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ARTICLE TITLE	THE EVOLUTION OF ARTIFICIAL INTELLIGENCE IN CARDIOLOGY: FROM PRECISE ARRHYTHMIA DETECTION TO PREDICTION OF CARDIOVASCULAR EVENTS AND MORTALITY RISK - A SYSTEMATIC REVIEW (2018–2026)
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THE EVOLUTION OF ARTIFICIAL INTELLIGENCE IN CARDIOLOGY: FROM PRECISE ARRHYTHMIA DETECTION TO PREDICTION OF CARDIOVASCULAR EVENTS AND MORTALITY RISK - A SYSTEMATIC REVIEW (2018–2026)

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ABSTRACT

Background: Cardiovascular disease is the leading cause of death globally, with cardiac arrhythmia being one of the main causes of adverse clinical events. In recent years, psychophysiological medicine has undergone a major transition; however, the first step in this process is the development of Artificial Intelligence (AI) for predicting cardiovascular risk and establishing a framework for prognostic modeling.

Aim: This systematic review aimed to evaluate how AI has been applied in Electrocardiography (ECG) in the period from 2018 to 2026. More specifically, we sought to determine the accuracy of AI in diagnosing arrhythmias and the emerging use of AI for the prediction of major cardiovascular events and death.

Methods: A systematic search of the MEDLINE (PubMed), Embase and Cochrane Library databases for original studies published from 2018 to 2026 was conducted. The focus was on deep learning-based algorithms that utilized 12-lead ECGs or signals derived from wearables. The risk of bias and quality of the studies was assessed using the QUADAS-2 tool.

Results: There were 30 initial studies included in the overall analysis. Most models were convolutional neural network (CNN) based and demonstrated excellent diagnostic accuracy as demonstrated by sensitivity and specificity commonly reported >90–95%. AI's ability to detect paroxysmal atrial fibrillation while in a normal sinus rhythm and for superior triage of occlusive myocardial infarction (STEMI equivalent) versus standard clinical criteria are important findings. Additionally, the establishment of "AI-ECG age" as a digital biomarker may enable long-term prediction of cardiovascular mortality and heart failure risk. Though there are substantial differences in methodological quality and limited standardized external validation among diverse populations are prominent obstacles.

Conclusion: This makes AI a revolutionary tool within cardiology where it can deliver results of accuracy equal to or greater than specialists on selective tasks. The transition from diagnostic to prognostic systems creates tremendous promise for the development of personalized medicine. Yet, in order to achieve appropriate integration into clinical practice, more standardized reporting, as well as rigorous validation to ensure patient safety and diminish the "black box" characteristics of deep learning models, must be undertaken within real-world, multi-national cohort studies.

KEYWORDS

Arrhythmia, Artificial Intelligence, Deep Learning, Electrocardiography, Atrial Fibrillation, Risk Prediction

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Introduction:

Cardiovascular diseases are one of the most important health problems, both as far as mortality and morbidity, which for decades has been the world's greatest challenge to the medical system [4,8,12]. In a continuously ageing world, the prognosis for cardiovascular incidents is and will be bad, mainly due to differences between physiological (or biological) ageing of patients and their chronological age [13,23]. Cardiac arrhythmias constitute a very common and interesting group of heterogeneous diseases which are precursors to serious, life threatening events [6,30]. The arrhythmic disturbance may vary from an isolated premature contraction through a few symptoms due to a paroxysmal tachycardia, caused by supraventricular tachycardia (SVT), to life threatening dangerous ventricular arrhythmias, and from temporary discomfort of patients with isolated symptoms of atrial fibrillation (AF) to serious morbid condition, which carries a risk of sudden cardiac death [1,6,7].

Atrial fibrillation (AF), the most common sustained cardiac arrhythmia, is a major public health problem currently growing into an epidemic in terms of morbidity, carrying a risk of stroke or hearth failure [5,10,15]. Typically the arrhythmia is frequently asymptomatic and paroxysmal, so it is easily missed on a standard one-time clinical encounter [3,11,19]. In reality, approximately 1 out of 3 patients with atrial fibrillation is

asymptomatic, and diagnosis is made by accident when the first manifestation of AF is an episode of disabling stroke [11,12,21]. Furthermore, a remarkable 25 % of stroke patients discover having AF at the time of the first neurological event, that would potentially be preventable with appropriate treatment [16,25].

Traditional assessment of different cardiac disturbances is based on a 12-lead electrocardiogram (ECG) – it is a non-invasive test which reflects heart's electrical activity [9,15,20]. Despite advances in technology, interpretation of ECG signals still rely on manual analysis performed by a clinician [20,25,30]. Although computer ECG interpretation systems assisting clinicians have evolved since 1960s, errors are often reported in curn bnbnnb m,nrent practise [9,15]. However, reliability of automated heart rhythm analysis has improved significantly. Legacy automated software can misclassify AF in up to 30% of recordings mainly due to interference from ventricular pacing, artefact, or premature atrial complexes [9,15,25]. It is essential that such errors do not go unnoticed, because they can delay the initiation of anticoagulation, and inappropriate therapy prescribed [9,15].

The emergence of artificial intelligence (AI), such as machine learning and deep learning, has redefined cardiac diagnosis by identification of paterns that the human eye cannot observe [3,20,30]. Machine learning models for ECG analysis are specifically tailored to recognize patterns in digital time-domain signals. Most existing models employ convolutional neural networks (CNNs) and serve as automatic feature extractors [10,19]. Therefore, they are capable of recognizing the "electrocardiographic signature" of AF even when patients are in a state of sinus rhythm during ECG recording [3,5]. Some models even attain specialist-level accuracy when it comes to the classification of complex arrhythmias [1,13] and the prediction of long QT syndrome genotypes for this syndrome [19].

The application of AI is expanding to long-term monitoring via customers devices, such as the Apple Watch or specialized ECG patches [11,18,20]. Studies like REGAL trial examine wherher these devices can predict AF in high-risk older adults through ambulatory monitoring [11,21]. Similarly, the use of AI-enabled stethoscopes that record single-lead ECG and phonocardiogram signals represents a compelling value proposition for abnormalities detection in primary care [8].

AI was initially introduced as a tool for precise arrhythmia detection, but its potential soon emerged in terms of prognostic [4]. Systems like AIRE, which from a single ECG can predict time-to-mortality and risk of subsequent events, including heart failure and atherosclerotic disease, have been developed [4]. A new, innovative concept, "electrocardiographic aging," (the difference between AI predicted age and actual age) has been proven as a powerful digital biomarker of cardiovascular diseases [13,23]. People found to be "electrophysiologically older" have a significantly higher risk of developing new AF and of early-onset AF [13,23]. In the setting of acute care, initial reports suggest that AI models can outperform traditional clinical triage, improving sensitivity of STEMI detection, while decreasing the number of unnecessary cath lab activations greater than 4-fold. An example of this would be the "Queen of Hearts" system [14,24].

Despite this rapid developmets, there are some limitations of the analysis of cardiovascular signals using deep learning algorithms, including data heterogeneity, "black-box" nature of many deep learning models, and variability of reporting results [4,8,13]. One of them is related to signal quality and necessity of high-quality signals for data extraction; despite that, in some cases, noise and artifacts can be misdiagnosed [1,17]. The present systematic review aims to present an overview of state-of-art of artificial intelligence in cardiology from 2018 to 2026, focusing from arrhythmia classification to predictive models for major cardiovascular risks and mortality.

Materials and Methods

Protocol and Registration: This systematic review was planned and conducted according to established methodology for diagnostic test accuracy studies to ensure transparency and reproducibility. The review followed the PRISMA-DTA (Preferred Reporting Items for a Systematic Review and Meta-analysis of Diagnostic Test Accuracy Studies) guidelines [21]. The primary objective was to analyze the evolution of artificial intelligence (AI) from basic arrhythmia detection to advanced prediction models in cardiology [4, 23].

Search Strategy: Relevant literature was identified by searching major databases, including MEDLINE (via PubMed), Embase, and the Cochrane Library [21]. A combination of keywords targeting both technological and clinical aspects was used, such as "Artificial Intelligence," "Machine Learning," "Deep Learning," "Electrocardiography," "ECG," "Atrial Fibrillation," and "Arrhythmia" [3, 21]. The search was restricted to original research articles published between 2018 and 2026 to capture recent advancements in this rapidly evolving field [24, 30].

Eligibility Criteria: In order to ensure that the comparison between the data is valid and reliable, we have set strict inclusion/exclusion criteria to our systematic review:

- Inclusion criteria: All articles included in our study focused on adult patients (ages 18 or older) who underwent ambulatory or clinical ECG registration [7, 21]. Additionally, all included articles evaluated a certain AI system used for cardiac rhythm analysis in terms of the ability to detect atrial fibrillation in ECG recording (e.g., convolutional neural networks (CNNs), deep neural networks (DNNs), support vector machine (SVMs))[1, 26].

- Exclusion criteria: We did not include in our paper any case reports, animal trials, editorials, or papers in which diagnostic characteristics (such as sensitivity, specificity or area under the curve (AUC)) were not defined [21]. Also, we excluded those articles whose data could be heavily biased due to confounding factors (e.g., pacing activity) [9, 15].

Selection of Studies and Data Extraction: Two reviewers performed an independent review of the titles and abstracts, followed by a comprehensive full-text assessment of the promising literature. Any differences in interpretation between the two reviewers were sorted out by discussion. In addition to extracting information regarding study design and the number of patients and ECG recordings analyzed, along with the details about the AI technology itself, we collected the precise figures regarding true positives, false positives, false negatives, and true negatives [14, 21].

Diagnostic and Clinical Methods: With a range of possibilities for performing an ECG, we grouped together the studies based on the hardware utilized:

- The use of standard 12-lead ECGs available in clinical practice [3, 14, 21].
- Continuous 14-day patch ECGs, as well as consumer-grade wristwatches, such as an Apple Watch, that have gained popularity in recent years [11, 20].
- The purpose for which the analysis was used, ranging from recognizing paroxysmal atrial fibrillation during sinus rhythm [19], discovering atypical STEMI equivalents during emergency visits [14], and calculating the "AI-ECG age" as a marker for cardiovascular disease risks [13, 23].

Quality assessment (Risk of Biast) To make sure the studies were reliable; we looked closely at their validation methods. We used the QUADAS-2 tool to assess the risk of bias across domains like patient selection, index test, and reference standard [21]. We checked whether the algorithms were just tested internally or if they went through rigorous external validation using independent, out-of-sample cohorts [4, 21]. We also paid attention to whether the "ground truth" (the reference standard) was established by board-certified cardiologists, which is crucial for proving the AI isn't simply learning from flawed data [9, 21].

Social, Ethical, and Regulatory Perspectives Finally, we didn't just look at the technical success of the models; we also assessed the real-world clinical consequences of AI errors.

- We analysed data on how false-positive AI readings could lead to unnecessary interventions, such as the inappropriate initiation of oral anticoagulation or unwarranted emergency catheterization lab activations [9, 14].
- We highlighted the consensus across the papers that AI should act as a support tool rather than a replacement for doctors, showing that mandatory cardiologist over-reading significantly improves accuracy and safeguards patients from preventable harm [9, 15].

Results

Predicting Cardiovascular Events and Death: The reviewed studies have identified that Artificial Intelligence has evolved from being a solely diagnostic tool to a robust prognostic tool. Study findings indicate that complex deep learning algorithms like the AI-ECG risk estimator (AIRE) can generate individualised survival curves for patients from a single normal 12-lead ECG [2]. Additionally, these modelling techniques provide significant accuracy for predicting mortality risk (both in the aggregate and by time to death), and for assessing the long-term risk of developing congestive heart failure or atherosclerosis [2, 4]. A second innovative digital biomarker consistently identified across studies internationally is "electro-cardiographic age" (that is, the difference between the patient's chronological age and the age predicted by the AI algorithm). Evaluating this difference (as measured by the AI-ECG) provides a unique prognostic tool [11, 13]. For patients classified as having an "electrophysiologically advanced" heart — where the AI algorithm has predicted a heart age that is much older than the patient's chronological age — there is a considerably greater hazard rate of developing new onset atrial fibrillation and/or experiencing premature or early onset of arrhythmia than for those patients with a normal age gap [11, 23].

Acute Emergency Triage and Clinical Impact: The role of AI in acute emergencies is not limited to long-term predictive capabilities. For example, in STEMI triage, AI models (e.g., the Queen of Hearts) have demonstrated improved diagnostic accuracy compared to standard clinical assessments [12, 14]. Our review has shown that these AI diagnostic systems significantly improve the ability to diagnose acute occlusive myocardial infarctions. AI has provided a substantial improvement for clinicians diagnosing atypical presentations of STEMI using ECGs (e.g., STEMI equivalents) that do not meet current ECG criteria and are commonly misdiagnosed by clinical professionals [14, 30]. Importantly, emergency departments that have implemented AI-based triage systems have shown a substantial reduction (>4x) in false-positive catheterization laboratory activations [12, 30]. Clinically, this represents a reduction in diagnostic uncertainty; it helps to reduce the number of unnecessary invasive procedures, and it reduces the time (and therefore increases the likelihood) of patients receiving timely reperfusion therapy who require it [12, 14].

Performance Metrics and Diagnostic: Accuracy Based on our quantitative synthesis, deep learning models have been consistently shown to provide excellent diagnostic accuracy across multiple technological modalities. For example, convolutional neural networks (CNNs) that assess standard 12-lead ECG signals to classify arrhythmias report a respective area under the receiver operating characteristic curve (AUC) of between 0.92 and >0.98 [1, 28]. Furthermore, wearable devices and smartphone-based photoplethysmography (PPG) for ambient monitoring are capable of detecting paroxysmal atrial fibrillation (AF) with >90% sensitivity, demonstrating their suitability as continuous monitoring devices [15, 17, 24]. Lastly, for acute STEMI detection, advanced artificial intelligence (AI) models provide >92% sensitivity, compared to >71% sensitivity of standard clinical triage used in emergency departments [12,14]

Discussion

Clinical Applications and Integration: Findings from this systematic review indicate that Artificial Intelligence (AI)-assisted electrocardiogram (ECG) interpretation has moved from experimental with retrospective validation to clinical real world application [4, 29]. Everyday clinicians can benefit in two ways from the use of AI algorithms; mass screening of asymptomatic high risk patients at primary care or outpatient facilities with consumer wearables and single-lead patches to identify hidden atrial fibrillation prior to a cerebrovascular accident (stroke) [9, 11]; as well as utilizing fast and effective triage in acute care hospital settings to quickly identify patients with high-risk ECGs (e.g., atypical STEMI equivalents) and prioritize them for immediate cardiologist review, streamlining emergency workflows and expediting life-saving reperfusion therapies [12, 14].

Limitations/Challenges: While many clinical applications are promising, our review revealed several major limitations and challenges that need to be addressed prior to widespread implementation. One of the biggest barriers is the "black box" nature of deep neural networks; clinicians are often reluctant to trust algorithms that do not provide them with clear and interpretable physiological explanations for their diagnostic or prognostic outputs [13, 29]. Furthermore, there are significant issues with data heterogeneity and algorithm bias; many of the models were developed using training data from specific limited populations, which raises questions about the applicability if implemented in other, much larger and more diverse, populations around the world [4, 28] Moreover, technical confounders like baseline noise, movement artifacts from wearable devices, and ventricular pacing are individual predictors of misclassification of AI [7, 15]. Errors like these can sometimes result in false-positive alerts causing a strain on an already overstretched healthcare system due to unnecessary follow-up visits or inappropriate prescriptions of oral anticoagulants [7, 14]. Finally, our analysis suggests that artificial intelligence tools, especially newer and broader models such as large language models will perform considerably differently based on the specificity of the clinical context they receive as input, reinforcing that AI has not yet reached the stage where it can independently diagnose [20].

Future Perspectives: Looking Ahead As we look to the future, the role of AI in cardiology will require a transition towards rigorous decentralized RCTs. Trials like the REGAL study are crucial for assessing the long-term impact of AI-assisted screening on not only the accuracy of diagnosis but also the long-term clinical outcomes and costs [9, 11]. Future investigations will also need to incorporate a high level of emphasis on the need for "explainable AI" (XAI) to build trust with clinical practitioners through visual documentation depicting the segments of ECGs used by the neural network as their focus [29]. In addition, there is an urgent requirement for these prognosis models integrating seamlessly, directly to EHR, in order to facilitate automated and real time risk rating for mortality and cardiovascular^events^ [4, 23]. Ultimately, AI is designed to complement clinician's abilities and skills rather than replace them. The goal of a future paradigm is a "human in the loop" model whereby AI takes care of complex and high volume pattern recognition, while the physician retains control over the final decision as to what will provide the most safety to patients [7, 14, 30].

Conclusions

The findings from this systematic review indicate that artificial intelligence is changing the way that electrocardiography (ECG) is practiced and treated, transitioning from primarily being used as a diagnostic supplemental tool to being able to provide robust prognostic capabilities. AI algorithms have demonstrated an ability to detect difficult-to-identify, complex cardiac arrhythmias (e.g., atrial fibrillation) with high degrees of sensitivity and specificity; indeed, AI performs this detection even when patients are in normal sinus rhythm. Furthermore, beyond simply detecting arrhythmias, digital biomarkers (e.g., "AI-ECG age") and mortality risk platforms are emerging as a significant advance toward achieving personalized cardiovascular medicine. Despite the exciting prospects that AI brings clinical triaging and chronic cardiovascular disease screening, AI continues to have limitations. The use of "black box" algorithms and the realization that legacy computerized systems have approximately a 30% margin of error reveal that AI technology is not yet capable of functioning autonomously. Consequently, the optimal clinical model during the years 2018–2026 and beyond will continue to revolve around the concept of a "human-in-the-loop" method of integration. In this type of configuration, AI should be used to supplement the expertise of cardiologists, thereby ensuring that the rapid development of technology is always accompanied by a thorough review of the clinical evidence for patient safety.

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