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Interpretation of ECG recordings using artificial intelligence

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Abstract

Artificial intelligence (AI) represents a significant advancement in the analysis and interpretation of electrocardiograms (ECGs). The implementation of machine learning and deep learning algorithms has enabled the detection of arrhythmias, ischemic alterations, and other cardiovascular abnormalities with speed and accuracy comparable to, or supportive of, clinical expertise. These developments have facilitated automated ECG interpretation, reduced diagnostic error, and provided timely decision support in both hospital-based and remote healthcare settings. AI models trained on large-scale ECG datasets are capable of continuous performance refinement and adaptation across diverse populations, thereby supporting the principles of precision medicine and proactive patient monitoring. With further research and careful integration into established clinical workflows, AI holds substantial potential to enhance early diagnosis and management of cardiovascular diseases, ultimately improving healthcare quality and clinical outcomes.

Keywords: *artificial intelligence, electrocardiogram, ECG analysis, cardiovascular diseases*

1. Introduction

The electrocardiogram (ECG) serves as a fundamental instrument in clinical practice, prized for its affordability, rapid measurement capabilities, and ease of use. As a noninvasive modality, the ECG requires only the strategic placement of electrodes on the body—whether with or without conductive gel—to accurately capture cardiac electrical activity. When conducted by a trained physician, ECG data acquisition is both swift and straightforward. It provides a continuous record of heart activity, ensuring that even subtle abnormalities are documented. This method reveals a wealth of information about the physiological, electrical, and mechanical functions of the heart within a specified timeframe, offering critical insights into various cardiovascular diseases and conditions. The ECG proves invaluable in diagnosing prevalent heart issues such as arrhythmias, myocardial infarctions, strokes, and heart failure, making it an essential tool in global healthcare. For elderly patients or those with existing heart conditions, the ECG remains the preferred choice for routine monitoring. Additionally, during surgical procedures or other medical interventions, continuous ECG monitoring is standard practice to assess vital health parameters. It is also widely utilized in preoperative evaluations to rule out any underlying cardiac conditions that could complicate surgical outcomes. However, apart from heart rate assessment, the accuracy and consistency of ECG diagnoses often hinge on physician expertise, which can lead to variability in interpretation (Shintomi et al., 2022).

The integration of artificial intelligence (AI) into ECG analysis marks a transformative shift in cardiac diagnostics. This advancement reflects a transition from traditional, experience-based interpretations to automated systems that promise significant improvements in accuracy and efficiency. AI's ability to surpass human experts in specific diagnostic tasks, combined with its capacity to process extensive datasets at impressive speeds, suggests a future where computational power is integral to enhancing, and potentially surpassing, human capabilities in ECG interpretation. Moreover, the applications of AI in ECG analysis are extending beyond conventional cardiac diagnostics. AI is now being employed for predicting future cardiovascular events, identifying asymptomatic cardiac conditions that might otherwise remain undetected, and even recognizing non-cardiac issues through subtle ECG patterns. This expanding horizon indicates that the ECG, when analyzed through the prism of artificial intelligence, is emerging as a powerful and versatile source of data, offering comprehensive insights into overall health and forecasting future health risks (Masataka et al., 2023).

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2. ECG Analysis

The 12-lead electrocardiogram (ECG) is a first-line, cost-effective modality for evaluating patients with suspected arrhythmias or acute coronary syndromes (Schläpfer et al., 2017). Its diagnostic value depends on timely acquisition and accurate interpretation: appropriate reading of ECGs shortens time to treatment and reduces adverse outcomes such as missed myocardial infarction or unnecessary interventions (McStay, 2019). However, clinician proficiency is often limited, and automated algorithm outputs vary because diagnostic criteria remain unstandardized (Schläpfer et al., 2017; Kashou et al., 2023). These shortcomings are especially impactful in outpatient and rural environments where specialist consultation is less available, increasing reliance on potentially fallible machine interpretations (Kim et al., 2024). Consequently, inaccurate ECG interpretation can produce treatment delays, unneeded procedures, or life-threatening misdiagnoses.

Resting 12-lead ECGs detect the cause of palpitations in roughly 40% of cases (Wexler et al., 2011), but many arrhythmias are episodic and escape capture during a standard recording. For ambulatory evaluation, extended monitoring—such as Holter recording—improves detection of transient and paroxysmal arrhythmias that would otherwise be missed in outpatient practice (Carrington et al., 2022). As hospitals reduce length of stay, the diagnostic capacity of outpatient tools must expand to identify subtle or intermittent cardiac conditions earlier in their course (Soon et al., 2020).

3. Artificial intelligence

Artificial intelligence (AI) refers broadly to computational methods that learn from data and apply that learning to perform tasks, including those involving pattern recognition, decision support, and aspects of planning or generation. The term originated with John McCarthy in 1956; one of AI's earliest clinical implementations was the MYCIN expert system, which assisted clinicians in identifying bacterial infections and recommending antimicrobials (McCarthy et al., 2006).

AI has since been integrated across clinical specialties. Examples include robotic surgical assistance (e.g., the da Vinci platform) used in complex oncologic procedures (Cheng et al., 2022) and AI-augmented mammography interpretation that can match the accuracy of conventional double readings (Lång et al., 2023). In cardiology, AI techniques have been applied to echocardiographic and CT image analysis (Upton et al., 2022; Zhang et al., 2024) as well as to ECG interpretation (Hopkins et al., 2000). ECG analytics employ a spectrum of methods—from classical machine-learning classifiers (Kagiyama et al., 2020) and early neural-network models (Baxt et al., 2002) to modern deep-learning architectures that learn hierarchical features directly from raw signals (Sun et al., 2021).

3.1. Artificial intelligence, machine learning and deep learning (differences and limitations)

Artificial intelligence (AI) is an umbrella term describing computational systems capable of performing tasks that typically require human cognitive abilities, including pattern recognition, reasoning, and adaptive learning (Quer et al., 2021). Within this broad domain, machine learning (ML) and deep learning (DL) represent key methodological branches. Although DL is commonly characterized as a specialized subset of ML, for the purpose of automated ECG interpretation it is conceptually practical to treat ML and DL as distinct modeling paradigms applied to classification problems. This distinction allows clearer comparison of their methodological assumptions and operational characteristics.

Conventional ML techniques used for classification encompass a wide spectrum of algorithms, such as linear and logistic regression, decision trees, support vector machines, k-nearest neighbors, ensemble approaches, and relatively shallow fully connected neural networks. A central feature of these methods is their reliance on predefined input variables. In other words, raw ECG signals are typically processed to extract clinically meaningful features that domain experts identify as relevant to the predictive task (Alzubaidi et al., 2021; Quer et al., 2021). These engineered features then serve as the basis for model training. Such strategies have been successfully implemented in AI-ECG systems designed to detect conditions such as acute myocardial ischemia (Bouzid et al., 2021).

In contrast, DL methodologies operate differently. Rather than depending on manually selected signal descriptors, DL models employ multilayer neural network architectures composed of numerous hidden layers that autonomously learn hierarchical data representations. Through iterative optimization, these networks progressively transform raw input signals into increasingly abstract feature maps, without requiring explicit domain-driven feature engineering (Alzubaidi et al., 2021). Among DL architectures, convolutional neural networks (CNNs) have become particularly prominent in ECG analysis due to their capacity to process structured waveform data efficiently. CNN-based AI models have demonstrated the ability to analyze standard 12-lead ECG recordings to detect left ventricular systolic dysfunction and to predict the future onset of atrial fibrillation (Attia et al., 2019).

A broad spectrum of AI-ECG methodologies is currently available, each characterized by specific strengths and inherent constraints related to development, implementation, and clinical translation. When evaluating ML and DL strategies at a general level, careful consideration of their comparative advantages and limitations is essential before selecting a modeling framework for a given task.

Traditional ML classifiers are typically built upon explicit feature selection or engineering guided by domain expertise. By constraining model input to a curated set of variables, overall architectural complexity can be reduced, often resulting in shorter training times and lower computational demands. This relative simplicity may also facilitate application to smaller or more homogeneous datasets. Additionally, ML models trained on well-annotated datasets may offer greater interpretability, as the contribution of individual predictors to model output can often be quantified (Alzubaidi et al., 2021). This transparency supports clinical understanding of model behavior and can improve external validation performance. Feature selection may further enhance the signal-to-noise ratio during training, thereby limiting overfitting and improving generalizability.

However, the same dependence on expert-defined features introduces potential drawbacks. Bias may arise from subjective variable selection, and important latent signal characteristics may remain undiscovered if they fall outside predefined feature sets.

DL classification systems, by design, seek to overcome these limitations by learning directly from large-scale raw datasets (Alzubaidi et al., 2021; Yang et al., 2021). Their deep, multilayered architectures enable the modeling of complex, nonlinear relationships that would be difficult to capture using traditional approaches. Consequently, DL algorithms are particularly suited to high-dimensional ECG data and complex diagnostic tasks. Nevertheless, their performance is closely linked to the availability of extensive training data. In practical terms, DL models are highly data-dependent, and insufficient dataset size may compromise robustness and generalizability.

Moreover, increased architectural complexity entails several challenges. Training deep neural networks is computationally intensive and often time-consuming. The risk of overfitting may be amplified due to high model variance, especially when external validation datasets differ from training populations. Finally, many DL systems lack transparent decision pathways, raising concerns regarding interpretability and the so-called “black box” phenomenon, which remains a critical issue in clinical medicine (Alzubaidi et al., 2021).

4. Artificial intelligence and heart diseases

Artificial intelligence has increasingly been integrated into cardiovascular medicine, with applications spanning diagnostic, prognostic, and risk stratification domains. Current AI-driven approaches are being applied to arrhythmia detection (including atrial fibrillation and ventricular tachyarrhythmias), valvular heart disease (such as aortic stenosis and mitral regurgitation), heart failure, cardiomyopathies (e.g., hypertrophic cardiomyopathy), myocardial infarction, pulmonary hypertension, and inherited channelopathies. Beyond strictly cardiac disorders, AI-enabled electrocardiographic analysis has also demonstrated utility in identifying extracardiac conditions, including hyperkalemia, anemia, and broader systemic clinical states.

In parallel with diagnostic applications, considerable research efforts are focused on predictive modeling. AI systems are being developed to identify individuals at risk of future cardiovascular disease before clinical manifestation, thereby enabling earlier intervention and potentially preventing irreversible structural or functional deterioration. Particular emphasis has been placed on predicting paroxysmal atrial fibrillation, progressive valvular disease (aortic stenosis and mitral insufficiency), heart failure with preserved ejection fraction, and acute clinical deterioration, including cardiac arrest.

4.1. Atrial fibrillation

Atrial fibrillation (AF) is strongly associated with thromboembolic events, heart failure, and increased mortality. According to the 2020 European Society of Cardiology (ESC) guidelines, a definitive diagnosis requires electrocardiographic documentation of AF using a 12-lead ECG, continuous telemetry, Holter monitoring, or implantable loop recorders (Hindricks et al., 2021). Despite these established diagnostic modalities, AF frequently remains undetected. Approximately one-third of patients are asymptomatic, while another quarter present with nonspecific or atypical symptoms (Siontis et al., 2016). Furthermore, the arrhythmia may occur in a paroxysmal and intermittent pattern, complicating detection; notably, paroxysmal AF has been identified in nearly 15% of patients previously classified as having cryptogenic stroke (Gladstone et al., 2014).

These diagnostic challenges have created a compelling rationale for AI-enhanced electrocardiography. Advanced computational models have demonstrated the capacity to identify subtle electrocardiographic markers of AF even when the ECG is recorded during sinus rhythm. These latent features—often referred to as the electrocardiographic “signature” of AF—are typically imperceptible to human observers. In a landmark study, Attia et al. (2019) developed a deep learning algorithm capable of detecting such patterns, achieving an area under the curve (AUC) of 0.87 for identifying AF. Similarly, Hygrell et al. (2023) reported that AI-based models can predict AF from single-lead sinus rhythm ECG recordings, with particularly strong performance in elderly populations. The BEAGLE trial (NCT04208971), the first

randomized controlled study evaluating AI-guided AF screening, is currently underway to validate an ECG-based algorithm designed to identify individuals at high risk for AF (Yao et al., 2021).

The potential to detect AF using single-channel ECG recordings has important implications for large-scale screening initiatives, as these recordings are readily obtained via wearable technologies. In addition to single-lead ECG systems, photoplethysmography (PPG) has emerged as an alternative noninvasive method incorporated into consumer devices such as smartwatches and smartphones. PPG operates by emitting light into the skin and measuring changes in light absorption through a photodetector, thereby capturing pulse wave dynamics (Dorr et al., 2019). When combined with deep neural network algorithms, PPG-derived data have shown promising results in AF detection in several large-scale clinical investigations, including smartwatch-based studies (Perez et al., 2019).

4.2. Aortic stenosis

Aortic stenosis (AS) represents the most prevalent valvular heart disease in developed countries, affecting approximately 0.4% of the general population. Its prevalence increases markedly with age, occurring in about 2% of individuals older than 65 years and up to 12% of those older than 75 years. The natural history of symptomatic severe AS is associated with poor prognosis, with reported survival rates of approximately 50% at two years following symptom onset (Otto & Prendergast, 2014).

Valve replacement—either surgical or transcatheter aortic valve implantation (TAVI)—remains the only effective treatment for severe AS. The advent of TAVI has significantly expanded therapeutic options, particularly for elderly patients or those considered high-risk or inoperable (Polimeni et al., 2020). Echocardiography currently serves as the gold standard for the diagnosis and hemodynamic quantification of AS (Hagendorff et al., 2020). However, because many patients with advanced disease remain asymptomatic, reliance on symptom-driven evaluation may delay diagnosis until irreversible myocardial damage has occurred.

This clinical gap underscores the need for accessible screening strategies. If clinically significant AS could be reliably identified using standard 12-lead ECG recordings or even single-lead devices, patients could be referred for confirmatory echocardiography at an earlier stage. The importance of early detection is further supported by accumulating evidence suggesting improved outcomes with timely intervention, even in asymptomatic individuals (Kang et al., 2020).

Recent advances in AI have enabled the identification of electrocardiographic patterns associated with manifest AS and early valvular pathology. Studies conducted across geographically and ethnically diverse populations have demonstrated the feasibility of deep learning algorithms in detecting valvular disease from ECG data alone. Notably, specific features such as alterations in the TP interval and U-wave morphology in right precordial leads have been identified as influential predictors.

Kwon et al. (2020) developed a deep learning model capable of detecting AS using both standard 12-lead and single-lead ECG recordings. The screening algorithm achieved an AUC between 0.86 and 0.88, with a negative predictive value exceeding 99%. Similarly, Cohen-Shelly et al. (2021) reported an AUC of 0.85 for detecting moderate-to-severe AS in asymptomatic individuals, with high sensitivity, specificity, and a negative predictive value of 99%. Importantly, their findings suggested that AI-assisted ECG analysis outperformed physician auscultation, as only 39% of clinicians were able to correctly identify aortic stenosis based on cardiac murmurs alone.

4.3. Ventricular dysfunction

Left ventricular dysfunction encompasses multiple clinical phenotypes defined according to left ventricular ejection fraction (LVEF). These include heart failure with reduced ejection fraction (HFrEF; LVEF $< 40\%$), heart failure with mildly reduced ejection fraction (HFmrEF; LVEF 41–49%), and heart failure with preserved ejection fraction (HFpEF; LVEF $\geq 50\%$) in the presence of characteristic symptoms, signs of congestion, and evidence of diastolic dysfunction. Epidemiological data suggest that approximately 6% of the general population may have asymptomatic and previously undiagnosed left ventricular systolic dysfunction (LVEF $< 50\%$).

Transthoracic echocardiography (TTE) remains the reference standard for assessing ventricular structure and systolic performance. However, its availability may be limited by cost, equipment requirements, and operator dependency. Measurement of natriuretic peptides provides a useful screening tool, but this approach requires venipuncture and laboratory analysis, making it minimally invasive rather than entirely noninvasive (Omland et al., 1996).

A resting 12-lead electrocardiogram has traditionally demonstrated limited sensitivity and modest positive predictive value for detecting left ventricular systolic dysfunction. Consequently, there is currently no inexpensive, widely accessible, and fully noninvasive screening modality capable of reliably identifying subclinical ventricular impairment. Earlier efforts to enhance ECG-based detection included the work of Schlegel et al. (2010), who evaluated an advanced computerized 12-lead ECG system incorporating seven electrocardiographic parameters into a multivariate analytical

model. This approach improved diagnostic sensitivity, specificity, and positive predictive value compared with conventional ECG interpretation.

More recently, artificial intelligence has significantly advanced this field. By applying deep neural networks to ECG data, investigators have demonstrated the capacity to detect subtle electrical signatures associated with impaired ventricular function. In a landmark study, Attia et al. (2019) trained a neural network using 97,829 paired ECG and TTE datasets. When validated on an independent cohort of 52,870 ECGs, the model achieved an area under the curve (AUC) of 0.93, with a sensitivity of 93.0%, specificity of 86.3%, and overall accuracy of 85.7%. Notably, individuals classified by the algorithm as having reduced ejection fraction despite normal findings on echocardiography ("false positives") exhibited a 10% increased risk of developing ventricular dysfunction within five years. This observation suggests that AI-enhanced ECG analysis may detect early or preclinical myocardial abnormalities before structural changes become evident on imaging.

4.4. Cardiomyopathies

Hypertrophic cardiomyopathy (HCM) is associated with a yearly cardiovascular mortality rate of approximately 1–2%, attributable to sudden cardiac death, progressive heart failure, and thromboembolic events (Elliott et al., 2006). In pediatric populations, overall mortality approaches 10%, with an annual risk of sudden cardiac death estimated at 1.2–1.5% (Lipshultz et al., 2013).

According to the 2023 European Society of Cardiology (ESC) guidelines, diagnosis is primarily established through imaging, most commonly echocardiography, demonstrating a maximal left ventricular wall thickness ≥ 15 mm in the absence of abnormal loading conditions sufficient to explain the hypertrophy (Arbelo et al., 2023). Risk stratification for sudden cardiac death over a five-year period (Class IB recommendation) is performed using the HCM Risk-SCD calculator.

Although imaging remains central to diagnosis, earlier identification of affected individuals—particularly asymptomatic patients—would be clinically valuable. Electrocardiography offers an attractive screening modality due to its simplicity, accessibility, and noninvasive nature. More than 90% of patients with HCM exhibit ECG abnormalities; however, these changes are frequently nonspecific and do not allow reliable differentiation from other causes of left ventricular hypertrophy or repolarization abnormalities.

Machine learning approaches have sought to address these limitations. An early investigation published in 2015 demonstrated the feasibility of detecting HCM using machine learning techniques applied to 12-lead ECG data. Building on this concept, Ko et al. (2020) evaluated a deep learning model trained to identify HCM directly from standard ECG recordings. The algorithm achieved an AUC of 0.96, with sensitivity of 87%, specificity of 91%, and a negative predictive value of 99%. These findings indicate that AI-based ECG analysis may serve as an effective screening strategy, particularly for excluding disease in low-risk populations while identifying individuals who warrant further imaging evaluation.

4.5. Myocardial infarction and ischemic cardiomyopathy

Acute coronary syndromes (ACS) remain a leading cause of global mortality and morbidity. Because clinical outcomes are highly time-dependent, rapid diagnosis and prompt initiation of evidence-based therapy are essential to reduce myocardial damage and improve survival. According to the most recent ESC guidelines, a standard 12-lead ECG should be performed within 10 minutes of first medical contact in patients presenting with chest pain or equivalent ischemic symptoms (Byrne et al., 2023). Electrocardiographic manifestations of acute myocardial infarction include ST-segment deviation, T-wave inversion, and the development of pathological Q waves. In particular, ST-segment elevation myocardial infarction (STEMI) is defined by persistent ST-segment elevation at the J-point in at least two contiguous leads.

Given the central role of ECG interpretation in ACS management, several studies have explored automated detection of myocardial infarction using artificial intelligence. Early investigations applied convolutional neural networks (CNNs) to single-lead ECG recordings. Acharya et al. (2017), for example, developed an 11-layer CNN capable of diagnosing myocardial infarction from single-channel ECG data, achieving an accuracy of 95.22%, sensitivity of 95.49%, and specificity of 94.19%.

Subsequent studies extended this approach to full 12-lead ECG datasets, enabling not only detection but also localization of infarction. In one such study, Chen et al. (2021) trained a CNN model using 15,285 ECGs for training and 6,552 for validation, with an independent test set of 205 ECGs. The final model achieved an accuracy of 82.7% in identifying and localizing myocardial infarction. Beyond classification performance, Chen et al. also proposed an automated system for detecting ST-segment elevation in hospitalized patients to facilitate rapid triage. The system demonstrated excellent diagnostic metrics, including an AUC of 0.997, accuracy of 0.992, precision of 0.889, and specificity of 0.994.

Importantly, implementation of the algorithm significantly reduced diagnostic delay, with a mean response time of 37.2 ± 11.3 seconds compared with 113.2 ± 369.4 seconds for physician interpretation ($p < 0.001$). These findings highlight the potential of AI-assisted ECG analysis to streamline acute cardiac care pathways.

Chronic coronary syndromes also require early identification to prevent progressive myocardial remodeling and ischemic cardiomyopathy. Myocardial scarring, a marker of prior infarction and predictor of adverse outcomes, is optimally assessed using cardiac magnetic resonance imaging (MRI) with late gadolinium enhancement. However, limited availability, high cost, and the need for specialized expertise restrict widespread use of this modality. To address this gap, Gampfer et al. (2020) developed a deep learning model for detecting myocardial scar from 12-lead ECG recordings. Using paired ECG and MRI data from 114 patients, the CNN achieved an accuracy of 78.0%, sensitivity of 70.0%, and specificity of 84.3%. Although preliminary, these results suggest that AI-enhanced ECG analysis may serve as a screening tool to identify patients who would benefit from advanced imaging.

4.6. Electrolyte abnormalities

Potassium plays a central role in myocardial depolarization and repolarization. Abnormal serum potassium levels can produce characteristic, though sometimes subtle, changes on the ECG. Hyperkalemia most commonly occurs in the context of renal failure, metabolic acidosis, or inadequate medication management. Because early electrolyte disturbances may be clinically silent, reliance on symptoms alone is insufficient.

Hyperkalemia is typically categorized as mild (5.0–5.5 mEq/L), moderate (5.5–6.0 mEq/L), or severe (>6.0 mEq/L) (Galloway et al., 2019). Elevated extracellular potassium concentrations—particularly above 6.0 mEq/L—are associated with progressive ECG changes, including peaked T waves, PR interval alterations, P-wave attenuation, and QRS widening. Severe hyperkalemia may precipitate life-threatening ventricular arrhythmias and cardiac arrest. ESC heart failure guidelines recommend regular monitoring of serum potassium and renal function, particularly in patients with renal impairment or those receiving medications affecting potassium homeostasis (McDonagh et al., 2021; McDonagh et al., 2023). However, repeated blood sampling, although relatively simple, remains minimally invasive and may limit frequent assessment.

The application of AI to ECG data offers a potential noninvasive alternative for potassium monitoring. Galloway et al. (2019) trained an 11-layer CNN on more than 1.5 million 12-lead ECGs to detect hyperkalemia, defined as serum potassium ≥ 5.5 mEq/L. The model demonstrated strong performance, with a negative predictive value of 99%, AUC ranging from 0.853 to 0.883, and sensitivity between 88.9% and 91.3%.

Deep learning techniques have also been applied to detect hypokalemia. Lin et al. (2020) implemented an 82-layer convolutional network capable of identifying serum potassium abnormalities from ECG recordings. Hypokalemia, characterized by prolonged PR interval, ST-segment depression, reduced or inverted T waves, QTc prolongation, and prominent U waves, was detected with sensitivity ranging from 84.5% to 95.6%, outperforming physician interpretation in some settings.

Earlier work by Attia et al. (2016) demonstrated the feasibility of estimating serum potassium levels from single-lead ECG recordings without blood sampling. Using T-wave morphology analysis—excluding complex or biphasic waveforms—the investigators achieved a mean estimation error of 0.5 ± 0.42 mmol/L. These findings suggest the possibility of developing continuous, remote, and noninvasive potassium monitoring systems capable of identifying dynamic trends and generating alerts for patients at high risk of arrhythmic complications, such as those with advanced renal disease or undergoing dialysis.

5. Conclusion

Artificial intelligence has emerged as a powerful adjunct in electrocardiographic analysis, with applications ranging from acute triage and disease screening to longitudinal monitoring through wearable technologies. By enhancing diagnostic sensitivity and enabling earlier detection of subclinical abnormalities, AI-driven ECG systems may expand access to cardiovascular evaluation while reducing diagnostic delays and clinician workload.

Despite these promising developments, important challenges persist. Model generalizability across diverse populations, computational demands, data privacy considerations, and the need for clinical interpretability remain critical issues. Continued validation in prospective, real-world settings and thoughtful integration into established clinical workflows will be essential. With careful implementation, AI has the potential to transform cardiovascular care by facilitating earlier diagnosis, improving risk stratification, and ultimately enhancing patient outcomes across a wide range of clinical environments.

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