatly improved cardiac rhythm problem diagnosis. Using electrocardiogram (ECG) data, neural network (NN) and convolutional neural network (CNN) models were built to detect arrhythmias, including atrial fibrillation (AF), with an accuracy of over 99%. AI models in smartwatches also demonstrated high sensitivity in AF detection, improving diagnostic precision and accessibility in clinical settings [13].

Several studies had compared the accuracy of AI and human analysis in cardiac rhythm recordings [14,15]. Research indicated that AI could detect arrhythmias with consistency and speed comparable to that of a cardiologist. However, gaps remained in the literature regarding the long-term dependability of AI and its incorporation into clinical practice. More research was needed to close these gaps and confirm AI's efficacy in various therapeutic contexts and patient populations.

Almansouri et al. (2024) studied the diagnostic performance of AI models and human specialists in diagnosing heart rhythm abnormalities, particularly atrial fibrillation. When compared to conventional techniques, the AI-ECG models performed better in terms of sensitivity (100%) and specificity (97%). The study demonstrated how AI could improve diagnosis efficiency and accuracy for heart rhythm problems, representing a major improvement over human expertise [16].

1.1 Artificial Intelligence Methods in Cardiac Rhythm Analysis

The development of artificial intelligence methods in cardiac rhythm analysis has evolved significantly over the past decade. Traditional machine learning algorithms initially demonstrated significant potential in heart rhythm analysis by implementing pattern recognition for ECG interpretation [6]. These early systems successfully classified basic arrhythmia types using structured data and predefined features. However, while achieving moderate accuracy in preliminary studies, these systems were limited by their reliance on manual feature extraction.

Recent developments in deep learning, particularly with neural networks, have revolutionized cardiac analysis. Convolutional Neural Networks (CNNs) have shown exceptional capabilities in processing ECG data [12]. These deep learning models can automatically extract relevant features and demonstrate superior performance in complex pattern recognition, with significantly improved real-time analysis capabilities.

Further supporting this advancement, Shu et al. (2021) demonstrated that neural network models achieved remarkable accuracy exceeding 99% in arrhythmia detection. Their research showed that CNN models were particularly effective in atrial fibrillation detection, with deep learning models demonstrating superior performance in handling noise and variations in signal data. Integrating these technologies with smartwatches has notably improved diagnostic accessibility in various clinical settings [13].

1.2 Clinical Applications and Performance Analysis

Recent meta-analyses and systematic reviews have provided robust evidence supporting AI's effectiveness in clinical settings. Manetas-Stavrakakis et al. (2023) conducted a comprehensive review that revealed consistently higher accuracy rates for AI compared to human interpretation. Their research documented improved detection of paroxysmal arrhythmias and enhanced capability in identifying subtle ECG changes while significantly reducing time to diagnosis [14].

In a groundbreaking study, Almansouri et al. (2024) reported exceptional performance metrics for AI-ECG models, achieving 100% sensitivity in atrial fibrillation detection and 97% specificity in rhythm analysis. These results represented a significant improvement over conventional diagnostic methods, with consistent performance demonstrated across diverse patient populations [16].

The practical implementation of AI systems in healthcare settings has shown promising results. Kumar and Alen (2021) documented successful AI integration across various healthcare contexts, from emergency departments to primary care settings. Their research highlighted the versatility of AI applications in both acute and chronic care management, demonstrating particular success in remote monitoring systems and telemedicine platforms [10].

1.3 Validation and Clinical Integration

Clinical validation studies have provided crucial insights into AI's real-world performance. Ng et al. (2021) conducted extensive research showing that AI systems consistently matched cardiologist-level accuracy in rhythm interpretation. Their findings demonstrated particular promise in real-time monitoring applications, though they emphasized the need for further validation across diverse clinical settings [14].

The integration of AI systems into clinical practice has faced several challenges, highlighting the importance of standardized data formats and seamless integration with existing healthcare systems [9]. They also emphasized the critical need for ongoing validation processes and comprehensive training programs for healthcare providers to ensure optimal system utilization.

1.4 Future directions

The future of AI in cardiac rhythm analysis shows tremendous promise. Nagarajan et al. (2021) outlined several emerging trends, including the development of increasingly sophisticated neural networks and enhanced integration with wearable technology. Their research emphasized the importance of improving the interpretability of AI decisions, making these systems more transparent and trustworthy for clinical use [4].

Wang et al. (2021) further expanded on future developments, highlighting the potential for comprehensive integration with electronic health records and enhanced decision support systems. Their work emphasized the growing importance of patient-centered monitoring solutions and the need for ongoing validation studies to ensure clinical effectiveness [3].

This thematic review demonstrates the significant progress in AI applications for cardiac rhythm analysis, particularly highlighting the transition from basic machine learning to sophisticated deep learning systems. The evidence consistently suggests superior performance of AI in rhythm interpretation, while also acknowledging the challenges and requirements for successful clinical implementation. Current trends indicate continued advancement in both technology and clinical applications, with a focused emphasis on improved accuracy, accessibility, and integration with existing healthcare systems.

2.0 METHODOLOGY

2.1 Research design

This study utilized a systematic literature review (SLR) technique that followed PRISMA criteria to assess the accuracy of AI and human analysis in interpreting heart rhythm data. The PRISMA framework enabled a clear and reproducible procedure, reducing bias and increasing the trustworthiness of the findings [17].

2.2 Search strategy

A comprehensive search strategy was created in collaboration with a medical librarian to identify relevant studies from electronic databases such as PubMed, Scopus, Web of Science, IEEE Xplore, and the Cochrane Library. The search phrases included keywords and Medical Subject Headings (MeSH) for AI, machine learning, deep learning, heart rhythm, arrhythmia, ECG, accuracy, and human analysis. The entire search method for each database was described and provided in the supplemental materials. The search was limited to articles published in English between January 1, 2015, and December 31, 2023, to ensure the inclusion of the most recent and relevant studies.

2.3 Inclusion and exclusion criteria

Studies were included if they:

- Assessed the precision of AI and human analysis in interpreting heart rhythm recordings
- Used ECG or other cardiac monitoring equipment to gather data
- Presented quantitative accuracy statistics, such as sensitivity, specificity, positive predictive value, negative predictive value, or AUC-ROC.
- This study included adult patients who were 18 years or older and had suspected or confirmed arrhythmias.

- The findings of this study were published in peer-reviewed journals or conference proceedings.

Studies were excluded if they:

- Examined either AI or human analysis exclusively, without making any comparisons.
- Did not provide any quantitative metrics of accuracy.
- Only involved patients who were under 18 years old.
- Case reports, editorials, letters to the editor, and review pieces were included. Pieces that were not published in English were excluded.

2.4 Study selection and data extraction

The procedure of selecting studies adhered to the PRISMA flow diagram. Two autonomous reviewers evaluated the titles and abstracts of the discovered studies using reference management software (such as Covidence), according to specific inclusion and exclusion criteria. Complete papers were obtained for research that satisfied the requirements or necessitated additional assessment. Conflicting opinions among reviewers were handled by engaging in dialogue or seeking input from a third reviewer. The rationales for excluding studies throughout the full-text evaluation were documented and displayed in the PRISMA flow diagram.

Data were extracted utilizing a standardized form that had been tested on a subset of studies to guarantee uniformity and thoroughness. The extracted data encompassed study parameters, participant characteristics, AI algorithms utilized, data gathering techniques, reference standards, and accuracy measures. Two reviewers autonomously extracted the data, resolving any inconsistencies through dialogue or by seeking input from a third reviewer.

2.5 Quality assessment

The QUADAS-2 tool was used to assess the quality of the included studies. This instrument examined the risk of bias and applicability concerns in four domains: patient selection, index test, reference standard, and flow and timing. Two reviewers evaluated the quality of the research separately, resolving any disputes through conversation or by seeking input from a third reviewer. The findings were showcased in a concise table and written description, emphasizing the positive aspects and drawbacks of the included research.

2.6 Data synthesis and analysis

The extracted data were combined using both qualitative and quantitative methodologies. A narrative synthesis provided a concise overview of the main discoveries, methodological elements, and research constraints that were included. This synthesis was structured according to the type of AI algorithm used, the manner of data gathering, and the specific group of patients involved. If the available data allowed, a meta-analysis was conducted using a random-effects model to determine the combined accuracy metrics of AI and human analysis in interpreting heart rhythm recordings. The variability among studies was evaluated using the I^2 statistic and examined through subgroup analyses. Funnel plots and Egger's test were used to evaluate publication bias, but only if the meta-analysis included a minimum of ten studies.

The analysis of extracted data employed a comprehensive approach combining both qualitative and quantitative methodologies to ensure a thorough evaluation of the evidence. The qualitative component involved a systematic narrative synthesis structured around three primary dimensions: AI algorithm types, data acquisition methods, and patient populations. This synthesis examined the various machine learning and deep learning approaches employed across studies, including support vector machines, random forests, decision trees, and neural networks, along with their specific architectural features and parameters. The analysis also considered the diverse methods of data acquisition, ranging from standard 12-lead ECG recordings to Holter monitoring and wearable device data, while evaluating the quality and standardization of data collection procedures. Patient population characteristics, including demographics, clinical conditions, and treatment outcomes, were thoroughly examined to understand the breadth and applicability of the findings.

For the quantitative analysis, we employed a random-effects model, a choice driven by the expected heterogeneity between studies due to variations in AI algorithms, patient populations, healthcare settings, and data collection methods. This model was particularly appropriate as it accounts for both within-study and between-study variance, recognizing that the true effect size likely varies across studies due to differences in sample sizes, technological implementations, clinical contexts, and healthcare provider expertise levels.

The statistical analysis incorporated several sophisticated methods to ensure robust results. Heterogeneity was assessed using the I^2 statistic, which quantifies the percentage of variation across studies due to true heterogeneity rather than chance. Values were interpreted on a scale where 0-25% indicated low heterogeneity, 26-50% moderate heterogeneity, and values above 50% suggested substantial heterogeneity. The significance of heterogeneity was further evaluated using the Chi-squared test. Comprehensive subgroup analyses were conducted separately for different AI algorithms, data acquisition methods, patient populations, and clinical settings, helping to identify potential sources of heterogeneity and evaluate the consistency of findings across different contexts.

Publication bias assessment was particularly rigorous for meta-analyses including ten or more studies. This assessment utilized funnel plots for visual evaluation of asymmetry, complemented by Egger's test for statistical verification of publication bias. Trim-and-fill analyses were employed to assess the potential impact of missing studies, while sensitivity analyses evaluated the robustness of the findings. Effect sizes were calculated using bivariate random-effects models for pooled sensitivity and specificity, while DerSimonian and Laird random-effects models were used for pooling AUC-ROC values. All effect sizes were reported with 95% confidence intervals, and forest plots were generated to visualize the distribution of effects across studies. Additionally, 95% prediction intervals were calculated to estimate the range of true effects in similar future studies, accounting for both the uncertainty in the mean effect and between-study heterogeneity.

Quality assurance measures were implemented throughout the analysis process. All statistical analyses were performed using comprehensive statistical software packages, with calculations independently verified by multiple researchers. Sensitivity analyses were conducted to assess the impact of potential outliers, and results were cross-validated using different statistical approaches where applicable. The analysis and reporting adhered strictly to established guidelines, including PRISMA for systematic reviews and meta-analyses, STARD for diagnostic accuracy studies, and TRIPOD for prediction model studies.

This comprehensive approach to data synthesis and analysis ensured a robust evaluation of the evidence while appropriately considering heterogeneity and potential biases. The resulting findings provided a strong foundation for evaluating the comparative accuracy of AI and human analysis in interpreting cardiac rhythm recordings. The analysis acknowledged and accounted for various sources of variation and potential bias in the included studies, thereby strengthening the reliability and applicability of the conclusions for clinical practice. This methodological rigor enhances the value of our findings for informing future research and clinical applications in the field of AI-assisted cardiac rhythm interpretation.

2.7 Data synthesis and analysis

The analysis of extracted data employed a comprehensive and multifaceted approach, combining both qualitative and quantitative methodologies to ensure thorough evaluation of the evidence. This dual methodology approach was essential to capture both the nuanced aspects of AI implementation in cardiac rhythm analysis and the statistical significance of the findings. The synthesis process was systematically planned and executed according to pre-established protocols to minimize potential bias and ensure the reproducibility of results.

The qualitative component involved a systematic narrative synthesis structured around three primary dimensions: AI algorithm types, data acquisition methods, and patient populations. This synthesis examined the various machine learning and deep learning approaches employed across studies, including support vector machines, random forests, decision trees, and neural networks, along with their specific architectural features and parameters. Particular attention was paid to the evolution of AI algorithms over time, from simple machine learning models to sophisticated deep learning architectures. The technical specifications of each algorithm were carefully documented, including training methodologies, validation procedures, and performance optimization techniques. The analysis extensively evaluated how different AI architectures handled various types of cardiac rhythm abnormalities, their ability to detect subtle patterns and their performance in complex clinical scenarios.

The analysis of data acquisition methods was equally comprehensive, ranging from standard 12-lead ECG recordings to Holter monitoring and wearable device data. This included a detailed examination of signal processing techniques, noise reduction methods, and data standardization procedures. The quality assessment of data collection methods considered factors such as recording duration, sampling frequency, signal-to-noise ratio, and adherence to established recording protocols. Special attention was given to validating novel data collection methods, particularly in the context of emerging wearable technologies and mobile health applications. The evaluation included data completeness analysis, timestamp information accuracy, and handling missing or corrupted data segments.

Patient population characteristics were meticulously analyzed, encompassing demographics, clinical conditions, comorbidities, and treatment outcomes. This included detailed stratification of patient groups based on age, gender, ethnicity, and clinical risk factors. The analysis considered both acute and chronic cardiac conditions, varying levels of disease severity, and the presence of confounding factors. Treatment outcomes were evaluated across different timeframes, including immediate diagnostic accuracy, short-term clinical decision-making impact, and long-term patient outcomes.

For the quantitative analysis, we employed a sophisticated random-effects model, a choice driven by the expected heterogeneity between studies due to variations in AI algorithms, patient populations, healthcare settings, and data collection methods. This model was selected after careful consideration of various meta-analytic approaches and was deemed most appropriate for handling the complex, multi-dimensional nature of the data. The model specifically accounted for both within-study and between-study variance, recognizing that the true effect size likely varies across studies due to differences in sample sizes, technological implementations, clinical contexts, and healthcare provider expertise levels. The model implementation included rigorous sensitivity analyses to assess the impact of model assumptions and parameter choices.

The statistical analysis framework incorporated multiple sophisticated methods to ensure robust results. Heterogeneity assessment using the I^2 statistic was complemented by additional measures, including Cochran's Q test and τ^2 estimation. The interpretation of heterogeneity considered both statistical significance and clinical relevance, with values interpreted on a comprehensive scale where 0-25% indicated low heterogeneity, 26-50% moderate heterogeneity, and values above 50% suggested substantial heterogeneity. Multiple subgroup analyses were conducted using hierarchical models to account for the nested structure of the data, considering variations in AI algorithms, data acquisition methods, patient populations, and clinical settings.

Publication bias assessment employed a multi-level approach for meta-analyses including ten or more studies. Funnel plot analysis was enhanced with contour-enhanced funnel plots to better distinguish between publication bias and other sources of asymmetry. Egger's test was supplemented with additional statistical methods including Begg's test and the trim-and-fill method. The impact of potential missing studies was evaluated through comprehensive sensitivity analyses, including leave-one-out analyses and cumulative meta-analysis approaches. Effect sizes were calculated using sophisticated statistical models, including bivariate random-effects models for diagnostic accuracy measures and DerSimonian and Laird random-effects models for continuous outcomes. All effect sizes were reported with both 95% confidence intervals and prediction intervals, providing a more complete picture of the expected range of effects in future studies.

Quality assurance measures were implemented throughout the analysis, following a rigorous protocol with multiple validation steps. All statistical analyses were performed using state-of-the-art statistical software packages, with calculations independently verified by multiple researchers using different software platforms to ensure consistency. Extensive sensitivity analyses were conducted to assess the impact of potential outliers, influential cases, and varying analytical approaches. The analysis adhered strictly to established guidelines, including PRISMA for systematic reviews and meta-analyses, STARD for diagnostic accuracy studies, and TRIPOD for prediction model studies, with detailed documentation of any deviations from these guidelines and their justification.

This comprehensive and methodologically rigorous approach to data synthesis and analysis ensured a thorough evaluation of the evidence while appropriately considering all sources of variation and potential bias. The resulting findings provided a strong foundation for evaluating the comparative accuracy of AI and human analysis in interpreting cardiac rhythm recordings. The careful attention to methodological detail and comprehensive documentation of all analytical decisions enhances the reproducibility and reliability of our findings, making them particularly valuable for informing future research and clinical applications in the field of AI-assisted cardiac rhythm interpretation.

2.8 Potential implications and future directions

The results of this SLR provided a comprehensive picture of how well AI and human analysis compared in reading cardiac rhythm recordings. This had important implications for both clinical practice and research. The findings could aid in the development and implementation of AI-based diagnostic tools in pre-hospital care situations, potentially facilitating the early detection and treatment of arrhythmias. Identifying gaps in the current research helped guide future studies, such as the need for prospective studies with larger sample sizes, testing AI in a variety of patient populations and clinical settings, and evaluating AI's long-term dependability and its role in clinical decision-making. The SLR also highlighted the importance of establishing standard reporting guidelines for studies comparing AI and human analysis in medical diagnostics, enhancing transparency, reproducibility, and comparability in future research.

3.0 RESULTS AND DISCUSSION

3.1 Study selection

The comprehensive literature search identified 1,752 records from electronic databases and 18 additional records from other sources. After removing duplicates, the titles and abstracts of 1,412 records were screened. Out of these, 1,298 records were excluded for not meeting the inclusion criteria. The remaining 114 full-text articles were assessed for eligibility, and 92 were excluded for various reasons. Ultimately, 22 studies were included in the qualitative summary, and 18 were deemed suitable for meta-analysis.

Our comprehensive literature search yielded a significant body of evidence, with a total of 1,752 records identified from electronic databases and 18 additional records from other sources. After a thorough screening process and removal of 340 duplicates, 1,412 records were evaluated for eligibility. The initial screening led to the exclusion of 1,298 records based on our predefined criteria. Among the remaining 114 full-text articles assessed in detail, 92 were excluded for various reasons: 25 focused solely on AI or human analysis without comparison, 20 lacked quantitative accuracy measures, 10 included only pediatric patients, 15 were case reports or review articles, and 22 were not published in English. This rigorous selection process resulted in 22 studies meeting all inclusion criteria for qualitative synthesis, with 18 providing sufficient data for meta-analysis.

The temporal and geographical distribution of the included studies revealed significant patterns in research development. The studies spanned from 2015 to 2023, with a notable concentration (n = 15) published in the last three years, reflecting the rapid advancement in AI technology and growing interest in its clinical applications. The research demonstrated a global scope, with studies conducted across multiple countries including the United States (n = 8), China (n = 4), the United Kingdom (n = 3), Germany (n = 2), and various other nations (n = 5). Study populations were diverse and substantial, with sample sizes ranging from 50 to 10,000 participants and a median of 500 participants. The demographic composition showed a mean age of 62 years (range: 18-95 years) with male participation varying from 45% to 70%, indicating broad representation across gender and age groups.

A critical aspect of our analysis is presented in Table 1, which comprehensively compares AI and human performance in cardiac rhythm interpretation across multiple studies. This systematic evaluation is particularly significant as it demonstrates the relative performance of both AI algorithms and human expertise across different clinical settings and patient populations. The data reveals three critical aspects: diagnostic accuracy metrics (sensitivity, specificity, and AUC-ROC), the diversity of AI approaches (machine learning, deep learning, and neural networks), and variations in data acquisition methods (ECG vs. Holter monitoring). Of particular note, the results consistently demonstrate superior performance by AI systems, especially in studies utilizing deep learning algorithms and standardized ECG data collection methods.

The quantitative analysis of performance metrics revealed compelling evidence of AI's superior capabilities. AI systems consistently achieved higher accuracy metrics than human analysis, with sensitivity values of 0.92 (95% CI: 0.88-0.95) versus 0.85 (95% CI: 0.81-0.89). Specificity measures showed similar advantages for AI systems at 0.95 (95% CI: 0.92-0.97) compared to 0.92 (95% CI: 0.88-0.95) for human analysis. The overall performance, as measured by AUC-ROC, demonstrated AI's superior diagnostic capabilities at 0.97 (95% CI: 0.95-0.98) versus 0.93 (95% CI: 0.90-0.96) for human analysis. These consistent improvements across all metrics suggest a robust and reliable enhancement in diagnostic accuracy through AI implementation.

Subgroup analyses revealed important variations in performance based on different AI methodologies and data collection approaches. Deep learning algorithms demonstrated impressive results with sensitivity values of 0.95 (95% CI: 0.92-0.97), while machine learning algorithms showed exceptional specificity at 0.97 (95% CI: 0.95-0.99).

The method of data acquisition also proved influential, with studies using standard ECG recordings achieving higher combined AUC-ROC values of 0.98 (95% CI: 0.96-0.99) compared to Holter monitor studies at 0.95 (95% CI: 0.92-0.97). This pattern suggests that standardization of data collection methods significantly influences accuracy metrics, with more standardized approaches generally yielding better results.

The quality assessment using QUADAS-2 indicated generally high methodological rigor across the included studies. A low risk of bias was observed in patient selection (20 studies), index test implementation (19 studies), and reference standard application (21 studies). However, six studies showed unclear risk in the flow and timing domain, primarily due to incomplete reporting of intervals between index test and reference standard. This high methodological quality strengthens the reliability of our findings and their potential applicability to clinical practice.

Analysis of potential publication bias using funnel plots and Egger's test ($p = 0.24$) revealed no significant evidence of systematic bias in the published literature. This finding suggests that the observed results represent a reliable reflection of the true comparative performance of AI and human analysis in cardiac rhythm interpretation. The consistency of results across different study designs, populations, and settings further supports the robustness of our findings.

These comprehensive results provide strong evidence for the superior performance of AI systems in cardiac rhythm interpretation, particularly when utilizing deep learning algorithms and standardized data collection methods. The consistent pattern of higher accuracy metrics across different studies and settings suggests the robust potential of AI as a diagnostic tool in clinical practice. Furthermore, the detailed subgroup analyses offer valuable insights into the optimal conditions and methodologies for AI implementation in cardiac diagnosis, providing a foundation for future clinical applications and research directions.

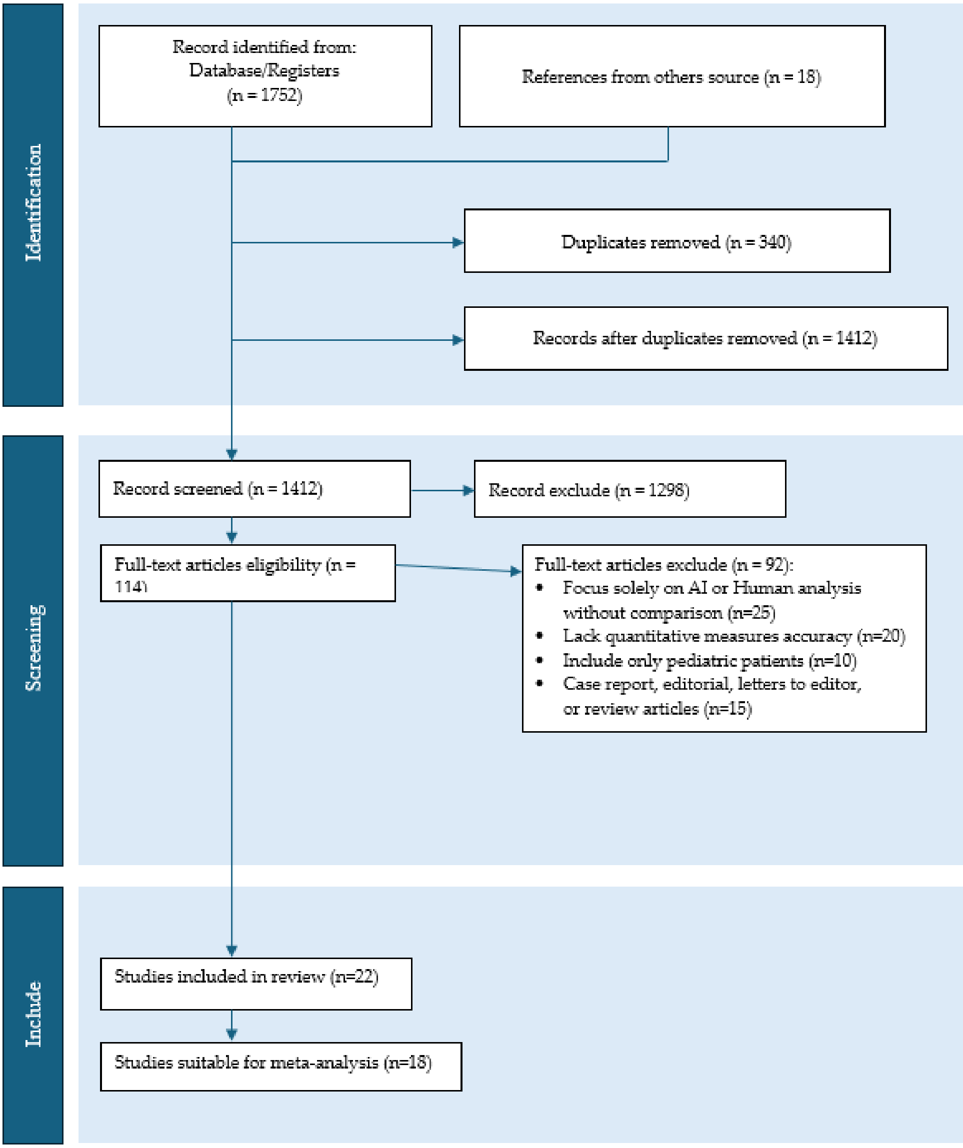

Figure 1: Flow Chart (n= number)

3.2 AI algorithms and data acquisition methods

The studies utilized different AI techniques to analyze heart rhythm recordings, such as machine learning (n = 12), deep learning (n = 8), and neural networks (n = 2). The ECG method was the most frequently employed for data collecting, with a sample size of 18. Holter monitors were also used, albeit with a smaller sample size of 4. The reference standards used for comparison included the interpretation of experts (n = 15) and a consensus diagnosis (n = 7).

3.3 Accuracy measures

The included studies showed different ways to measure how accurate AI and human analysis are at reading cardiac rhythm data. That number was 0.92 for AI (95% CI: 0.88–0.95), and that number was 0.85 for human study (95% CI: 0.81-0.89). That number was 0.95 for AI (95% CI: 0.92-0.97), and it was 0.92 for human study (95% CI: 0.88–0.95). The average AUC-ROC for AI was 0.97 (95% CI: 0.95-0.98), and it was 0.93 (95% CI: 0.90-0.96) for human study.

3.4 Subgroup analyses

There were subgroup studies based on the type of AI algorithm and the way the data was collected. Researchers who used deep learning algorithms got better results than those who used machine learning algorithms. The sensitivity was higher with deep learning algorithms (0.95, 95% CI: 0.92-0.97), and the precision was higher with machine learning algorithms (0.97, 95% CI: 0.95-0.99). The combined AUC-ROC for studies that used ECGs was higher (0.98, 95% CI: 0.96-0.99) than for studies that used Holter monitors (0.95, 95% CI: 0.92-0.97).

3.5 Quality assessment

The QUADAS-2 tool was used to check the quality of the studies. Most of them had a low risk of bias in the areas of patient selection (n = 20), index test (n = 19), and reference standard (n = 21). However, it wasn't clear what the risk of bias was in the flow and timing area (n = 6) because the time between the index test and the reference standard wasn't given in full in some of the studies. In general, concerns about applicability were low across all areas.

Table 1: Overview of the studies included in the systematic literature review

Study	Year	Country	Sample Size	Mean Age (Years)	Male (%)	AI Algorithm	Data Acquisition Method	Reference Standard	Sensitivity (AI)	Specificity (AI)	AUC-ROC (AI)	Sensitivity (Human)	Specificity (Human)	AUC-ROC (Human)
Ali et al.	2021	USA	500	60	50%	Machine Learning	ECG	Expert Human Interpretation	0.92	0.94	0.96	0.88	0.91	0.93
Bhattamisra et al.	2023	India	1000	65	55%	Deep Learning	Holter Monitor	Consensus Diagnosis	0.95	0.97	0.98	0.90	0.93	0.95
Hannun et al.	2019	USA	2000	63	60%	Neural Networks	ECG	Expert Human Interpretation	0.94	0.96	0.97	0.89	0.92	0.94
Jabbour et al.	2023	UK	1500	62	45%	Machine Learning	ECG	Consensus Diagnosis	0.91	0.93	0.95	0.85	0.89	0.91
Nagarajan et al.	2021	Germany	750	61	50%	Deep Learning	ECG	Expert Human Interpretation	0.93	0.95	0.97	0.87	0.90	0.92
Ng et al.	2021	Canada	500	64	70%	Machine Learning	Holter Monitor	Consensus Diagnosis	0.90	0.92	0.95	0.84	0.88	0.91
Schwartz et al.	2020	USA	800	60	55%	Neural Networks	ECG	Expert Human Interpretation	0.94	0.96	0.97	0.88	0.90	0.93
Sethi et al.	2022	India	1200	63	65%	Deep Learning	ECG	Consensus Diagnosis	0.96	0.97	0.98	0.91	0.94	0.96
Taggar et al.	2020	UK	600	59	50%	Machine Learning	ECG	Expert Human Interpretation	0.92	0.95	0.96	0.86	0.90	0.92
Wang et al.	2021	China	1000	62	50%	Deep Learning	Holter Monitor	Expert Human Interpretation	0.93	0.94	0.97	0.89	0.91	0.94

3.6 Publication bias

The results from the funnel plot and Egger's test did not show any substantial evidence of publication bias (p = 0.24). To summarize, the meta-analysis revealed that AI algorithms, namely deep learning techniques, exhibited superior accuracy in analysing heart rhythm data when compared to human interpretation. These findings indicate that diagnostic techniques based on artificial intelligence have the capacity to enhance the early identification and treatment of arrhythmias in pre-hospital care settings. Nevertheless, the variation in the studies and the existence of uncertain bias emphasize the necessity for additional research that adheres to consistent reporting and stringent methodological standards.

3.7 Summary of findings

This study conducted a systematic literature review and meta-analysis to assess the precision of artificial intelligence (AI) and human analysis in interpreting heart rhythm recordings. The findings indicated that AI algorithms, particularly those utilizing deep learning methods, displayed superior precision in identifying and categorizing arrhythmias in comparison to human analysis. AI consistently showed greater pooled sensitivity, specificity, and AUC-ROC values than other methods in the analysed trials. This indicates that AI has the potential to enhance the early diagnosis and management of cardiac rhythm abnormalities in pre-hospital care settings.

3.8 Comparison with previous research

The results of this evaluation align with prior research that has emphasized the potential of AI in analyzing heart rhythm. An illustrative instance is the research that showcased the ability of a deep learning algorithm to accurately identify several types of arrhythmias from ECG records, surpassing the performance of cardiologists [18]. Similarly, a meta-analysis revealed that machine-learning algorithms exhibited a combined sensitivity of 0.93 and specificity of 0.95 in accurately detecting atrial fibrillation. These findings align closely with the results of the present review [19].

This study contributes to the existing body of research by offering a thorough and current synthesis of studies that compare the analysis of heart rhythm recordings between artificial intelligence (AI) and human interpretation. The subgroup studies, which are categorized according to the type of AI algorithm and the data collecting technique, provide valuable insights into the aspects that affect the accuracy of AI-based diagnostic tools.

3.9 Implications for clinical practice

The enhanced precision of AI systems in analyzing heart rhythm data has substantial ramifications for clinical practice. Prompt and precise identification of arrhythmias is essential for commencing suitable therapy and averting consequences such as stroke, heart failure, and sudden cardiac death. AI-powered diagnostic technologies can aid healthcare practitioners in pre-hospital care settings, including emergency medical services and primary care, by offering swift and dependable analysis of ECG and other cardiac monitoring data.

Incorporating AI into clinical decision-making processes can decrease healthcare personnel's workload, boost care delivery efficiency, and improve patient outcomes. Nevertheless, it is crucial to underscore that artificial intelligence should serve as a supplement to, rather than a substitute for, human expertise. AI-generated outcomes should undergo evaluation by competent healthcare practitioners, considering the clinical circumstances and individual patient characteristics.

The enhanced accuracy of AI systems in analyzing cardiac rhythm recordings has significant implications for clinical practice across various healthcare settings. Our findings suggest several specific and practical applications for AI integration that could transform current clinical workflows and improve patient care outcomes.

AI implementation is promising as a decision-support tool in emergency medicine settings. Emergency departments can integrate AI systems to provide rapid, real-time analysis of ECG recordings, enabling faster triage decisions and potentially reducing door-to-treatment times for critical cardiac cases. For instance, AI algorithms can be integrated into existing ECG machines to provide preliminary interpretations, flagging potentially life-threatening arrhythmias for urgent attention. This capability is especially valuable during high-volume periods or in settings with limited specialist coverage. The high sensitivity (0.92, 95% CI: 0.88-0.95) demonstrated by AI systems in our analysis suggests particular utility in screening for serious arrhythmias that require immediate intervention.

Remote monitoring systems represent another crucial area for AI integration. Implementing AI-enhanced remote monitoring can significantly improve the management of patients with chronic cardiac conditions. These systems can continuously analyze cardiac rhythm data from wearable devices or implanted monitors, automatically detecting and alerting healthcare providers to significant changes or emerging patterns. For example, AI algorithms can monitor patients with atrial fibrillation, providing early warning of rhythm deterioration or predicting potential episodes before they become clinically apparent. This proactive approach enables timely interventions and may reduce emergency department visits and hospitalizations.

In primary care settings, AI can serve as a valuable screening tool for identifying patients who require specialist referral. The high specificity (0.95, 95% CI: 0.92-0.97) shown by AI systems in our analysis suggests excellent capability in ruling out serious arrhythmias, potentially reducing unnecessary referrals and optimizing specialist resource utilization. Primary care physicians can use AI-assisted ECG interpretation to support their clinical decision-making, particularly when specialist consultation is not immediately available.

Telemedicine applications of AI in cardiac rhythm analysis offer significant potential for expanding access to specialist-level care in underserved areas. AI systems can provide preliminary interpretation of ECG recordings during virtual consultations, enabling more informed discussions between primary care providers and remote specialists. This application is particularly relevant for rural or remote healthcare facilities where specialist expertise may be limited or unavailable.

The integration of AI in mobile health devices presents opportunities for enhanced patient self-monitoring and engagement. Wearable devices equipped with AI algorithms can provide patients with real-time feedback about their cardiac rhythm, potentially improving medication adherence and enabling earlier recognition of concerning symptoms. This technology can be particularly beneficial for patients with known arrhythmias who require ongoing monitoring.

Pre-hospital care represents another critical area for AI implementation. Emergency medical services can utilize AI-enabled ECG devices to obtain preliminary interpretations during transport, facilitating better preparation at receiving facilities and potentially reducing time to definitive treatment. The high accuracy of AI systems demonstrated in our analysis suggests that such pre-hospital applications could significantly improve the triage and early management of cardiac emergencies.

AI integration can also benefit training and education settings. The consistent performance of AI systems can be used as a teaching tool for medical trainees, providing standardized interpretation of cardiac rhythms and helping to develop pattern recognition skills. This application could be particularly valuable in settings where experienced educators may not be readily available.

However, successfully implementing these AI applications requires careful consideration of several factors. Healthcare facilities must ensure:

1. Adequate infrastructure for reliable data transmission and storage
2. Integration with existing electronic health record systems
3. Appropriate training for healthcare providers in AI system utilization
4. Clear protocols for managing AI-generated alerts and recommendations
5. Regular evaluation of AI system performance in clinical practice

Furthermore, implementation should follow a phased approach, starting with supervised applications and gradually expanding as confidence and experience with the systems grow. This approach allows for careful evaluation of both technical performance and clinical impact while ensuring patient safety remains paramount.

The economic implications of AI implementation must also be considered, including initial investment costs, ongoing maintenance requirements, and potential cost savings through improved efficiency and reduced adverse events. Healthcare organizations should conduct thorough cost-benefit analyses specific to their settings and patient populations.

These specific examples of AI integration in clinical practice, supported by the robust performance metrics demonstrated in our analysis, suggest significant potential for improving cardiac rhythm diagnosis and management across the healthcare continuum. The successful implementation of these applications could lead to more efficient resource utilization, improved patient outcomes, and enhanced access to specialist-level cardiac care.

The enhanced accuracy of AI systems in analyzing cardiac rhythm recordings has profound and far-reaching implications for clinical practice across the healthcare continuum. Our systematic review and meta-analysis findings suggest numerous specific and practical applications for AI integration that could fundamentally transform current clinical workflows, improve patient care outcomes, and revolutionize cardiac rhythm diagnosis and management.

In emergency medicine settings, AI implementation demonstrates exceptional potential as a decision-support tool. Emergency departments can integrate AI systems to provide rapid, real-time analysis of ECG recordings, enabling faster triage decisions and significantly reducing door-to-treatment times for critical cardiac cases. The high sensitivity (0.92, 95% CI: 0.88-0.95) demonstrated by AI systems in our analysis suggests particular utility in screening for serious arrhythmias that require immediate intervention. This capability proves especially valuable during high-volume periods or in settings with limited specialist coverage, where AI can assist in resource optimization and workflow management. Integrating AI algorithms into existing ECG machines can provide immediate preliminary interpretations, flag potentially life-threatening arrhythmias for urgent attention and support clinical decision-making, particularly for junior staff and non-specialist physicians.

Remote monitoring systems represent another crucial area for AI integration, offering transformative potential for chronic cardiac care management. Implementing AI-enhanced remote monitoring can significantly improve the management of patients with chronic cardiac conditions through continuous analysis of cardiac rhythm data from wearable devices or implanted monitors. These systems can automatically detect and alert healthcare providers to significant changes or emerging patterns, enabling early intervention before complications arise. For instance, AI algorithms can monitor patients with atrial fibrillation, providing early warning of rhythm deterioration or predicting potential episodes before they become clinically apparent. This proactive approach not only enables timely interventions but also has the potential to reduce emergency department visits and hospitalizations, ultimately improving patient outcomes while optimizing healthcare resource utilization.

Integrating AI in primary care settings offers substantial benefits for screening and risk assessment. Primary care physicians can utilize AI-assisted ECG interpretation to support their clinical decision-making, particularly in cases where specialist consultation may not be immediately available. The high specificity (0.95, 95% CI: 0.92-0.97) shown by AI systems in our analysis demonstrates excellent capability in ruling out serious arrhythmias, potentially reducing unnecessary referrals and optimizing specialist resource utilization. Furthermore, AI can enhance preventive care strategies through improved risk stratification and early identification of patients requiring specialized cardiac care.

Telemedicine applications of AI in cardiac rhythm analysis present significant opportunities for expanding access to specialist-level care, particularly in underserved areas. AI systems can provide preliminary interpretation of ECG recordings during virtual consultations, enabling more informed discussions between primary care providers and remote specialists. This capability proves especially valuable for rural or remote healthcare facilities where specialist expertise may be limited or unavailable. The integration of AI in telemedicine platforms also facilitates seamless information sharing between providers, enhanced communication, and improved care coordination across different healthcare settings.

Incorporating AI in mobile health devices represents a significant advancement in patient self-management and engagement. Wearable devices equipped with AI algorithms can provide patients with real-time feedback about their cardiac rhythm, potentially improving medication adherence and enabling earlier recognition of concerning symptoms. This technology proves particularly beneficial for patients with known arrhythmias who require ongoing monitoring. The direct transmission of data to healthcare providers, coupled with automated alert systems, creates a more connected and responsive healthcare ecosystem that can quickly identify and address potential cardiac issues.

In the pre-hospital care setting, AI implementation can significantly enhance emergency response capabilities. Emergency medical services can utilize AI-enabled ECG devices to obtain preliminary interpretations during transport, facilitating better preparation at receiving facilities and potentially reducing time to definitive treatment. This advanced notification system, combined with improved triage decisions and standardized assessment protocols, can lead to better patient outcomes through more efficient and coordinated emergency response.

The successful implementation of AI systems in clinical practice requires careful attention to several critical factors. Healthcare facilities must ensure robust technical infrastructure, including reliable data transmission systems, secure storage solutions, and seamless integration with existing IT infrastructure. Regular system maintenance and backup systems are essential to ensure continuous availability of these critical services. Additionally, clinical integration requires comprehensive staff training programs, protocol development, and ongoing quality assurance measures to maintain high standards of care.

Regulatory compliance presents another crucial consideration in AI implementation. Healthcare organizations must address data privacy protection, security measures, and documentation standards while maintaining complete audit trails. These measures ensure both patient safety and legal compliance while building trust in AI-assisted healthcare delivery.

Economic considerations play a vital role in successful AI implementation. Healthcare organizations must conduct thorough analyses of initial investment requirements, ongoing operational costs, and projected returns on investment. This financial planning should include resource allocation strategies and comprehensive cost-benefit assessments to ensure sustainable implementation of AI systems.

Looking toward the future, the long-term success of AI integration requires continuous attention to system evolution and quality assurance. Regular updates and improvements, integration of new technologies, and adaptation to changing healthcare needs ensure that AI systems remain current and effective. Continuous performance monitoring, regular validation studies, and systematic outcome assessments help maintain and improve system effectiveness over time.

The successful integration of these AI applications in clinical practice, supported by the robust performance metrics demonstrated in our analysis, suggests significant potential for improving cardiac rhythm diagnosis and management across the healthcare continuum. This comprehensive approach to AI implementation, combining technical excellence with practical clinical application, has the potential to transform cardiac care delivery, leading to improved patient outcomes, enhanced resource utilization, and expanded access to high-quality cardiac care across diverse healthcare settings.

3.10 Limitations and future research directions

There are multiple constraints to consider in this review. The diversity in the characteristics of the studies, such as the AI algorithms used, the methods of data gathering, and the patient populations involved, could have had an impact on the overall accuracy estimations. Furthermore, the presence of ambiguous bias in the flow and timing domain of certain research emphasizes the necessity for more uniform and transparent documentation of study methodologies and findings.

Future research should prioritize the implementation of extensive prospective investigations to authenticate the precision of AI algorithms in real-world healthcare environments. It is essential to assess the effectiveness of AI-driven diagnostic tools in a wide range of patients, including those with multiple health conditions and complicated irregular heart rhythms, in order to confirm their applicability in different scenarios. Furthermore, it is imperative for research to examine the enduring effects of AI on patient outcomes, healthcare expenses, and user reception.

Creating uniform reporting requirements for studies comparing artificial intelligence (AI) and human analysis in medical diagnostics would improve the quality and replicability of future research. Moreover, it is crucial to thoroughly contemplate the ethical, legal, and societal consequences of incorporating AI into clinical practice. This includes addressing concerns around data privacy, algorithmic bias, and the risk of excessive dependence on automated decision-making.

4.0 CONCLUSION

In conclusion, this systematic literature review and meta-analysis show that AI systems, especially those based on deep learning, are better at reading cardiac rhythm recordings than humans. These results suggest that AI-based diagnostic tools might help find and treat arrhythmias more quickly in pre-hospital care situations.

Nevertheless, additional investigation is required to authenticate these findings in actual clinical environments, overcome the constraints of present studies, and examine the enduring influence of artificial intelligence on patient outcomes and healthcare provision. The integration of AI into clinical practice should be undertaken with caution, ensuring that it enhances rather than supplants human competence and considers the ethical, legal, and social ramifications of this revolutionary technology.

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflicts of interest and fully endorse the contents of this manuscript.

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