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State of the Art Review

Artificial Intelligence-Enabled Electrocardiography in Practice: A State-of-the-Art Review

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AUTHOR'S SUMMARY

Artificial intelligence-enabled electrocardiography (AI-ECG) is rapidly expanding, yet its real-world clinical integration remains limited by data heterogeneity, unclear workflows, and uncertainty about clinical impact. This review synthesizes evidence from pragmatic trials and prospective studies demonstrating that AI-ECG can improve early detection, enable opportunistic screening, and guide personalized care across diverse settings. We highlight persistent challenges—including bias, explainability, and regulatory adaptation—and propose practical strategies for safe, scalable deployment. By integrating clinical and technical perspectives, this review outlines how AI-ECG can evolve into a reliable digital biomarker that enhances cardiovascular care.

ABSTRACT

Artificial intelligence-enabled electrocardiography (AI-ECG) has rapidly advanced from experimental models to clinically deployed tools. This review outlines the evolution of AI-ECG across key domains including arrhythmia detection, structural heart disease diagnosis, and digital biomarker development. We summarize recent evidence from pragmatic

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randomized trials and prospective cohort studies that demonstrate the real-world utility of this approach across diverse populations and care settings. AI-ECG has demonstrated consistent accuracy in identifying conditions such as left ventricular systolic dysfunction, hypertrophic cardiomyopathy, and atrial fibrillation, with some studies reporting improved diagnostic rates, earlier intervention, and selected settings, reduced mortality. In addition to diagnostic support, AI-ECG enables longitudinal risk monitoring and screening for systemic diseases. Despite these advances, challenges remain around model generalizability, workflow integration, and regulatory adaptation. This review highlights both the clinical promise and the implementation hurdles of AI-ECG, underscoring the need for rigorous validation and thoughtful deployment to ensure its safe and effective integration into routine care.

Keywords: Artificial intelligence; Deep learning; Electrocardiogram; Digital health; Innovation

INTRODUCTION

Over the past few years, research on artificial intelligence-enabled electrocardiography (AI-ECG) has accelerated at an unprecedented pace. What began as a niche endeavor for specialized engineering teams—developing sophisticated algorithms to mine hidden signals in electrocardiogram (ECG) waveforms—has rapidly evolved into a broad suite of clinical applications. Advances in deep learning have opened new frontiers, from screening for asymptomatic arrhythmias to the early detection of structural heart disease.[1)2)] Fueled by dramatic increases in computational power and the aggregation of vast, meticulously annotated ECG datasets, AI-ECG has matured from an experimental curiosity into a practical tool at the bedside. Modern deep neural networks can now accurately identify reduced ejection fraction (EF), valvular diseases, and various cardiomyopathies from standard 12-lead tracings—often outperforming conventional interpretation methods.[3-5)] These models are already being deployed for continuous monitoring via wearables and remote telemetry and have begun to inform point-of-care decision-making in primary care settings.[6)]

Yet, despite this momentum, many frontline clinicians remain uncertain about how these models work, when and where they should be applied, and what their real-world impact on patient care can be. Inconsistent datasets and evaluation metrics across studies complicate the interpretation of results, and concrete guidance on integrating AI-ECG into existing clinical workflows or navigating regulatory and ethical review processes remains limited.[7)] For AI-ECG to move from promise to practice, a clear understanding of "why," "when," and "how" to deploy these tools is essential.

Although artificial intelligence (AI) encompasses many modalities and methods, this review focuses on deep-learning approaches in electrocardiography, showcasing how convolutional neural networks (CNNs) and related architectures are transforming everything from arrhythmia screening to digital biomarker discovery. We begin by tracing the development of the first AI-powered AF detection systems and then examine the evolution of AI-ECG into a robust prognostic tool. Next, we distill the most compelling evidence from pragmatic randomized trials and large prospective cohorts, before surveying how AI-ECG is being deployed in handheld devices, smart stethoscopes, and remote monitoring platforms. Alongside these advances, we highlight the persistent hurdles—data heterogeneity, external validation requirements, clinical workflow integration, and regulatory and ethical complexities—that must be addressed if AI-ECG is to fulfill its promise of earlier diagnosis and improved patient outcomes.

ELECTROCARDIOGRAM ARRHYTHMIA DETECTION: FROM MANUAL RULES TO NEURAL NETWORKS

Traditional analysis and rule-based algorithms

ECG interpretation has long depended on expert clinicians' visual pattern recognition and standardized, rule-based algorithms that measure intervals and wave morphologies. In the late twentieth century, computerized ECG analysis employing fixed, rule-based logic was introduced to detect rhythm disturbances and automatically quantify parameters. While these traditional systems improved throughput and consistency, they showed significant limitations when confronted with non-sinus rhythm or noisy recordings.[8-10] Widely deployed in commercial ECG devices, rule-based interpretation often misclassifies arrhythmias or artifacts, potentially compromising clinical decisions. Consequently, early automated reads required expert over-read to suppress false alerts and avoid missed diagnoses.

Emergence of artificial intelligence and deep-learning-based classification

Over the past decade, AI and machine learning have fundamentally reshaped ECG interpretation, with the detection of atrial fibrillation (AF) emerging as a flagship application. Deep CNNs trained on large, labeled datasets now accurately classify AF from both 12-lead and single-lead recordings, achieving expert-level performance. For example, a CNN trained on 91,232 single-lead ECGs from 53,549 patients achieved a mean area under the curve of 0.97 and an F_1 score of 0.837, surpassing general cardiologists (F_1=0.780) in both sensitivity and specificity.[9] These AI-ECG–based AF detection methods have also been adapted for use in wearable devices.[11]

Additionally, AI-ECG capabilities now extend well beyond AF detection to encompass a broad spectrum of arrhythmias. Deep learning models accurately distinguish atrial flutter, supraventricular tachycardia, various degrees of atrioventricular block, and ventricular tachycardia/fibrillation—often recognizing subtle patterns that elude human readers.[12][13] In some instances, AI has outperformed experts in detecting particular AV-block patterns. These AI tools focus primarily on classification, providing clear and actionable diagnoses of "what arrhythmia is present now."

Clinical deployment and performance validation

In this context, efforts are underway to integrate AI-ECG for arrhythmia detection into clinical practice. Early implementations in emergency department (ED) settings have demonstrated improved accuracy in arrhythmia classification and AF detection.[14] Several AI-ECG systems have obtained regulatory approval and, in initial real-world use, have supported clinicians by rapidly and accurately flagging arrhythmias.[8][15] However, most validation studies to date have been limited, and large-scale prospective clinical trials encompassing diverse patient populations and care settings remain scarce. Issues such as performance drift when models trained on a single dataset are deployed in new environments and the challenge of ensuring consistent, high-quality ECG annotation for both training and evaluation underscore the need for continuous monitoring and rigorous post-deployment validation.

In parallel, ambulatory monitoring has emerged as another key area of real-world AI-ECG application. Commercial platforms such as Cardiologs and Cardiomatics have been integrated into clinical workflows for the detection of arrhythmias from Holter monitors and wearable ECG devices.[16-18] These AI-ECG platforms leverage deep learning algorithms to automatically interpret long-term ambulatory ECG recordings. They have been increasingly adopted across various clinical settings in Europe and beyond for rhythm monitoring outside of hospitals. Several systems have demonstrated specialist-level performance in arrhythmia detection, supporting a wide range of use cases including extended event monitoring and mobile ECG telemetry. Although peer-reviewed comparative studies remain limited, their growing clinical deployment underscores the expanding role of AI-ECG in outpatient and decentralized care environments.

ARTIFICIAL INTELLIGENCE-ENABLED ELECTROCARDIOGRAPHY AS A DIGITAL BIOMARKER

Key roles of electrocardiogram digital biomarkers

The explosive growth in computational power and the assembly of massive, well-annotated ECG datasets have turned formerly academic curiosities into actionable clinical insights.[19-22] This evolution has given rise to a new class of digital biomarkers—ECG-derived signals that go far beyond heart rhythm, enabling diagnosis, prognosis, and risk stratification across a host of cardiac conditions (**Figure 1**). Traditionally, biomarkers such as troponin or brain natriuretic peptide have served discrete diagnostic or prognostic purposes. In contrast, digital biomarkers expand these functions by leveraging advanced measurements to support not only diagnostic aid and prognosis prediction but also novel phenotyping, extension of physician efficiency and efficacy, continuous clinical monitoring, targeted therapy selection, and multimodal data integration.[19] A vast and rapidly growing body of research—spanning multiple methodological layers, diverse patient populations, and varied analytical frameworks—has emerged to validate and refine these digital biomarker applications.[1]

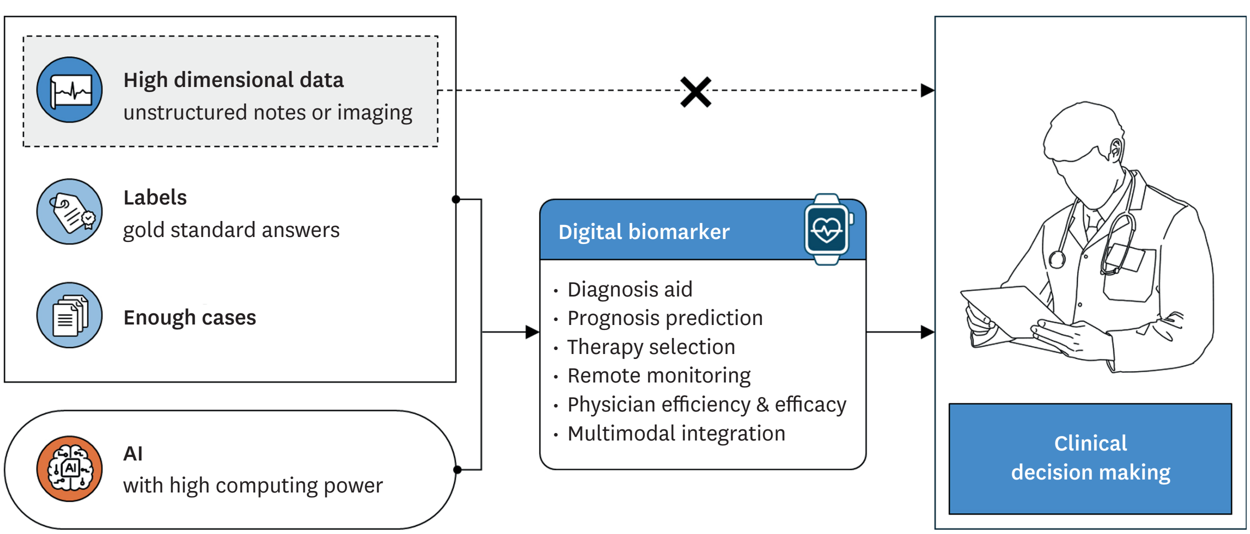

Figure 1. Foundations of AI-ECG–driven digital biomarker development and clinical decision support.
Schematic illustrating the core components required for the development of AI-enabled digital biomarkers: 1) high-dimensional input data (e.g., unstructured notes or imaging), 2) gold-standard labels, 3) sufficient training cases, and 4) high-performance computing resources. When successfully trained and validated, these AI models can transform ECG data into digital biomarkers that support diagnosis, prognosis, therapy selection, remote monitoring, physician efficiency, and multimodal data integration. These biomarkers ultimately contribute to enhanced clinical decision-making.
AI = artificial intelligence; AI-ECG = artificial intelligence-enabled electrocardiography; ECG = electrocardiogram.

Broad-spectrum artificial intelligence-enabled electrocardiography biomarker applications

AI-ECG has evolved into a suite of digital biomarkers capable of delivering diagnostic, prognostic, and risk-stratification insights from a single ECG trace—capabilities that were previously unattainable (**Figure 2**). **Table 1** summarizes representative studies[3)5)23-58)] across a broad spectrum of applications, ranging from disease detection to therapy optimization. First, as a diagnostic aid, AI-enabled models excel at detecting left ventricular systolic dysfunction (LVSD).[23-28)] Deep neural networks trained on paired ECG and echocardiogram data now identify patients with reduced EF with high accuracy, often flagging asymptomatic LVSD months before clinical presentation. These models have been validated across diverse populations, care settings, and device types, underscoring their generalizability and clinical relevance.[59)60)] Likewise, algorithms have been developed to screen for structural heart diseases—such as hypertrophic cardiomyopathy, aortic stenosis, and cardiac amyloidosis—and even to detect acute myocardial infarction, including non-ST elevation myocardial infarction (NSTEMI), directly from ECGs, providing a rapid "first look" when imaging or blood biomarkers are not immediately available.[3)29-33)35-37)40)61)62)] More recently, studies have begun to explore the prediction of diastolic dysfunction using AI-ECG models, with successful validation across diverse clinical environments.[38)] This emerging application highlights the expanding utility of AI-ECG beyond conventional systolic metrics, offering new opportunities for broader clinical integration and earlier detection of subtle cardiac abnormalities.[63)]

In addition to systems that detect individual conditions, there has been a proliferation of AI-ECG models designed to detect multiple cardiovascular conditions, including multiple types of valve diseases as well as nearly any abnormality on echocardiography. These types of models to detect broad composites of structural heart disease are designed to explicitly serve in opportunistic screening capacities to identify patients most likely to benefit from follow-up echocardiography.

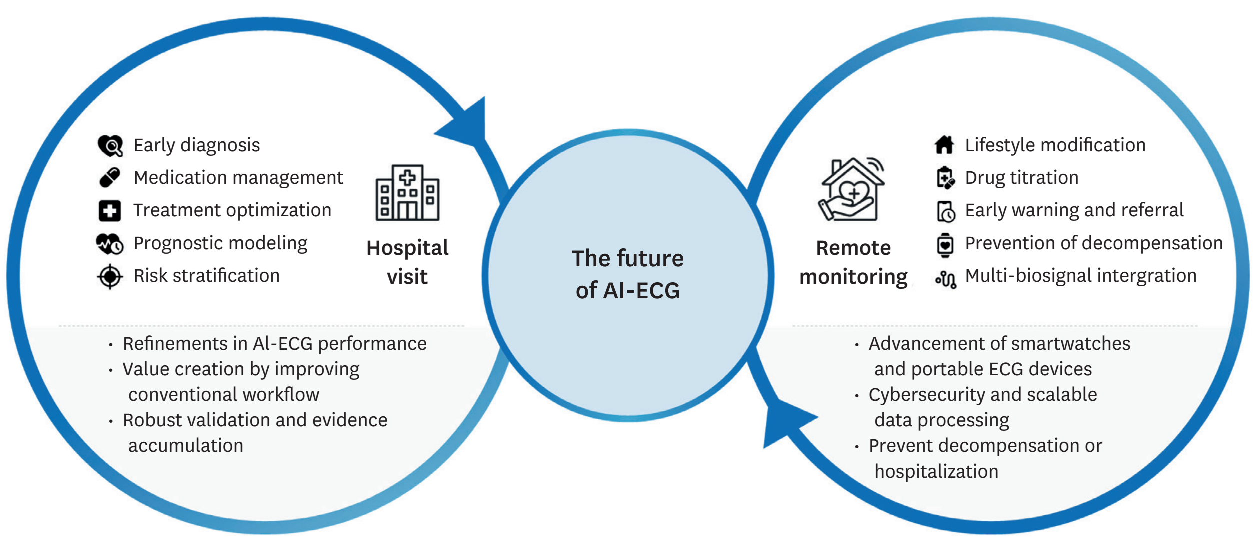

Figure 2. Future directions for AI-ECG integration in clinical and remote settings.
Illustration of the dual trajectory shaping the future of AI-ECG. On the left, hospital-centered progress focuses on performance refinement, workflow optimization, and evidence-based validation. On the right, remote care advancements emphasize the development of smartwatch and portable ECG devices, secure and scalable data infrastructure, and early detection of clinical deterioration to prevent rehospitalization. Together, these directions represent a convergence of centralized and decentralized healthcare innovations driven by AI-ECG.
AI-ECG = artificial intelligence-enabled electrocardiography; ECG = electrocardiogram.

Table 1. Summary of broad-spectrum AI-ECG biomarker applications and representative studies

Application	Targets	Author of representative study (year)	Clinical role
Diagnostic aid	• Left ventricular systolic dysfunction	Attia et al.[23] (2019); Kwon et al.[24] (2019); Attia et al.[25] (2022); Bachtiger et al.[26] (2022); Sangha et al.[27] (2023); Dhingra et al.[28] (2025)	Initial screening and early detection
	• Myocardial infarction	Al-Zaiti et al.[29] (2023); Herman et al.[30] (2023); Lee et al.[31] (2024)	
	• Hypertrophic cardiomyopathy	Ko et al.[32] (2020); Love et al.[33] (2025); Sangha et al.[34] (2025)	
	• Aortic stenosis	Kwon et al.[3] (2020); Cohen-Shelly et al.[35] (2021)	
	• Cardiac amyloidosis	Grogan et al.[36] (2021); Harmon et al.[37] (2023)	
	• Diastolic dysfunction	Lee et al.[38] (2024)	
	• Structural heart disease (multi-condition detection)	Ulloa-Cerna et al.[39] (2022); Elias et al.[40] (2022); Poterucha et al.[41] (2025)	
Prognostic prediction	• Atrial fibrillation (in sinus rhythm ECG)	Attia et al.[5] (2019); Yuan et al.[42] (2023)	Targeted monitoring and early treatment decision-making
	• CRT response	Wouters et al.[43] (2023)	
Phenotyping	• Sex • Biological age	Attia et al.[44] (2019); Cho et al.[45] (2025); Sau et al.[46] (2025)	Patient stratification and risk profiling
Rare disease detection	• Long QT syndrome • Brugada syndrome	Bos et al.[47] (2021); Liu et al.[48] (2022); Călburean et al.[49] (2024)	Early identification of rare cardiac and systemic diseases
Risk stratification & monitoring	• Sudden cardiac death • All-cause mortality	Holmstrom et al.[50] (2024); Lin et al.[51] (2024); Oberdier et al.[52] (2025)	Tailored follow-up, early intervention, resource allocation
Other disease screening	• Hypertension • Chronic kidney disease • Liver cirrhosis • Dyskalemia • Anemia • Hyperthyroidism	Al-Alusi et al.[53] (2025); Holmstrom et al.[54] (2023); Ahn et al.[55] (2022); Lin et al.[56] (2022); Kwon et al.[57] (2020); Choi et al.[58] (2022)	Non-invasive, ECG-based screening for systemic conditions

AI-ECG = artificial intelligence-enabled electrocardiography; CRT = cardiac resynchronization therapy; ECG = electrocardiogram.

Second, the prognostic prediction role of AI-ECG is increasingly prominent. Subtle electrical patterns in a sinus-rhythm 12-lead ECG can predict incident AF up to one year in advance, creating opportunities for intensified monitoring or the early initiation of anticoagulation or rhythm-control therapies.[5)42)] Notably, diagnostic-aid models also exhibit this dual benefit—their false-positive cohorts often experience higher rates of future adverse events, underscoring the prognostic value inherent in their outputs. Recent studies have extended this domain to include the prediction of cardiac resynchronization therapy response, enabling more personalized treatment strategies.[43)]

Third, phenotyping has emerged as another promising application of AI-ECG. Algorithms can determine a patient's sex with over 90% accuracy, and estimates of "biological ECG age" have been shown to correlate strongly with cardiovascular risk factors and long-term outcomes.[44-46)] In the area of rare disease detection, early studies have demonstrated that deep learning models can identify characteristic ECG signatures associated with uncommon but clinically significant channelopathies such as long QT syndrome and Brugada syndrome, offering the potential for early diagnosis and timely intervention.[47-49)64)65)]

From a risk stratification and monitoring perspective, AI-ECG platforms integrate ECG-derived biomarkers with clinical data to classify patients into high- and low-risk categories, enabling personalized follow-up and more efficient allocation of resources.[50-52)66)67)] In the short term, this includes predicting adverse events such as sudden cardiac death, while in the longer term, AI-ECG–based risk models have shown potential not only to forecast all-cause mortality but also to inform clinical decisions that may improve outcomes through earlier or more intensive care.

Finally, other disease screening represents a novel and expanding frontier for AI-ECG.[53-58] Recent research suggests that a variety of systemic conditions—many of which influence cardiac electrophysiology either directly or indirectly—can be detected through ECG-based deep learning analysis. These include hypertension, chronic kidney disease, liver cirrhosis, dyskalemia, anemia, and hyperthyroidism. The ability to identify such conditions through a single, non-invasive test expands the clinical utility of the ECG. Interestingly, many of these models, although developed for distinct diagnostic purposes, appear to extract shared ECG-based signatures.[68)69] This has led to the incidental detection of off-target conditions, suggesting that AI-ECG may capture underlying physiologic patterns that transcend organ-specific boundaries. It opens the door to broader integration of AI-ECG in general health screening. In sum, AI-ECG is rapidly advancing beyond its initial role in arrhythmia detection to support a wide range of functions, including diagnostic support, prognostic prediction, phenotyping, risk stratification, and real-time monitoring. This evolution positions AI-ECG as a foundational tool in the future of data-driven, personalized clinical decision-making.

Bridging the gap: from biomarker discovery to patient benefit

Although AI-ECG models have proliferated rapidly and many retrospective validation studies have reported promising results, several key limitations still hinder their translation into meaningful clinical benefits.[2)7)70] Most existing studies are based on historical ECG archives or data from single-center cohorts, limiting their generalizability across diverse populations, device manufacturers, and clinical environments. Moreover, many models are developed and evaluated outside of live clinical workflows, creating uncertainty about how and when their predictions should be integrated into real-time clinical decision-making. Even with strong predictive performance, there are still very few examples where AI-ECG outputs have directly influenced therapeutic decisions or improved patient outcomes. In addition, essential factors such as clinician acceptance, interpretability of false positives, and patient trust remain insufficiently addressed.

Importantly, false-positive AI-ECG results should not be viewed simply as diagnostic noise. Multiple studies have shown that patients flagged as “positive” despite normal imaging often carry higher long-term risks of heart failure, arrhythmias, or other adverse cardiovascular events. In this sense, some false positives may function as early risk signals that warrant closer monitoring rather than immediate dismissal. At the same time, these patterns underscore that AI-ECG is not intended to replace echocardiography or other imaging modalities; instead, it should serve as a triage and prioritization tool to guide which patients may benefit most from confirmatory testing or longitudinal follow-up.

To overcome these challenges, prospective clinical studies are urgently needed to evaluate the actual clinical utility of AI-ECG tools. Randomized controlled trials (RCTs) comparing AI-assisted care with standard care would be designed to assess hard clinical endpoints such as time to diagnosis, hospitalization rates, treatment modifications, and long-term survival. However, significant practical barriers to such studies still exist. Nonetheless, if successfully conducted, these studies could demonstrate that AI-driven digital biomarkers are not only capable of detecting disease earlier but can also reshape care pathways and improve real-world patient outcomes.

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EVIDENCE FROM PRAGMATIC RANDOMIZED CONTROLLED TRIALS AND PROSPECTIVE STUDIES

Establishing real-world utility through prospective studies

To meet both the enthusiasm of researchers and the growing expectations of this era, a rising number of pragmatic RCTs and prospective studies have begun to lay the foundation for real-world clinical implementation of AI-ECG. These studies extend beyond traditional model performance metrics to evaluate how AI-ECG influences diagnostic timing, treatment decisions, and, most critically, clinical outcomes.

Representative studies of these efforts are summarized in **Table 2**,[25)26)31)33)47)51)62)71-75)] which outlines the study design, study population, and key findings for each study. Recent RCTs and large-scale observational studies have evaluated AI-ECG in a wide range of clinical settings, including primary care, EDs, peripartum populations, and remote monitoring environments, using both standard 12-lead ECGs and portable or consumer-grade ECG devices.[25)26)31)33)47)51)71-73)75)] For example, a cluster-randomized trial demonstrated that AI-ECG screening significantly increased early detection of LVSD, especially among patients without AI-ECG.[71)] Other studies have confirmed the feasibility, accuracy, and equity of AI-ECG–based screening across diverse populations and devices—from stethoscope-based ECGs in community clinics to smartwatch-enabled ECGs at home—reinforcing its flexibility as a digital biomarker platform.[25)26)]

More importantly, several recent pragmatic trials have moved beyond diagnostic validation and have demonstrated true clinical impact, which represents the highest level of real-world evidence. Among these, the trial by Yao et al.[71)] is particularly instructive—not because it produced a better area under the receiver operating characteristic curve or higher detection sensitivity, but because it showed that embedding AI-ECG within routine primary care workflows changed physician behavior and increased actionable diagnoses of LVSD. This “opportunistic screening” effect highlights how AI-ECG can reshape care pathways even without new hardware, new staffing, or major workflow restructuring. Similarly, the randomized trial by Lin et al.[74)] (STEMI ARISE) illustrates the next logical step: AI-ECG not only identified high-risk patients more accurately but also translated this early detection into measurable improvements in treatment timeliness and reductions in cardiac mortality. This is one of the first large-scale demonstrations that an AI-ECG intervention—implemented across both ED and inpatient workflows—can genuinely improve patient-centered outcomes.

In one of the largest randomized trials conducted to date, an AI-ECG–based alert system significantly reduced 90-day all-cause mortality, with the most significant impact seen in high-risk patients.[6)] In another study, AI-guided screening enabled earlier diagnosis of cardiomyopathy in postpartum women—traditionally a diagnostic blind spot—highlighting the model’s ability to reach underserved groups.[73)] Collectively, these trials underscore a crucial shift in the field: AI-ECG is no longer merely a diagnostic classifier; it is emerging as a clinical intervention capable of altering trajectories of care.

Importantly, several of these trials moved beyond technical validation and addressed real-world integration, demonstrating that AI-ECG can be effectively implemented within existing workflows across multicenter health systems. Moreover, they underscore the promise of installation-based, real-world implementation studies, which are essential to understanding how AI-ECG can be meaningfully integrated into clinical workflows and translated into patient

Table 2. Representative pragmatic and prospective studies evaluating AI-enabled ECG in real-world clinical settings

Author (year)	Study design	Target/Objective	Study population	Key findings
Yao et al.[71] (2021)	Pragmatic, cluster-randomized trial	Early detection of low EF (≤50%) in primary care	22,641 adults without prior HF from 120 primary care teams (11,573 intervention, 11,068 control)	AI-ECG significantly increased the number of new diagnoses of EF ≤50% (2.1% vs. 1.6%, OR, 1.32; p=0.007). Among high-likelihood AI-ECG positives (6% of total), diagnosis increased from 14.5% to 19.5% (p=0.01). The use of echocardiograms increased significantly in AI-positive patients (49.6% vs. 38.1%, p<0.001).
Bachtiger et al.[26] (2022)	Prospective, multicenter	Point-of-care LVSD detection (AI stethoscope)	1,050 patients from NHS clinics (UK)	Single-lead AI-ECG showed an AUROC of 0.85 for EF ≤40% at the pulmonary valve position; a rule-based model combining two positions improved the AUROC to 0.91. Performance is consistent across all age, sex, and ethnic groups.
Noseworthy et al.[72] (2022)	Prospective interventional	AF detection via AI-ECG + EHR	1,003 US patients	AI-guided risk stratification significantly increased AF detection (10.6% vs. 3.6% in high-risk group, p<0.0001). OR for high vs. low risk: 4.98. Feasibility of remote monitoring.
Attia et al.[25] (2022)	Prospective, decentralized	LVSD detection via smartwatch ECG	2,454 patients from 46 states & 11 countries	Smartwatch AI-ECG detected EF ≤40% with AUC 0.88. Demonstrated feasibility of consumer-level remote AI-ECG screening using single-lead ECGs.
Lin et al.[51] (2024)	Pragmatic RCT (single-blind)	All-cause mortality risk stratification (AI alert)	15,965 hospitalized patients	AI-ECG alert reduced 90-day mortality (HR, 0.83; p<0.05); in the high-risk ECG group, cardiac death was reduced (0.2% vs. 2.4%, HR, 0.07). The intervention group received earlier and more intensive care.
Adedinsewo et al.[73] (2024)	Pragmatic RCT, open-label	LVSD screening in peripartum women	1,232 women (pregnant/postpartum), 6 hospitals in Nigeria	AI-guided stethoscope screening increased the detection of LVSD (4.1% vs. 2.0%, OR, 2.12; p=0.032). No adverse events. Strongest effects in older and high-risk pregnancy subgroups.
Lin et al.[74] (2024)	Pragmatic, open-label, cluster randomized controlled trial	AI-ECG–assisted rapid identification and triage of STEMI	43,234 eligible adults (mean age 60; 49.5% male) in ED or inpatient wards across Tri-Service General Hospital, Taiwan	AI-ECG achieved PPV 89.5% and NPV 99.9% for STEMI with occluded vessel(s). In ED patients, median door-to-balloon time decreased from 96.0 to 82.0 min (p=0.002). Across ED + inpatient cases, ECG-to-balloon time decreased from 83.6 to 78.0 min (p=0.011). Cardiac death was lower in intervention group (85 vs. 116, OR, 0.73; p=0.029). No significant difference in new-onset HFrEF or all-cause mortality. Demonstrated improved treatment times with AI-ECG–assisted triage.
Lee et al.[31] (2025)	Prospective, multicenter cohort	AMI screening and risk stratification	8,493 ED patients (1,586 diagnosed with AMI)	AI-ECG demonstrated an AUROC of 0.878 for AMI diagnosis, comparable to the HEART score. For 30-day MACE, AUROC 0.866. Integration improved the net reclassification index by 19.6% vs. HEART alone.
Lim et al.[75] (2025)	Prospective, single-center	Portable ECG for LVSD screening	1,635 adults undergoing echo with 6-lead AI-ECG	AI-ECG showed AUROC 0.924 (6-lead), sensitivity 83.4%, specificity 88.7%. Comparable accuracy to 12-lead ECG, validating the scalability of portable ECG in real-world screening.
Love et al.[33] (2025)	Prospective, multicenter cohort	HCM detection via AI-ECG clinical implementation	145,848 patients screened, 217 enrolled from 5 health systems (USA)	7.8% newly diagnosed with HCM. 69% of alerts were viewed by users. Median 7.5 days to imaging. Algorithm adjustment reduced alert burden without decreasing enrollment. Demonstrated real-world feasibility.
Desai et al.[62] (2025)	Prospective, real-world deployment	HCM detection using AI-ECG	45,873 patients with 103,492 ECGs from Cleveland Clinic	AI-ECG flagged 2.7% (1,265) for potential HCM; of these, 40.4% had confirmed HCM, 5% were newly diagnosed, and 54.6% had alternate diagnoses. At ≥0.85 threshold, sensitivity 95%, specificity & accuracy >98%. Demonstrated strong performance across age/sex.

AF = atrial fibrillation; AI = artificial intelligence; AI-ECG = artificial intelligence-enabled electrocardiography; AMI = acute myocardial infarction; AUC = area under the curve; AUROC = area under the receiver operating characteristic curve; ECG = electrocardiogram; ED = emergency department; EF = ejection fraction; EHR = electronic health record; HCM = hypertrophic cardiomyopathy; HFrEF = heart failure with reduced ejection fraction; HR = hazard ratio; LVSD = left ventricular systolic dysfunction; MACE = major adverse cardiovascular event; NPV = negative predictive value; OR = odds ratio; PPV = positive predictive value; RCT = randomized controlled trial; STEMI = ST-elevation myocardial infarction.

benefit. Ultimately, these trials highlight not only the technical validity of AI-ECG models but also their growing clinical relevance and practical feasibility in everyday care settings.

Future directions: from scalability to system-level integration

The next frontier for AI-ECG lies in its full integration into both traditional and decentralized healthcare delivery systems.[76-78] On one side, AI-ECG is being further embedded into hospital-based workflows to enhance early diagnosis, support medication management, and optimize treatment strategies. Prognostic modeling and risk stratification are also gaining traction as AI-ECG outputs become increasingly actionable. Continued refinements in model performance and ongoing clinical validation will be critical for solidifying its value within conventional care pathways.

On the other side, the development of portable and wearable ECG technologies—including smartwatches, stethoscope-enabled ECGs, and 6-lead handheld devices—has expanded the reach of AI-ECG into patients' homes.[75][79] These advances facilitate remote monitoring, early warning alerts, drug titration, and even lifestyle management. By identifying early signs of decompensation and enabling timely referral or intervention, AI-ECG has the potential to reduce hospitalizations and improve long-term outcomes. However, most AI-ECG algorithms to date have been developed and validated using 12-lead ECG databases, and cross-device deployment to wearable or portable platforms inevitably leads to performance degradation. Rather than merely reducing the number of leads during model development, future work should prioritize the collection and use of native wearable-device ECG datasets to ensure robust, device-specific performance.

Looking ahead, scalable implementation will require careful attention to cybersecurity, real-time data processing, and integration with multimodal biosignal platforms. As these technical and clinical infrastructures mature, AI-ECG is poised to transition from a point-of-care tool into a longitudinal digital biomarker that spans the full continuum of cardiovascular care—from prevention to acute management and remote follow-up.[78] At present, nearly all AI-ECG models analyze single ECG snapshots, ignoring the rich temporal information contained in serial tracings. Integrating multiple ECGs acquired over time—capturing trajectories of electrical remodeling and treatment response—represents an important, yet underexplored, future direction that could substantially enhance prognostic power and individualize care.

CHALLENGES AND CONSIDERATIONS

Despite the growing momentum and expanding clinical potential of AI-ECG, several critical challenges continue to hinder its widespread adoption and impact.[7][80] To address these issues, transparent and rational data governance, value-based care frameworks, and aligned incentives across stakeholders—researchers, industry partners, and regulatory bodies—are essential. The following are key domains where limitations persist (**Figure 3**).

Data quality and bias

The performance of AI-ECG models is intrinsically linked to the quality, format, and diversity of the training data.[81] The definition and curation of the development cohort can directly affect model generalizability and clinical value. Significant variability exists in ECG acquisition, including raw signal versus scanned image inputs, sampling frequency, and device-specific noise characteristics, all of which impact downstream model performance. While both raw signal–based and image-based models have shown high diagnostic accuracy, no head-to-head comparisons have established the superiority of one format over the other.[82-84]

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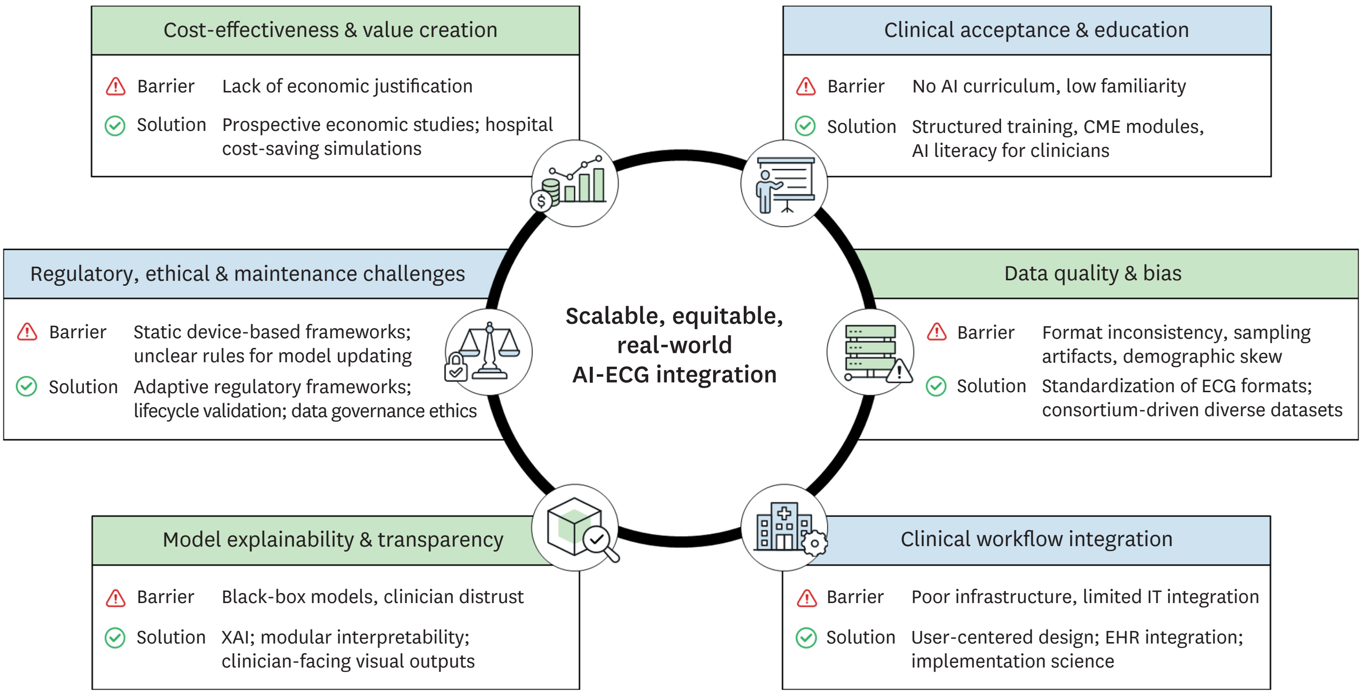

Figure 3. Barriers and solutions for real-world integration of AI-ECG.
Overview of 6 key challenges and corresponding solutions for achieving scalable, equitable, real-world integration of AI-ECG. These include: 1) lack of economic justification, addressed through cost-effectiveness studies; 2) limited clinician familiarity, resolved via structured AI education; 3) inconsistent data quality and demographic bias, mitigated by standardization and diverse datasets; 4) static regulatory frameworks, requiring adaptive validation and governance; 5) limited model transparency, countered with explainable AI tools; and 6) suboptimal IT infrastructure, requiring workflow-integrated system design. These coordinated efforts are essential to transition AI-ECG from research to routine clinical practice.
AI = artificial intelligence; AI-ECG = artificial intelligence-enabled electrocardiography; ECG = electrocardiogram; EHR = electronic health record; XAI = explainable artificial intelligence.

Beyond technical heterogeneity, many AI-ECG models are validated primarily by their original developers using institution-specific datasets, limiting independent replication and inflating estimated performance.[85] Real-world data from diverse clinical environments remain scarce, and many published datasets lack sufficient description of acquisition protocols, population characteristics, and preprocessing steps, hindering reproducibility and external applicability. Additionally, demographic and institutional biases in training data may restrict model applicability in underrepresented populations.[86-88] Standardizing ECG data formats and developing consensus-driven validation protocols will be critical steps toward mitigating these issues.

Clinical workflow integration

Although several prospective trials have demonstrated feasibility, integration of AI-ECG tools into routine care remains limited. Many clinical environments lack the technical infrastructure, personnel bandwidth, or incentive models to support the adoption of AI at scale.[7] In a rapidly evolving technological ecosystem, time and resource constraints hinder iterative deployment and feedback cycles between developers and clinicians. Beyond these systemic barriers, practical opportunities exist—such as partnering with ECG device manufacturers to enable direct, on-device AI integration, or developing workflows that allow clinicians to upload PDFs, screenshots, or scanned ECG images with seamless embedding into vendor-neutral archives (VNA). These real-world, implementation-ready pathways may substantially reduce adoption friction. Moreover, several integration features—such as real-time device-level processing, enterprise-wide ECG routing, and large-scale VNA integration—will likely require collaboration with commercial partners to execute effectively within health systems. Another emerging consideration is how many AI-ECG algorithms a health system can realistically deploy. A practical strategy may involve using a broad structural heart disease or composite-risk model as a "base layer," complemented by a limited number of focused models targeting specific high-impact conditions. This tiered approach may optimize clinical benefit while minimizing workflow complexity. Bridging this gap will require robust implementation science and user-centered system design.

Model explainability and transparency

Most deep learning–based AI-ECG models operate as "black boxes," providing limited interpretability for end-users. This opaqueness reduces clinician trust, particularly in high-stakes scenarios.[89)90)] While novel explainable artificial intelligence (XAI) techniques—such as testing with concept activation vectors and attention mechanisms—are emerging to bridge this gap, standardization and clinical validation of these approaches are still lacking.[43)91)92)] However, improved explainability does not necessarily equate to improved trustworthiness. Certain XAI methods may generate visually plausible but misleading explanations, creating a false sense of confidence among clinicians that does not reflect the model's true decision-making process.[93)] This risk of "false trust" underscores the need for rigorous evaluation of XAI tools, ensuring that explanations are not only intuitive but also faithfully representative of underlying model behavior. Importantly, some experts argue that explainability may be less critical for AI-ECG than for other high-stakes AI applications. Because AI-ECG functions primarily as a screening and risk stratification tool—rather than as a definitive diagnostic mechanism—its clinical value depends more on accuracy, reliability, and workflow integration than on the transparency of internal feature representations. As highlighted by clinical leaders such as Paul Friedman, overemphasizing explainability may distract from the more urgent objective of ensuring that AI-ECG systems deliver reproducible, high-performance predictions that meaningfully improve patient outcomes. Furthermore, different clinical contexts may require different types of interpretability, underscoring the need for adaptable and modular XAI tools. The challenge ahead is not merely to "open the black box," but to determine when, where, and for whom interpretability adds real clinical utility—while avoiding unnecessary burdens that could slow down adoption of models already proven to be clinically impactful.

Regulatory, ethical, and maintenance barriers

Although several AI-ECG systems have received regulatory clearance, including Food and Drug Administration 510(k) approvals, the pathways for post-deployment model updates, revalidation, and real-world monitoring remain poorly defined.[94)] The current regulatory frameworks, initially designed for static medical devices, often fail to match the adaptive and iterative nature of AI.[94-96)] In practice, rule-based ECG analysis systems continue to obtain regulatory clearance far more readily than deep-learning–based AI-ECG tools, reflecting a regulatory environment that remains cautious toward adaptive algorithms. This disparity creates a substantial barrier for real-world deployment because the systems with the strongest clinical performance often face the steepest approval hurdles. There is a growing call for regulators to modernize approval pathways—allowing controlled, modular updates and risk-based evidence requirements—to ensure that high-performing AI models can reach patients without unnecessary delays. Additionally, ethical concerns—ranging from data privacy and patient autonomy to algorithmic fairness and accountability—must be addressed via structured oversight and robust governance.[96)]

Cost-effectiveness and value creation

Demonstrating economic value is essential for long-term sustainability.[77)] While AI-ECG has shown promise in enhancing workflow efficiency and enabling earlier diagnosis, formal cost-effectiveness evaluations remain scarce.[51)91)97)98)] This is particularly important because most AI-ECG deployment strategies identify patients who require additional testing, imaging, or more intensive clinical follow-up—pathways that may increase short-term healthcare expenditures. Future studies must integrate economic endpoints such as reduced hospitalizations, decreased use of redundant diagnostics, and improved allocation of clinical resources alongside traditional clinical efficacy measures.

Clinical acceptance and education

The adoption of AI-ECG tools is hindered by variations in clinician experience and proficiency, as well as the absence of standardized educational frameworks.[94)] Without structured training, intuitive user interfaces, and seamless integration into existing clinical decision-making pathways, many healthcare providers remain hesitant to rely on or actively utilize AI-generated predictions. This creates a paradoxical situation: technically mature tools remain underutilized in practice due to insufficient operational readiness. Ultimately, incremental education in data science and AI must be strengthened, ideally through formal training pathways or ongoing professional development.[99)]

SUMMARY

AI-ECG has rapidly progressed from a novel research tool to a clinically meaningful technology with wide-ranging applications in cardiovascular care. It has shown strong performance in detecting structural heart disease, guiding risk stratification, and identifying systemic conditions beyond traditional cardiology. Its potential as a digital biomarker is increasingly supported by both retrospective validation and prospective clinical trials.

Despite this progress, several barriers remain. Technical issues such as data variability and limited model interpretability, as well as clinical challenges involving workflow integration, regulatory clarity, and clinician engagement, continue to hinder widespread adoption. Addressing these challenges will require standardized validation protocols, transparent governance, and targeted education for clinical users. Looking forward, the promise of AI-ECG lies in its role as a longitudinal digital biomarker that connects traditional hospital care with remote monitoring. With coordinated efforts across research, industry, and regulatory sectors, AI-ECG can transition from innovation to impact, transforming the detection, monitoring, and management of cardiovascular disease.

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