Narrative Review Article

Investigating the Impact of Artificial Intelligence in Early Detection, Diagnosis, and Treatment of Cardiovascular Diseases

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ABSTRACT

Cardiovascular disease remains one of the leading causes of death worldwide. Early diagnosis of these diseases is crucial to improving patient outcomes. The electrocardiogram (ECG) is a widely used, non-invasive tool to help detect some of these abnormalities by utilizing the electricity the heart conducts. However, traditional ECG interpretation relies on manual analysis and may fail to identify subtle indicators of disease. Recent advancements in artificial intelligence (AI) have enhanced ECG analysis by identifying complex patterns associated with arrhythmias, coronary artery disease, heart failure, and structural heart disease. This review discusses how AI improves the detection, treatment, and monitoring of cardiovascular diseases through ECG-based models, personalized therapy planning, AI-enabled wearables, and telemonitoring systems. This review also explores digital biomarkers, such as AI-derived heart age and vascular age, for continuous risk assessment and monitoring. Ethical and practical challenges–such as data quality, algorithmic bias, privacy, and the need for human oversight–are also covered. Overall, this review highlights AI's potential to advance preventive, precise, and equitable cardiovascular care.

Keywords: Artificial Intelligence; Cardiovascular Disease; Electrocardiogram; Cardiology; Heart Failure

INTRODUCTION

Cardiovascular disease (CVD) is a major health concern and is one of the leading causes of death worldwide (1). CVD includes a host of conditions such as coronary artery disease, arrhythmias, and heart failure. Many of these conditions can develop silently over time before ballooning into severe, life-threatening events. Early detection is therefore critical to identify and diagnose these conditions promptly, allowing for the implementation of appropriate interventions. One of the most important tools in making an early diagnosis is the Electrocardiogram (ECG). However, ECGs require a manual interpretation of their graphs, leaving room for human variability, time constraints, and potential misreadings of graphs.

In the last few years, rapid advancements in AI have begun to transform the field of cardiology and cardiovascular medicine (2). AI is now capable of detecting hidden patterns and indicators within ECG graphs that may go unnoticed by the human eye. Because ECG data is cost-effective, widely accessible, and non-invasive, it offers the opportunity to improve diagnostic accuracy and quicker interventions.

This review first investigates how ECGs work, how AI can be used to detect Cardiovascular Disease through ECG interpretation, including arrhythmia detection, atrial fibrillation detection, and early identification of

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myocardial infarction. This review describes how AI can help physicians formulate specific care plans and advice for specific treatments based on the patient's diagnosis. This review also demonstrates how AI can be integrated to monitor patients using tools such as personal monitoring devices, smart watches, and predictive risk modeling, potentially enabling earlier predictions and reducing the risk of hospitalization. Ethical and practical issues such as over-reliance on technology, data privacy, algorithmic bias, and the necessity for human supervision are also discussed throughout this review.

Overall, this review focuses on how AI can advance early detection and diagnosis of cardiac diseases through ECG graph analysis. The goal of this review is to maintain a balanced focus on both the transformative potential and the ethical and practical implications of AI integration.

THE ELECTROCARDIOGRAM

An electrocardiogram (ECG) records the heart's electrical activity over a period of time. On the grid paper, the horizontal axis (x-axis) records time while the vertical axis (y-axis) measures the electrical output of the heart in millivolts (mV) (Figure 1).

The first wave in a normal ECG graph is the P Wave, which represents atrial depolarization (when the atria contract). After the P wave, there is a flat line called the PR Segment, which represents the time it takes the electrical signal to reach the ventricles. The PR Interval starts from the start of the P wave and ends at the start of the QRS Wave. A normal PR interval lasts about 0.12-0.20 seconds. Next is the QRS complex, which is usually the largest wave on an ECG, and it represents ventricular depolarization (when the ventricles contract). The QRS complex lasts less than 0.12 seconds. After the QRS, there is the ST segment, which should lie on the baseline of the graph. An elevation or depression of the ST segment could indicate ischemia or myocardial infarction. The final major wave is the T wave, which represents ventricular repolarization (the resetting of the ventricles to prepare for the next heartbeat). The QT interval spans from the beginning of the QRS complex to the end of the T wave, representing the total time for ventricular polarization and depolarization. Prolonged QT intervals can indicate electrolyte imbalances or risk of dangerous arrhythmias.

Identifying and measuring these key components of ECGs (Figure 2) is crucial for diagnosing cardiovascular disease. AI algorithms utilize this information to detect subtle patterns that may be missed by manual interpretation, enabling quicker and more accurate detections for CVD.

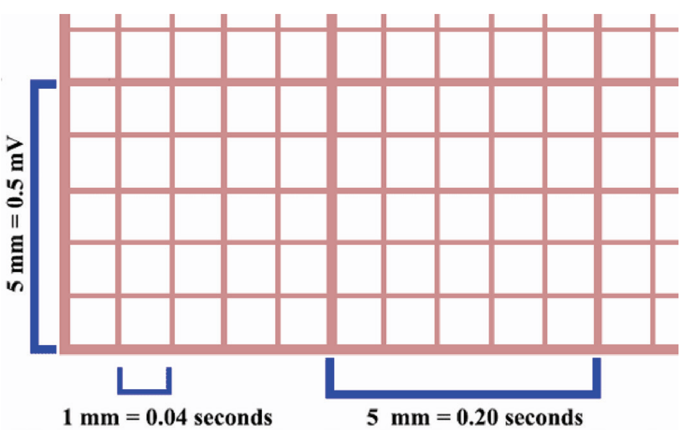


Figure 1. *Standard electrocardiogram (ECG) grid illustrating time and voltage calibration. Horizontally, 1 mm corresponds to 0.04 seconds and 5 mm corresponds to 0.20 seconds; vertically, 5 mm represents 0.5 mV, consistent with standard ECG recording settings (3).*

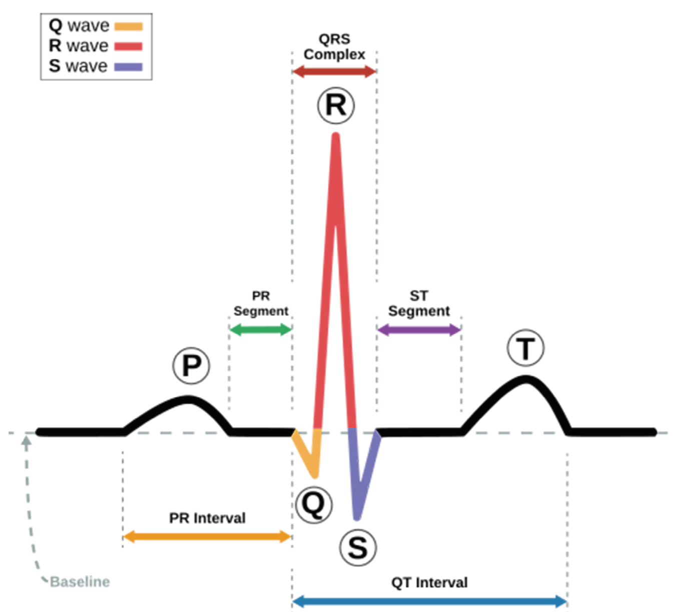


Figure 2. *Diagram representation of a single cardiac cycle on an electrocardiogram, illustrating the P wave, QRS complex, and T wave, along with key intervals commonly used for ECG feature extraction and clinical interpretation (4).*

CARDIOVASCULAR DISEASE: WHAT IS IT?

CVD is a broad term that refers to a group of disorders affecting the heart and blood vessels. It is one of the leading causes of illness and death worldwide, afflicting millions each year. CVD occurs when the normal function of the heart or the circulatory system is disrupted. This can often be the result of narrowed or blocked blood vessels, weakened heart muscle, or irregular heart rhythms. The most common type of CVD is coronary artery disease (CAD), which occurs when the arteries that supply blood become narrow or blocked, causing chest pain and heart attacks. On an ECG, CAD may appear as elevation/depression of the ST segment, elevation potentially indicating transmural ischemia (lack of blood flow to the outer ventricular wall), and depression potentially indicating subendocardial ischemia (lack of blood flow to the inner ventricular wall). CAD may also present as T-wave inversions reflecting abnormalities due to previously mentioned ischemia (Figure 3).

Heart Failure is another major type of CVD. Heart failure is a condition in which the heart cannot pump blood effectively, leading to fluid buildup, fatigue, and structural and electrical changes. On an ECG, heart failure does not have a single specific ECG pattern, but it may show indirect signs, such as the widening of the QRS complex or atrial fibrillation (disappearance of discernible P waves on an ECG) (Figure 4).

Finally, the last common CVD is Arrhythmias.

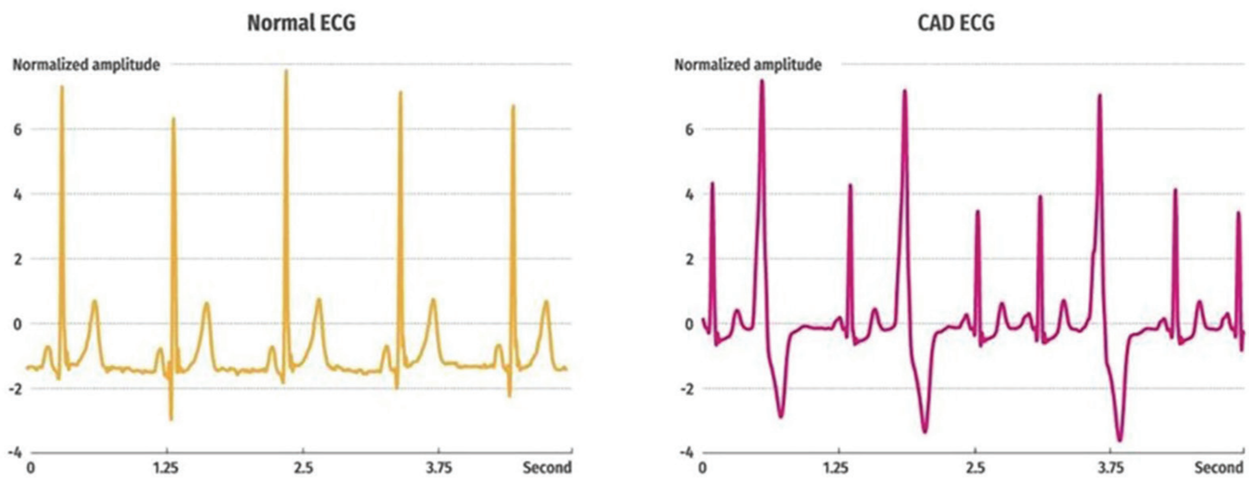
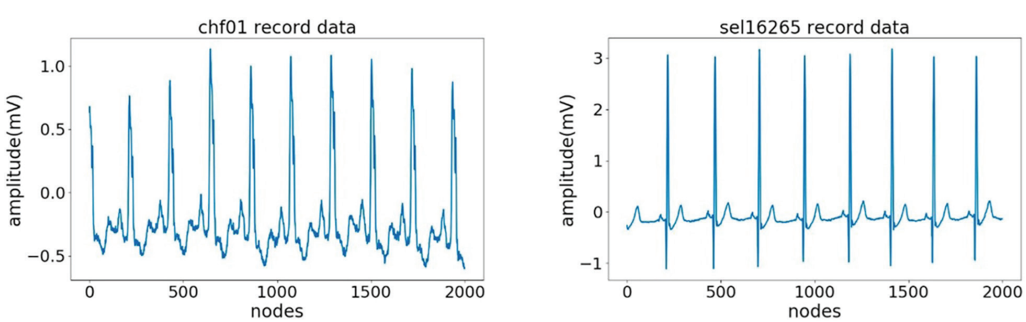


Figure 3. *Comparison of normalized electrocardiogram (ECG) signals from a healthy subject (left) and a patient with coronary artery disease (CAD) (right), illustrating differences in waveform and signal patterns relevant to AI-based cardiovascular risk prediction; CAD ECG contains depressed ST-segments (5).*



(a) Congestive Heart Failure

(b) Normal Sinus Rhythm

Figure 4. *ECG waveforms illustrate congestive heart failure (a) and normal sinus rhythm (b). The heart failure ECG demonstrates altered waveform morphology and absent discernible P waves compared to the regular pattern observed in a normal sinus rhythm; utilized in AI-based cardiovascular risk assessment (6).*

Arrhythmias are abnormal heart rhythms that can affect the heart's ability to pump blood efficiently, increasing the risk of stroke and sudden cardiac death. Some of these abnormal rhythms occur when the heart is beating too fast, such as Atrial Fibrillation (AFiB), Atrial Flutter, Supraventricular Tachycardia (SVT), Tachycardia, and Ventricular Tachycardia (VT). Arrhythmias also occur when the heart is in Ventricular Fibrillation (V-fib) or Bradycardia (Figure 5).

Understanding the different types of CVD is essential for both clinical interpretation and the development of reliable artificial intelligence models. Changes in the intervals, segments, and complexes of an ECG reflect pathophysiological processes associated with CVD. AI models leverage these features by learning complex patterns within ECG data that may not be fully interpretable by the human eye alone. These models can identify disease-specific characteristics and highlight their location on ECGs, possibly enabling quicker risk detection and the potential to improve diagnostic accuracy. In the following sections, this review explores how CVDs are diagnosed using AI, how AI can help treat and monitor patients, and much more.

AI IN THE DETECTION OF CARDIOVASCULAR DISEASE

Despite its usefulness, the 12-lead ECG remains underutilized in detecting many forms of CVD at early preclinical stages. Conventional ECG interpretations may overlook subtle waveform features or defects that can indicate early CVD. Recent advances in AI are now able to extract and analyze these subtle inflections, possibly enabling earlier and more accurate detection of conditions such as heart failure, CAD, and arrhythmias. For example, Columbia's EchoNext model detects structural heart disease on ECG with 77% accuracy compared to 64% for cardiologists (8). However, the researchers do recognize nuance, particularly that this study was conducted in a controlled setting and that results may not translate to real-life cases.

One of the most promising applications of AI in cardiac care is the use of deep learning networks to detect left ventricular dysfunction (LVD, when the left ventricle is weakened by CAD) from routine ECG graph recordings. For example, a neural network trained on patients with an apparently normal sinus rhythm ECG could, years in advance, accurately predict future LVD before the dysfunction was visible on an ECG (9). In the study, the deep neural network derived "ECG-EF" (ejection fraction, measurement of how much blood the heart's left ventricle pumps out with each contraction) achieved an area under the curve (AUC, which measures how well a model can distinguish between positive and negative cases) greater than 0.93 in both validation and follow-up cohorts (for patients with an EF<35%) and an AUC greater than 0.87 for both cohorts with an EF <50%. Both sensitivity and specificity correlate well with ECG-EF and independently predict major cardiovascular adverse events (10). Comparable results in the follow-up

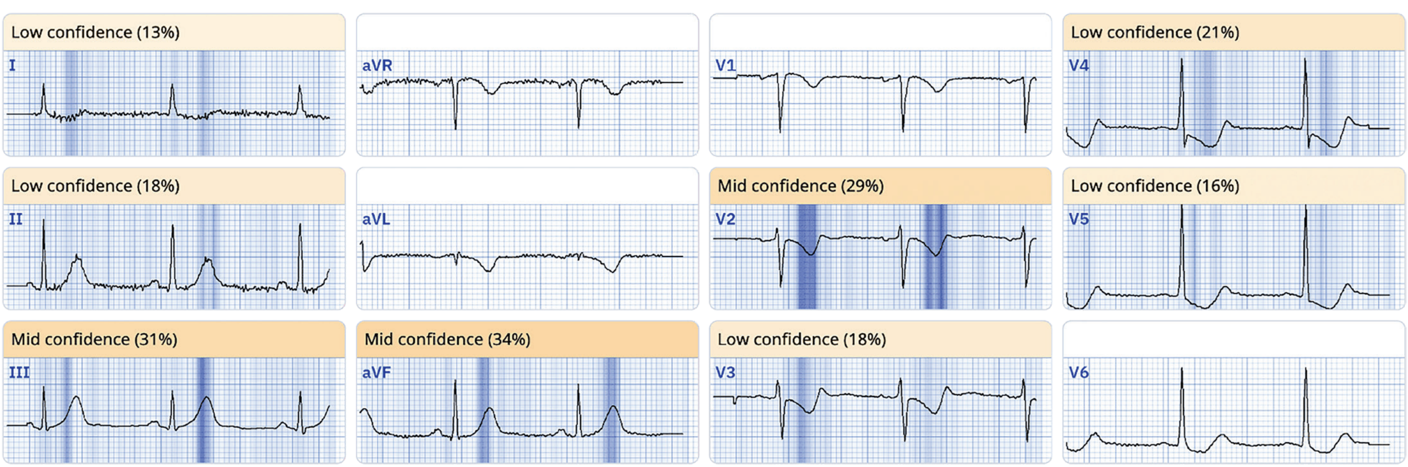


Figure 5. *Visualization of the AI-enabled ECG model highlighting specific features used for prediction. Shaded regions indicate ECG segments contributing to the model's confidence in identifying cardiovascular conditions, including heart failure and coronary artery disease, demonstrating how AI captures clinically relevant electrical patterns across multiple ECG leads (7).*

cohort confirmed the model's robustness and stability over time, indicating that AI-ECG has the potential to serve as a non-invasive, inexpensive screening tool to identify patients at high risk of heart failure, potentially years before symptoms appear (Figure 6).

Under controlled experimental conditions, AI models have achieved a high percentage classification rate of ECG rhythms across multiple arrhythmia types. For example, experts report >97% accuracy for atrial fibrillation detection and an overall classification accuracy of 98% across multiple arrhythmias (11). AI algorithms have also been shown to detect acute coronary syndromes (ACS, secondary to CAD) from ECGs, including subtle presentations that may be overlooked by clinicians. In a large study, a neural network trained on 145,000 emergency ECGs achieved an AUC of 0.91 for detecting heart attacks, such as STEMIs, and outperformed standard clinical interpretation in selected use cases, which had an AUC of 0.65 (12). AI ECG has shown potential for earlier risk identification compared with conventional ECG interpretation. For instance, the model ValvNet was integrated into a standard 12-lead ECG to predict asymptomatic LVD, achieving an AUC of 0.93 (11). Similarly, AI-ECG models have identified reduced ejection fraction and elevated biomarkers with an AUC of 0.89 (11). ValvNet accurately categorized patients with severe LVD solely from ECG data, illustrating consistent performance across racial groups under controlled experimental conditions. Mayo Clinic teams have also incorporated AI to detect hidden cardiomyopathies. For example, AI-ECG algorithms can now flag cardiac amyloidosis (a protein deposit in the heart muscle that causes it to become stiff) and hypertrophic cardiomyopathy (thickening of the myocardium) based on subtle ECG changes (13). Mayo's AI-ECG for heart failure has earned FDA clearance and

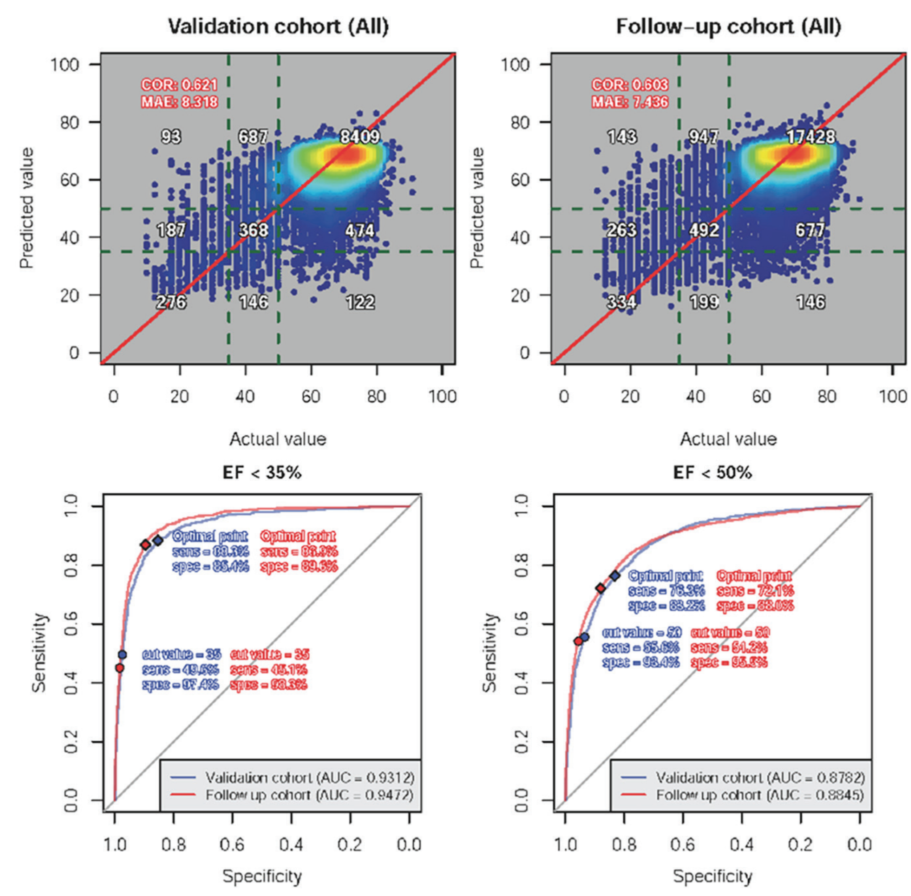


Figure 6. Performance of the AI-enabled ECG model for predicting left ventricular ejection fraction (EF) and detecting reduced EF. Scatter plots show agreement between AI-predicted and measured EF in validation and follow-up cohorts, while AUC curves demonstrate high diagnostic accuracy for identifying EF <35% and EF <50% (10).

commercial licensing for clinical use (13).

Despite these breakthroughs, real-world deployment faces several challenges. Chief among them is generalizability. So far, AI has performed extremely well in controlled groups or small to medium-sized patient cohorts, but this accuracy often declines when applied to larger, more diverse populations. A model too closely trained on a single hospital's ECG data might memorize patterns that do not apply elsewhere (14). To address this, models should be trained on diverse, multi-center datasets and tested across different ECG machines and patient demographics. Data quality also remains a concern. ECGs come from various manufacturers and formats, and recordings can be corrupted by lead misplacement. Moreover, AI models are often viewed as "black boxes," making physicians hesitant to trust diagnoses that lack transparent reasoning (15). To mitigate this, researchers and clinicians emphasize explainable AI techniques and validation processes. These models will require rigorous clinical trials, standardized methodologies, and legal frameworks before widespread adoption (16).

In summary, AI has the potential to elevate the diagnostic capabilities of ECGs for CVD. Multiple studies have shown AI's ability to achieve strong classification performance under controlled conditions, including an over 98% accuracy in arrhythmia classifications (11), a 0.91 AUC for myocardial infarction detection (12), a 0.93 AUC for LVD prediction (11), and 77% accuracy for broad heart failure screening. These findings showcase AI's potential to transform ECGs from a basic rhythm test into a comprehensive screening instrument. However, successful integration into clinical practice requires addressing overfitting, ensuring performance across diverse populations, and fostering clinician trust in AI-derived interpretations. With AI integration, ECGs have the potential to serve as early warning tools, enabling well-timed intervention well before symptoms emerge.

AI IN THE TREATMENT OF CARIOVASCULAR DISEASE

Even though CVD remains the leading cause of death worldwide, treatments have been broad and traditionally slow to develop. AI presents the potential of overcoming these limitations by analyzing vast amounts of biomedical datasets to discover new therapies and personalized care (17, 18). Researchers at the University of Virginia School of Medicine developed an AI-driven drug discovery platform called LogiRX, tasked with accelerating and identifying therapeutic candidates for CVD. Specifically, LogiRx predicts how existing drugs influence both cellular pathways and biological processes, enabling researchers to identify both the beneficial and adverse effects that may help treat specific CVDs. Retrospective clinical data highlighted that patients taking the antidepressant escitalopram (Lexapro) may have a significantly reduced risk of heart failure, suggesting possible repurposing for preventing heart failure (19). AI has shown a particular strength in drug repurposing, where AI identifies clinically approved medications to target CVDs. For example, the platform LogiRx was designed to predict how drugs influence biological pathways rather than merely identifying statistical correlations. By utilizing this approach, the model proposed that the drug escitalopram can modulate hypertrophic abnormalities in cardiomyocytes (19). Because repurposed drugs have already undergone clinical screening, a higher proportion (estimated 30%) successfully progresses towards clinical use compared to traditional methods of drug manufacturing (20).

Unlike some general treatments given to patients, AI could contribute to personalized treatment planning for CVD patients. By integrating a patient's medical history, genetics, imaging, and lifestyle, AI systems can predict a patient's disease risk and can respond with the appropriate treatment (21). These systems constantly adapt: for example, machine learning models that are updated with patient information can dynamically refine risk scores and suggest new therapy plans. In one study, AI models analyzed ECG data from wearable devices and identified people who were 3-7x more likely to develop heart failure than average (22). Armed with these predictions, physicians can proactively adjust medications or interventions before a crisis. In addition to predicting who is at risk for CVD, AI has demonstrated the ability to predict who will respond positively to a therapy in a controlled experimental setting. In a study, an AI algorithm accurately identified which patients with hypertrophic cardiomyopathy would benefit from a new drug treatment, mavacamten, and recommended the treatment over invasive surgery (23).

AI-powered wearables and telemedicine extend cardiovascular care beyond a visit to the clinic. Wearable sensors and home devices capture patient data, which AI algorithms can analyze for early warning signs. For example, one system utilizes daily activity, weight, and symptoms to detect early heart failure decomposition. The model also utilizes drops in activity or disturbed sleep patterns to identify latent disease risk in asymptomatic populations (24). In practice, AI-enabled programs like the American Heart Association's Connected Care use real-time vital monitoring and 24/7 virtual support to prevent readmissions. The platform's AI can triage alerts and ensure patients receive timely interventions, all from their homes (25). AI-integrated telemonitoring provides early alerting, 24/7 assistance, and continuous telemonitoring of the patient.

AI also offers a scalable approach to CVD treatment. By combining AI with omics and systems biology, researchers can design precision therapies like targeted RNA drugs and gene therapies. AI models can analyze complex disease-associated networks, supporting the identification and design of molecules that may alter specific disease pathways.

For example, Ballingand and colleagues outlined how precision cardiovascular medicine can address the fundamental heterogeneity that limits traditional CVD therapies. The authors recognize that CVDs stem from complex pathobiological mechanisms, making universal drug development ineffective.

In the future, these AI-designed drugs have the potential to expand treatment toward previously difficult-to-control symptoms such as inflammatory or fibrotic signaling pathways, while also potentially reducing development costs and improving the efficiency of the drug discovery pipeline. In the study, the authors employed AI integration of multi-omics data (genomics, transcriptomics, proteomics, metabolomics) and network analysis to more accurately identify disease mechanisms and highlight novel therapeutic targets, biomarkers, and patient subgroups with distinct treatment responses (26). Additionally, the study notes that success rates for traditional drug candidates are low, with approximately 90% of new compounds failing regulatory approval, showcasing the possibility of AI assisting in overcoming these challenges. Though the authors point out the potential of AI in the drug discovery pipeline, the lack of coordinated infrastructure and shared resources limits the ability to translate into meaningful therapies (26).

Current evidence shows promise of AI containing the opportunity to reshape cardiovascular treatment. Studies demonstrating AI-guided drug repurposing, such as the identification of escitalopram's potential to prevent heart failure (19), and AI's correct prediction of a patient's response to mavacamten (23) showcase AI's ability to repurpose existing drugs and predict their effectiveness against CVD. However, most of these successes remained confined to experimental studies or early clinical stages, with limited evidence showing improved population-level outcomes or reductions in mortality. Despite its promise, AI-based CVD treatment faces significant challenges. Like the problem with AI-ECGs, high-quality data is crucial, but medical records and sensor data are often fragmented and heterogeneous. Also, AI models may not be obvious and offer a straightforward explanation on how they achieved their treatment option, causing physicians and patients to be wary about their decisions (15, 27). To counteract this, establishing baseline data standards, explainable AI methods, and regulatory frameworks will be necessary to unlock AI's potential in treating CVD. Thus, while AI CVD treatment is advancing, its widespread implementation and impact will depend on rigorous prospective trials.

AI IN THE MONITORING OF CARDIOVASCULAR DISEASE

AI has the potential to augment current clinical monitoring at both the individual and population level. Machine learning systems can analyze clinical data from ECGs, blood lab tests, and imaging studies to detect subtle physiological changes before symptoms arise. In retrospective analyses, AI models have shown the ability to identify short-term trends in biomarkers such as natriuretic peptides, cardiac troponins, and inflammatory markers that are associated with an increased risk of heart failure (28). Additionally, AI-driven analysis of ECGs and cardiac MRIs has been shown to detect subtle reductions in myocardial strain that may precede cardiomyopathy in selected patient cohorts (29).

Population-level monitoring has now expanded through wearables, mobile sensors, and large registries of data. Smartwatches and photoplethysmography (PPG) based devices can identify individuals at an increased risk before clinical diagnosis in retrospective analyses. PPG combined with AI now supports arrhythmia prediction, autonomic function assessment, and ischemia detection. The Apple Heart Study demonstrated that AI algorithms showed potential for detecting Atrial Fibrillation (AF), which involved more than 400,000 participants and showed clinically meaningful sensitivity at a national scale (30). More research has shown that integrating PPG, pulse transit time, and peripheral perfusion can improve early hypertension detection and heart failure risk prediction. Beyond traditional diagnostics, AI has introduced new categories of digital biomarkers for cardiovascular health monitoring. One promising metric is the AI-ECG Heart Age, which was derived from deep neural networks trained on hundreds of thousands of routine 12-lead ECGs. In a study of 425,051 ECGs with an external validation set of 97.058, a learning model predicted a person's current "biological heart age" and predicted that individuals whose AI predicted hearts exceeded their chronological age by ≥ 6 years faced ~60% increase in all-cause mortality and nearly double the risk of major adverse cardiovascular events (31). More recently, researchers have introduced AI-derived Vascular Age, a noninvasive biomarker that has been extracted from raw PPG waveforms. Utilizing data from about 90,000 UK Biobank participants and an additional 113,559 in a separate validation cohort, researchers found that individuals whose vascular age exceeded chronological age by >9 years had a hazard ratio (HR) of about 2.37 for major adverse cardiovascular events, stroke, coronary disease, hypertension, and heart failure (32).

AI models have been shown to detect structural heart disease using simple ECGs. The EchoNext model, trained on more than 1.2 million ECGs and Echocardiograms from over 230,000 patients, identified valvular disease, cardiomyopathies, hypertension, and other structural abnormalities with higher accuracy than physician ECG interpretation (77% vs. 64%), under controlled evaluation settings (33). When deployed across ~85,000 patients without prior imaging, the model flagged ~9% as high risk. Among those who returned to have an echocardiography, approximately 75% were confirmed to have structural heart disease (8, 33). At the population level, models such as ASCENDgtp have demonstrated the ability to predict long-term cardiovascular outcomes using electronic health records. By reducing more than 47,000 diagnosis codes into 176 clinically meaningful phenotypes, ASCENDgtp achieved a C index (which measures a model's ability to correctly rank the risk of events, such as patient survival rate) of 0.816 for outcomes such as myocardial infarction, stroke, CVD, and all-cause mortality (34). Models such as ASCENDgtp allow for system-level risk across millions of individuals and can inform targeted public health interventions.

In all, these advances demonstrate how AI can enhance cardiovascular monitoring by detecting subclinical physiological changes at both the individual and population level, using data from ECGs, biomarkers, imaging, and wearable sensors (28–34). Rather than relying solely on clinical encounters, clinicians have the opportunity to use AI-integrated ECGs, wearable monitoring devices, digital biomarkers, and more predictive models to achieve early detection, risk tracking, and proactive prevention.

However, findings diverge in AI's clinical reliability: while large datasets and controlled operations (such as EchoNext's and ASCENDgtp's population-level studies) demonstrate high predictive accuracy (30, 33, 34), evidence that these results directly translate into real, improved clinical outcomes remains scarce. At the population level, large-scale monitoring with wearables and public data registries can create thousands of opportunities to detect arrhythmias, hypertension, heart failure risk, and CVD risk across a diverse population, possibly positioning AI to become a central pillar in the early detection and management of CVD.

RISKS, LIMITATIONS, AND CHALLENGES OF USING AI IN CARDIOLOGY

Despite its promising performance, AI-integrated ECG analysis faces substantial challenges that complicate its installation from research to clinical practice. Researchers and clinicians caution that without careful handling, these tools could underdeliver or introduce new risks.

A key challenge for AI ECG systems lies in the inherently noisy nature of real-world ECG data. Signal distortion can arise from muscle movements, electrical interference, poor electrode placement, or baseline drift. One study notes that many AI ECG studies rely on high-quality, clean recordings, which do not reflect the variability and uncertainty encountered in everyday clinical settings (35, 36). Because ECG data come from numerous diverse sources, models that are trained on one set of data may perform unpredictably when confronted with devices or settings (37). Furthermore, class imbalance in training data (where normal ECGs vastly outnumber rare cases like certain arrhythmias or cardiomyopathies) can bias models, reduce sensitivity, and specificity for underrepresented diseases (35). Although many AI ECG models can report high accuracy in developmental stages, the performance often degrades when applied to external populations. A 2024 systematic review found that fewer than 33% of studies reported patient ethnicity, and most datasets originated from high-income countries, often not including ethnicity (38). Additionally, external validation remains rare: many high-performing algorithms have been tested only on internal or homogeneous datasets (37). Without large multi-center validation studies, it's unclear whether reported measures (such as >98% arrhythmia classification accuracy [11]) will hold across diverse healthcare groups.

Models can even learn demographic "shortcuts," in which non-pathophysiological features are correlated with race, sex, or age, are used to generate predictions rather than the underlying disease itself (39). As a result, models may rely on single ECG characteristics that may vary across demographic groups (such as baseline voltage differences, QT interval duration, sex hormones, and heart rate variability) rather than disease-specific markers that show up on ECGs (40). Without intervention, such shortcut learning can lead to systemic performance disparities where models demonstrate high accuracy but underperform in underrepresented populations (39, 41). This risk is particularly concerning because ECG morphology has been known to vary across sex and racial groups, even among healthy individuals. Previous studies have shown that sex and race differences in QRS complexes, ST segments, and repolarization characteristics may be misclassified as pathological when evaluated by algorithms trained predominantly on homogeneous datasets (42, 43). Consequently, AI-ECG systems may produce higher false positive rates in some groups while failing to diagnose diseases in others, potentially exacerbating existing disparities in cardiovascular diagnosis and treatment (41).

In a large AI ECG-based study, a model detecting low left ventricular ejection fraction (LVEF <35%) reported strong overall discrimination across racial and ethnic subgroups. The model obtained AUC values of 0.931 for Non-Hispanic White patients, 0.961 for Asian patients, 0.937 for Black/African American patients, 0.937 for Hispanic/Latino patients, and 0.938 for American Indian/Native Alaskan patients (44). While these results are promising, the authors emphasized that subtle but clinically meaningful differences in sensitivity and specificity emerged between the groups, despite the overall high AUCs. Moreover, secondary analysis shows that the model could detect racial subgroups from ECG signals with an AUC up to 0.84, indicating the presence of demographic signal patterns independent of disease (44). These features are not caused by disease; they are normal variations across groups. This presents risk as the model may use race-related patterns instead of true disease markers to make predictions, potentially causing bias, unequal care, and ethical problems if not intervened in.

An often-overlooked methodological problem is label leakage, where outcome information that would not be available at the time of diagnosis is included in model training (45). For example, diagnostic codes created only after a hospital stay can become features in prediction models if not properly time-aligned, leading to artificially high retrospective performance (AUCs of 0.97–0.98 for mortality prediction) that do not reflect prospective clinical utility because the model is effectively "seeing" outcomes before it is meant to predict them (46). Without strict regulation of diagnostic codes, label leakage can make AI prognosis appear highly accurate in retrospective evaluations but fail in real clinical implementations, where future information is unavailable.

Model drift (the degradation of model performance over time due to changes in clinical practice, population characteristics, or ECG device hardware) represents a significant risk for AI ECG systems deployed without continuous monitoring and updates. The model can gradually degrade as the data distribution diverges from what the model was trained on, potentially introducing new biases or reducing accuracy if not recalibrated (47). Thus, systems may misclassify arrhythmias or overlook structural heart disease, reducing diagnosis sensitivity and accuracy. Drift may also worsen health disparities, as underrepresented populations in the original training data may be disproportionately affected by degradation. Techniques such as incremental learning, domain adaptation, and robust validation across multiple clinical data sets are necessary to mitigate shift. Additionally, clear documentation of model versioning, performance metrics, and drift detection protocols/software is critical for maintaining optimal performance and maintaining clinician trust (48, 49).

Deep learning models often function as black boxes, frequently producing diagnoses without transparent explanations. This opacity undermines clinician trust and complicates decision-making, especially in critical contexts like cardiac care. To address this, some newer models integrate Explainable AI (XAI) features, which produce saliency maps or highlight ECG segments that contributed to the diagnosis. For example, a 2025 model named EXGnet reportedly achieved ~98.9% arrhythmia classification accuracy while using XAI-guided analysis (50) (Figure 7).

However, while XAI improves transparency, it does not fully resolve concerns about liability and clinical responsibility. Sensitivity in AI ECG screening is valuable, but if the positive predictive value is low, many flagged patients may undergo unnecessary follow-ups, causing patient anxiety and unnecessary stress on the health care system. A recent AI ECG model for valvular disease demonstrated a good balance of sensitivity but with a modest positive predictive

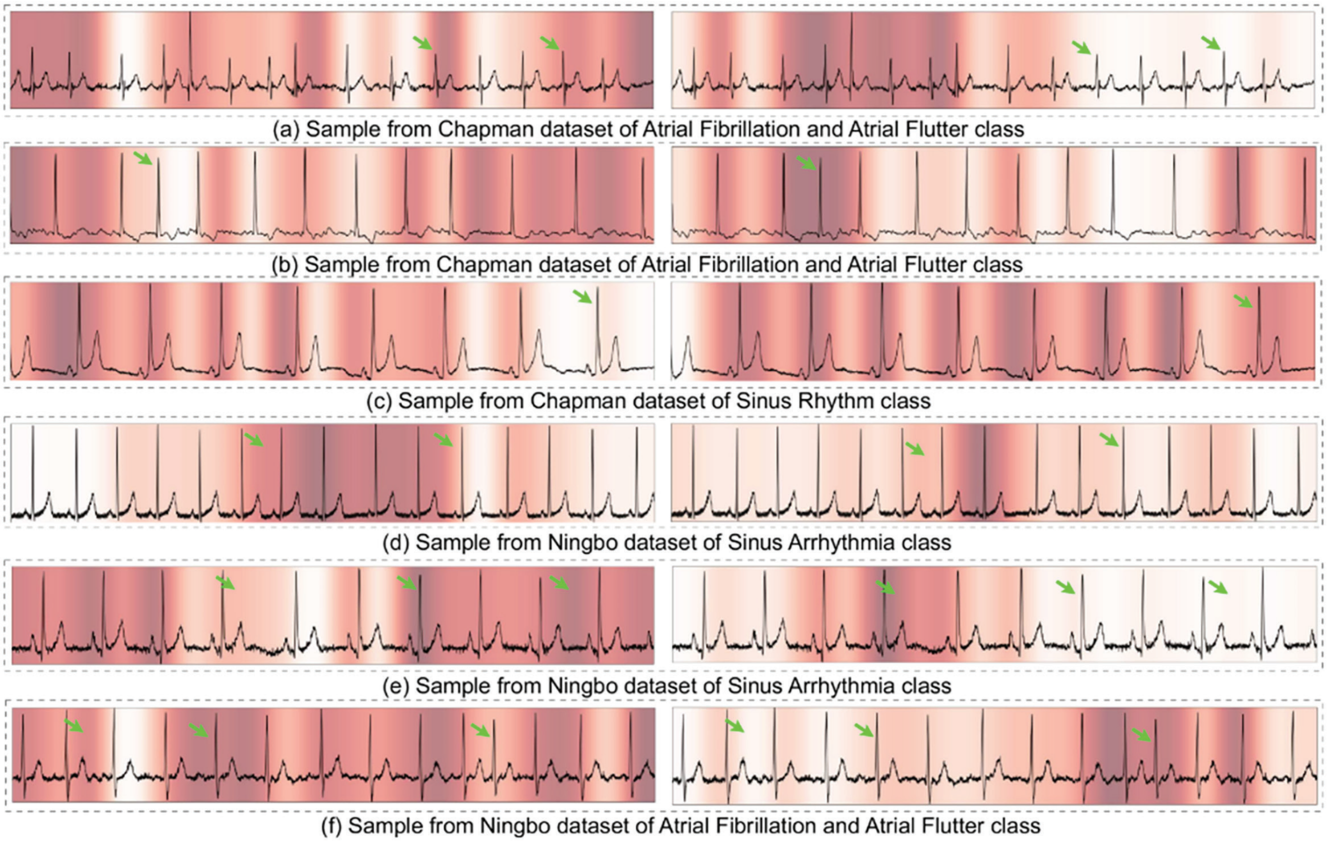


Figure 7. *Visualization of the effect of XAI guidance on the proposed network. The left side shows the CAM outputs from the model without XAI guidance, while the right side displays the outputs when XAI guidance is applied. Green marks indicate the regions where XAI guidance enhances focus and thus improves reliability with clinicians (50).*

value (PPV), meaning many "positives" would be false alarms (51). Most ECG AI models do demonstrate high diagnostic accuracy; however, few studies have linked AI ECG use to improved clinical outcomes such as reduced mortality, fewer hospitalizations, and long-term health benefits. Studies have highlighted that most research focuses on diagnostic metrics rather than patient-centered outcomes (52).

All in all, while AI ECG analysis can offer exciting potential to detect CVD earlier, cheaper, and at a larger scale, realizing that successful implementation depends not only on algorithmic performance but also on careful attention to data quality, fairness, clinical acceptance, and interpretability creates formidable obstacles to overcome. Without addressing these challenges, even the most accurate and promising models risk never leaving their trial phase, preventing implementation into clinical practice and limiting their potential to improve patient care.

CONCLUSION

Artificial intelligence is growing in the diagnosis, treatment, and monitoring of cardiovascular care. In controlled and retrospective analyses, AI-based ECG models have identified subtle patterns associated with multiple cardiac conditions, though the clinical significance and timing relative to symptom onset require further prospective validation. These models have the potential to elevate the ECG from a basic diagnostic test to a powerful predictive instrument that can identify patients' risks earlier and with greater accuracy than traditional interpretation alone. At the same time, AI-driven treatment models such as multi-combination analysis are helping to advance drug discovery, accelerating repurposing of existing medicines, and presenting the option of potential personalized therapy tailored to each patient's genetics and lifestyle. Continuous monitoring using AI-derived predictive biomarkers (such as estimated heart age, vascular age, and population-scale risk models) further highlights AI's potential to shift cardiology from reactive treatment toward more of a preventive model of care.

However, this progress comes with some nuances as significant challenges constrain clinical implementation. Data set biases and underrepresentation have plagued AI-ECG research, presenting the potential for unequal performance across demographic subgroups unless models are trained on diverse, representative data sources. Additionally, most AI applications have a nature of barriers that prevent the trust of clinicians. Since clinicians are often unable to interpret how a model arrives at a specific diagnosis, this creates a lack of trust with clinicians, furthering the constraints of AI-ECGs; however, models are implementing Explainable AI (XAI) features to demonstrate how the model reaches its conclusions, attempting to build clinicians' trust. It is important to note that while many AI-ECG models do demonstrate high diagnostic accuracy, few studies have linked AI ECG use to improving clinical outcomes, such as lowering the mortality rate and reducing the number of hospitalizations.

Evidence that is still missing includes robust national trials that validate these tools in diverse clinical environments and a standardized metric for performance and safety. Future studies must address these gaps by creating a large, multi-ethnic ECG and cardiovascular database with live updates of said data. They must conduct rigorous, randomized, and prospective clinical trials that demonstrate real-world efficacy and an impact on clinical outcomes. Studies must also develop explainable AI frameworks that clinicians can quickly interpret and trust. Future models and studies must establish clear approved pathways, accountability standards, and data governance protections.

Overall, the integration of AI into cardiovascular medicine holds immense promise. When paired with strong clinical guidance and ethical safeguards, AI-assisted interpretation and monitoring can significantly improve early diagnosis, creating individualized treatments and reducing the burden of CVD. As this technology continues to develop, the most significant contribution may be creating a more accessible and precise feature for heart health, one that may detect life-threatening conditions years earlier, enable more effective interventions, and tailor patient outcomes to their specific needs.

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