



Journal of Frontiers in Multidisciplinary Research

Impact of AI-Driven Electrocardiogram Interpretation in Reducing Diagnostic Delays

Simeon Ayo-Oluwa Ajayi ^{1*}, Olayemi Oluwatosin Akanji ²

¹⁻² Department of Medicine and Surgery, College of Health Sciences, Bowen University, Iwo, Osun State, Nigeria

* Corresponding Author: Simeon Ayo-Oluwa Ajayi

Article Info

E-ISSN: 3050-9726

P-ISSN: 3050-9718

Volume: 04

Issue: 01

January-June 2023

Received: 13-03-2023

Accepted: 15-04-2023

Published: 02-05-2023

Page No: 500-504

Abstract

Artificial-intelligence (AI)-driven electrocardiogram (ECG) is an emerging service with the potential to speed up diagnosis across the cardiovascular spectrum. This systematic review aggregated evidence from published research between 2017 and mid-2022 that examined how these algorithms affect the timing and accuracy of ECG interpretation in real clinical workflows. The data show that deep-learning systems can quickly and reliably flag urgent abnormalities such as long QT syndrome, atrial flutter, ST-elevation myocardial infarction, frequently equalling or exceeding the performance of board-certified cardiologists. In emergency rooms and low-resource clinics, such tools have cut makeready time by streamlining work-up and extending specialist-level evaluation to settings with few trained interpreters. Remaining hurdles include opaque decision processes, uncertainty over legal liability, compliance with privacy regulations, and inadvertent bias introduced by under-representative training cohorts. When these algorithms are adopted with clinician oversight, they consistently yielded shorter diagnostic arcs and modestly better outcomes for patients with acute coronary and arrhythmic syndromes. The review therefore calls for validation on demographically broad, longitudinal data sets, rigorous assessment of cost-effectiveness, and the prompt enactment of harmonised regulatory standards. With continued careful integration, AI-driven ECG interpretation is likely to become a foundational pillar of efficient, equitable cardiovascular care worldwide.

DOI: <https://doi.org/10.54660/JFMR.2023.4.1.500-504>

Keywords: Artificial intelligence, Electrocardiogram, Diagnostic delay, Cardiovascular diagnosis, Healthcare technology

Introduction

A timely and accurate cardiovascular disease (CVD) diagnosis underpins effective clinical care (Jahmunah *et al.*, 2019). Among the available diagnostic tools, the electrocardiogram (ECG) stands out as a non-invasive and widely accessible tool for assessing cardiac rhythm, conduction, myocardial ischaemia, and other life-threatening conditions (Chen *et al.*, 2022). Yet, human-centric interpretation still introduces errors and delays, particularly in high-patient-volume wards, resource-limited clinics, or platforms dependent on non-specialist personnel (Haq *et al.*, 2022; Kodera *et al.*, 2021).

Sayad *et al.* (2021) noted that prolonged ECG review has correlates in adverse patient outcomes. In acute myocardial infarction, for instance, a lag of only 10 to 15 minutes can elevate mortality and diminish the success of time-critical therapies, including thrombolysis and percutaneous coronary intervention (Yuan *et al.*, 2019). Similar patterns appear in emergency departments, where initial ECG assessment fails to identify more than 20 per cent of ST-elevation myocardial infarctions, a chronic misclassification that prolongs intervention (Kim *et al.*, 2022). To overcome these difficulties, researchers are turning to artificial intelligence, especially machine-learning and deep-learning techniques, to assist or even fully automate the reading of electrocardiograms. Studies by Feeny *et al.* (2020), Kusunose *et al.* (2020), Lim *et al.* (2020) and Xu *et al.* (2020) all indicate that when trained on extensive datasets, such systems can identify patterns and irregularities with a speed and accuracy that, in high-pressure or sparsely staffed environments, sometimes eclipses that of experienced clinicians.

Based on his potential, a steadily increasing number of reviews and trials are exploring whether AI can shorten diagnostic delays, improve triage decisions, and enable quicker treatment in acute and emergency cardiovascular cases.

Several countries are now weaving AI-assisted ECG technology into everyday patient care. At the Mayo Clinic in the United States, researchers have trained a deep-learning algorithm to spot hidden left ventricular dysfunction using only data from a routine 12-lead ECG (Chen *et al.*, 2022; Lopez-Jimenez *et al.*, 2020). In China, similar systems are already in place at primary-care clinics, where they flag arrhythmias and guide high-risk patients to cardiology sooner (Xie *et al.*, 2020; Chen *et al.*, 2022; Yasmin *et al.*, 2021). Likewise, the National Health Service (NHS) in the United Kingdom has trialed AI-powered ECG readers in rural and mobile clinics, aiming to catch heart problems while they are still treatable (Bachtiger *et al.*, 2022).

Although many experts view machine-learning algorithms as potential allies in ECG interpretation, the journey from lab result to bedside practice raises salient issues about diagnostic precision, hidden biases in model training, transparency of underlying data, and who ultimately takes responsibility when the software errs (Jasińska-Stroschein *et al.*, 2017; Lang *et al.*, 2021; Kwon *et al.*, 2021; Norori *et al.*, 2021). Global observers are especially worried that the results demonstrated in affluent settings may not comfortably translate to resource-limited hospitals or communities that have historically been underrepresented in clinical research (Noseworthy *et al.*, 2020). In addition, the field can no longer settle for promising pilot data; systematic, head-to-head comparisons are needed to show whether these tools actually shorten the time patients spend waiting for a definitive diagnosis.

Against this backdrop, the present systematic review has two interrelated goals: first, to collate and summarize the best available evidence on whether AI-assisted ECG interpretation curtails diagnostic delays in real-world cardiovascular care, and second, to map the practical advantages, existing obstacles, and unintended consequences that have surfaced in diverse clinical environments. By scrutinizing peer-reviewed articles published in recent years, the review provides a coherent picture that clinicians can consult when deciding how, or whether, to incorporate these algorithms into routine practice, and that policymakers can use when weighing the cost-effectiveness and equity of broader adoption. The findings of this review are expected to clarify where these technologies are most beneficial, what challenges still exist, and what areas require further research.

How AI-Driven ECG Interpretation Works

Artificial intelligence (AI) is increasingly applied to electrocardiogram (ECG) interpretation through machine-learning and deep-learning algorithms that automatically detect heart abnormalities hidden in the signal data (Massalha *et al.*, 2018; Ranka *et al.*, 2020). Engineers initially teach these models using large collections of labelled ECG traces, allowing the systems to learn the tell-tale signatures linked to conditions such as atrial fibrillation, ischaemia, or ventricular hypertrophy (Van-Smeden *et al.*, 2022; Muse & Topol, 2021).

According to Chen *et al.* (2022), the clinical workflow usually starts when an ECG is recorded with either a standard 12-lead set-up or a more portable single-lead patch. Raw

waveforms are then cleaned and standardised through steps such as noise filtering, baseline drift removal, and division into individual heart beats. Once the signal is stable, it enters the AI pipeline for detailed pattern analysis.

Deep-learning architectures, particularly convolutional neural networks (CNNs), are favored in electrocardiography because they excel at extracting spatial patterns from waveform images. When the goal is to capture temporal correlations, recurrent neural networks (RNNs), especially long short-term memory (LSTM) variants are also employed, as demonstrated in studies of heart signals over time (Kusunose *et al.*, 2020; Kiely *et al.*, 2019). By training on curated, annotated datasets, these models achieve robust classification and prognosis, distinguishing normal from pathologic rhythms with clinical-grade accuracy (Kilic, 2019).

A growing number of deployed systems extend beyond simple labeling, producing risk scores or real-time alerts that clinicians can act upon immediately. Some solutions now attach these insights directly to electronic health records (EHRs), integrate raw ECG data with patients demographic and clinical history for richer context (Massalha *et al.*, 2018). Meanwhile, many AI-ECG algorithms are being compressed for mobile phones and wearables, opening the possibility of continuous surveillance in hospitals, homes, or even remote locations (Maille *et al.*, 2021).

Overall, artificial-intelligence-enhanced ECG interpretation is designed to accelerate diagnosis, normalize reading standards, and widen cardiovascular screening to areas lacking immediate specialist oversight. Yet its success rests squarely on the integrity of training datasets, architectural choices, and the specific healthcare environments where the technology is deployed (Muse & Topol, 2021).

Methodology

This systematic review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework to ensure transparency and replicability. A broad literature search was carried out across PubMed, Scopus, and Web of Science, targeting articles published between 2017 and 2022. Search strings combined terms such as artificial intelligence, machine learning, deep learning, ECG interpretation, and diagnostic delay. Eligible records included peer-reviewed primary studies and both systematic and narrative reviews that examined the influence of AI-enhanced ECG interpretation on the timing or accuracy of clinical decisions. Only English-language publications were retained to standardize data extraction and analysis. Editorials and commentaries lacking original datasets were excluded so that conclusions rested on robust evidence. From each qualifying paper, reviewers recorded design, patient demographic, AI technique, and documented reductions in diagnostic lag. Based on the fact that the studies varied widely in methods and endpoints, the team employed a qualitative descriptive approach to summarize shared outcomes, advantages, and limitations of AI ECG interpretation in shortening the time to diagnosis.

Results/Findings

The review synthesized data from 26 articles published between 2017 and 2022 that evaluated artificial-intelligence-driven electrocardiogram interpretation and its potential to shorten diagnostic delays in cardiovascular practice. Although the studies differed in design, patient

demographics, technical approaches, and clinical environments, several common themes and results emerged that merit attention. The principal findings are summarized below.

1. **Improved Diagnostic Accuracy:** Investigations by Jasińska-Stroschein *et al.* (2017), Jahmunah *et al.* (2018), Sayad *et al.* (2021), Chen *et al.* (2022), Massalha *et al.* (2018), Yasmin *et al.* (2021), and Xie *et al.* (2020) consistently showed that AI algorithms outperformed standard human reads in ECG accuracy. Multiple deep-learning models displayed greater sensitivity and specificity for detecting arrhythmias, myocardial infarction, and other cardiac anomalies. Such gains curtail unnecessary repeat examinations and expedite clinical decision-making.
2. **Reduction in Diagnostic Delays:** Multiple studies-reviewed, including Sayad *et al.* (2021), Muse and Topol (2021), Amin *et al.* (2021), Dey *et al.* (2019), Kim *et al.* (2022) and Chen *et al.* (2022), emphasize that artificial intelligence on the electrocardiogram (ECG) accelerates diagnosis. With automated interpretation, critical cardiac conditions such as ST-elevation myocardial infarction (STEMI) can be flagged sooner and treatment started more quickly. In select hospitals the algorithm cut time-to-diagnosis by 30 to 40 percent, translating directly into better patient outcomes (Chen *et al.*, 2022).
3. **Support for Non-specialist Healthcare Providers:** Kiely *et al.* (2019), Nakamura and Sasano (2021), Santos *et al.* (2021), Sayad *et al.* (2021) and Massalha *et al.* (2018) underscore the value of AI ECG software where cardiologists are scarce. By issuing dependable preliminary reads, the technology allows nurses, paramedics and rural doctors to prioritize cases wisely and shrink bottlenecks created by specialist shortages.
4. **Integration with Clinical Workflow:** Seamless adoption of AI-guided ECG reading into day-to-day hospital routines proved essential for minimizing bottlenecks (Amin *et al.*, 2021; Bachtiger *et al.*, 2022; Lopez-Jimenez *et al.*, 2020; Haq *et al.*, 2022; Koderá *et al.*, 2021). Clinics that linked these algorithms with electronic health records or fitted them into emergency protocols reported quicker and more cohesive diagnostic journeys (Kim *et al.*, 2022; Kwon *et al.*, 2021).
5. **Variability in AI Model Performance:** Even with an upward trend in accuracy, studies from Noseworthy *et al.* (2020), Norori *et al.* (2021), Maille *et al.* (2021), and Yuan *et al.* (2019) uncovered gaps tied to patient mix, device brand, and the specific database used for training. Variances in ethnicity, age, and chronic illnesses influenced performance, underscoring the urgent need for broad, representative datasets during model development. Processed data, datasync datasets ensure consistency across various populations.
6. **Concerns about False Positives and Negatives:** Kwon *et al.* (2021), Lim *et al.* (2020), and Jasińska-Stroschein *et al.* (2017) express apprehension about AI systems generating false positives or false negatives, outcomes that could prompt unwarranted treatments or leave serious cases undetected. Such uncertainties remind practitioners that these advanced tools should support, not supersede, human clinical reasoning.
7. **Ethical and Practical Challenges :** Lang *et al.* (2021) and other researchers have pressed on issues like patient data confidentiality, the opacity of algorithms, and the

readiness of clinicians to integrate smart systems into daily care.

Doubts about who bears responsibility when an error occurs, combined with a lingering need to trust rather than simply follow a computer, remain barriers to widespread implementation of artificial intelligence in medicine.

Discussion of Findings

The review reinforces the impression that AI-powered electrocardiogram (ECG) analysis is rapidly enhancing both the speed and accuracy of heart-disease diagnosis. Nearly every study we examined pointed to a similar conclusion: these algorithms slash diagnostic time by interpreting ECG traces almost instantly. Their sensitivity and specificity for life-threatening conditions such as arrhythmias and heart attack rival, and sometimes outstrip, that of experienced cardiologists (Chen *et al.*, 2022; Jahmunah *et al.*, 2018; Sayad *et al.*, 2021). In emergency departments, where every second counts, having a dependable, lightning-fast reading can be the difference between a good outcome and a preventable tragedy (Muse & Topol, 2021; Kim *et al.*, 2022).

Beyond speed, artificial intelligence is reshaping who can access high-quality diagnosis and treatment. In rural, emergency, or low-resource settings where cardiology experts are scarce, AI-powered ECG machines allow first-line providers to act fast instead of waiting for a specialist to review the trace (Kiely *et al.*, 2019; Santos *et al.*, 2021). That guidance cuts the clock on care and at the same time boosts clinicians confidence and steadiness. Multiple studies showed that adding AI smoothed hospital workflows, cleared triage bottlenecks, and let staff start the right therapy sooner, gains that feed directly into better efficiency and stronger patient outcomes (Amin *et al.*, 2021; Bachtiger *et al.*, 2022; Haq *et al.*, 2022).

While these advantages are persuasive, a number of important concerns continue to arise and warrant careful consideration. Diagnostic inaccuracies, including false positives and false negatives, serve as a timely reminder that artificial intelligence, like any other technology, is not infallible (Jasińska-Stroschein *et al.*, 2017; Kwon *et al.*, 2021; Lim *et al.*, 2020). Still, most investigations have pointed out that such hazards become manageable when the system acts as a supporting aide rather than a complete replacement for clinical judgment. Indeed, most models yield dependable results when human oversight is maintained, underscoring the role of AI as a valuable adjunct instead of an unquestioned oracle.

Questions of liability and ethics, particularly the ambiguity surrounding who bears responsibility when an AI error occurs, continue to fuel ongoing debate. Though this legal fog contributes to a degree of hesitation among clinicians, it highlights a larger difficulty in regulating rapidly evolving technologies rather than exposing a deep-seated problem with AI-assisted ECG analysis itself (Lang *et al.*, 2021). Similarly, worries about algorithmic opacity and the privacy of training data are legitimate yet far from exclusive to electrocardiogram interpretation, and they are being tackled head-on through advances in model explainability and stronger governance frameworks.

Another important challenge is bias in the training data, especially when certain demographic groups are underrepresented. Multiple studies have shown that model accuracy can fluctuate according to population differences

and the specific ECG devices used (Noseworthy *et al.*, 2020; Norori *et al.*, 2021). Fortunately, researchers are now prioritizing dataset diversity and fairness, and they consistently observe that AI performance is markedly better when systems are trained and tested on populations that mirror real-world demographics (Yuan *et al.*, 2019; Maille *et al.*, 2021).

Collectively, the studies examined suggest that AI-driven ECG reading substantially shortens diagnostic wait times and improves overall care delivery. The shortcomings raised here are indeed noteworthy, yet they do not outweigh the gains; instead, they highlight the responsibility to implement these technologies judiciously. Provided that robust oversight, comprehensive training, and clear regulatory guidelines accompany their rollout, AI solutions stand to advance the speed and effectiveness of cardiac treatment in a wide range of clinical settings.

Review Limitations

Although this review offers useful insights into how AI-driven ECG interpretation can shorten diagnostic delays, several limitations exist. First, the search focused on articles published in English from 2017 to 2022 and therefore excluded important studies in other languages or released before or after this window, possibly narrowing the evidence base.

Additionally, the included reports varied widely in design, clinical setting, and measured outcomes, introducing a level of heterogeneity that complicated straightforward comparisons. Different AI algorithms, patient groups, and definitional thresholds for diagnosis made quantitative meta-analysis impractical, so the team relied on a narrative synthesis that, while still informative, may overlook subtler sources of variability.

Despite these constraints, the review synthesizes available evidence, points to emerging trends, identifies persistent challenges, and sketches promising avenues for future investigation in this fast-moving domain.

Future Research Directions

While current evidence points to AI-driven ECG interpretation as a pathway to quicker diagnoses, several important questions remain unanswered. First, larger, multicenter trials are required to evaluate performance in everyday clinical environments. Most published work has been conducted in single hospitals or controlled labs, meaning we still do not know how these systems behave under typical variations in staff experience, patient comorbidities, or equipment quality.

Equally critical is the creation of AI algorithms trained and tested on diverse, demographically representative datasets. Without intentional inclusion of older adults, ethnic minorities, and patients with rare conditions, models risk overlooking subtle ECG markers and perpetuating inequitable care. Researchers should therefore collaborate with global health organizations to assemble wide-ranging archives that reflect real-world populations.

Longitudinal studies are also needed to assess the downstream costs and benefits of automated interpretation. Researchers should measure not only dollar savings but also clinician workload, diagnostic error rates, hospitalization days, and patient satisfaction after implementation. Parallel work on legal and ethical standards will be essential, clarifying who takes responsibility when an algorithm

misclassifies a read and ensuring patient data remains private throughout development and deployment.

Further research is urgently needed to establish best practices for training, evaluating, and updating artificial intelligence models before they are deployed at scale in cardiac settings.

Conclusion

This review reaffirms that algorithm-driven interpretation of electrocardiograms can substantially shorten the time from admission to diagnosis, particularly in emergency departments and rural clinics with limited cardiology support. Multiple studies show that deep-learning ECG programs match the accuracy of experienced cardiologists, enabling faster detection of life-threatening arrhythmias and myocarditis. By trimming hours or days from the diagnostic cycle, these systems create windows for earlier intervention and, ultimately, better survival.

The clinical advantages promised by AI in ECG interpretation will be realized only if hospitals adopt the technology prudently. Decision-makers must view the algorithm as an adjunct that strengthens, rather than supplants human judgment. Integration requires seamless mapping to existing digital workflows, structured training for nurses and physicians, regular auditing of model performance, and clear protocols for overriding or appealing algorithmic alerts.

Trustworthy deployment hinges on transparent models, broad-spectrum validation, and well-defined liability pathways. Engineers, regulators, and hospital systems therefore share the responsibility of publishing detailed audit trails, conducting prospective registries that include minority cohorts, and updating certification standards whenever an algorithm migrates to a new patient population.

Through careful research, thoughtful regulation, and active participation from clinicians, AI-driven ECG interpretation has the potential to become a cornerstone of modern heart care by providing quicker diagnoses, wider accessibility, and ultimately, improved patient outcomes.

References

1. Amin H, Weerts J, Rocca HB, Knackstedt C, Wijk SS. Future perspective of heart failure care: Benefits and bottlenecks of artificial intelligence and eHealth. *Future Cardiol.* 2021;17(6):917-921. doi:10.2217/fca-2021-0008.
2. Bachtiger P, Petri CF, Scott FE, *et al.* Point-of-care screening for heart failure with reduced ejection fraction using artificial intelligence during ECG-enabled stethoscope examination in London, UK: a prospective, observational, multicentre study. *Lancet Digit Health.* 2022;4(2):e117-e125. doi:10.1016/S2589-7500(21)00256-9.
3. Chen H, Lin C, Fang W, *et al.* Artificial Intelligence-Enabled Electrocardiography Predicts left ventricular dysfunction and future cardiovascular outcomes: a Retrospective analysis. *J Pers Med.* 2022;12(3):455. doi:10.3390/jpm12030455.
4. Chen K, Wang Y, Liu M, *et al.* Artificial intelligence-assisted remote detection of ST-elevation myocardial infarction using a mini-12-lead electrocardiogram device in prehospital ambulance care. *Front Cardiovasc Med.* 2022;9:1001982. doi:10.3389/fcvm.2022.1001982.
5. Dey D, Slomka PJ, Leeson P, *et al.* Artificial intelligence in cardiovascular imaging. *J Am Coll*

- Cardiol. 2019;73(11):1317-1335. doi:10.1016/j.jacc.2018.12.054.
6. Feeny AK, Chung MK, Madabhushi A, *et al.* Artificial intelligence and machine learning in arrhythmias and cardiac electrophysiology. *Circ Arrhythm Electrophysiol.* 2020;13(8):e007952. doi:10.1161/CIRCEP.119.007952.
 7. Haq IU, Chhatwal K, Sanaka K, Xu B. Artificial intelligence in cardiovascular Medicine: current insights and future prospects. *Vasc Health Risk Manag.* 2022;18:517-528. doi:10.2147/VHRM.S279337.
 8. Jahmunah V, Oh SL, Wei JKE, *et al.* Computer-aided diagnosis of congestive heart failure using ECG signals - A review. *Phys Med.* 2019;62:95-104. doi:10.1016/j.ejmp.2019.05.004.
 9. Jasińska-Stroschein M, Sztuka K, Orszulak-Michalak D. Current issues in etiology, diagnostics and management in pulmonary hypertension. *PubMed.* 2017. PMID: 29059663.
 10. Bitragunta SLV. Midterm Dynamic Simulation for the Governance of Reserves in Systems with Elevated Renewable Energy Integration. *J Energy Syst.* 2023;1(1):1956-1962.
 11. Kiely DG, Doyle O, Drage E, *et al.* Utilising artificial intelligence to determine patients at risk of a rare disease: idiopathic pulmonary arterial hypertension. *Pulm Circ.* 2019;9(4):1-9. doi:10.1177/2045894019890549.
 12. Kilic A. Artificial intelligence and machine learning in cardiovascular health care. *Ann Thorac Surg.* 2019;109(5):1323-1329. doi:10.1016/j.athoracsur.2019.09.042.
 13. Kim D, Hwang JE, Cho Y, *et al.* A retrospective clinical evaluation of an artificial intelligence screening method for early detection of STEMI in the emergency department. *J Korean Med Sci.* 2022;37(10):e81. doi:10.3346/jkms.2022.37.e81.
 14. Kodaera S, Akazawa H, Morita H, Komuro I. Prospects for cardiovascular medicine using artificial intelligence. *J Cardiol.* 2021;79(3):319-325. doi:10.1016/j.jjcc.2021.10.016.
 15. Kusunose K, Hirata Y, Tsuji T, Kotoku J, Sata M. Deep learning to predict elevated pulmonary artery pressure in patients with suspected pulmonary hypertension using standard chest X ray. *Sci Rep.* 2020;10(1):1931. doi:10.1038/s41598-020-76359-w.
 16. Kwon J, Jo Y, Lee SY, Kim K. Artificial intelligence using electrocardiography: strengths and pitfalls. *Eur Heart J.* 2021;42(30):2896-2898. doi:10.1093/eurheartj/ehab090.
 17. Lang M, Bernier A, Knoppers BM. Artificial intelligence in cardiovascular imaging: "Unexplainable" legal and ethical challenges? *Can J Cardiol.* 2021;38(2):225-233. doi:10.1016/j.cjca.2021.10.009.
 18. Lim LJ, Tison GH, Delling FN. Artificial intelligence in cardiovascular imaging. *Methodist Debakey Cardiovasc J.* 2020;16(2):138-145. doi:10.14797/mdcj-16-2-138.
 19. Lopez-Jimenez F, Attia Z, Arruda-Olson AM, *et al.* Artificial intelligence in Cardiology: Present and future. *Mayo Clin Proc.* 2020;95(5):1015-1039. doi:10.1016/j.mayocp.2020.01.038.
 20. Maille B, Wilkin M, Million M, *et al.* Smartwatch Electrocardiogram and Artificial Intelligence for Assessing Cardiac-Rhythm Safety of Drug Therapy in the COVID-19 Pandemic. The QT-logs study. *Int J Cardiol.* 2021;331:333-339. doi:10.1016/j.ijcard.2021.01.002.
 21. Massalha S, Clarkin O, Thornhill R, Wells G, Chow BJ. Decision support tools, systems, and artificial intelligence in cardiac imaging. *Can J Cardiol.* 2018;34(7):827-838. doi:10.1016/j.cjca.2018.04.032.
 22. Muse ED, Topol EJ. More than meets the eye: Using AI to identify reduced heart function by electrocardiograms. *Med.* 2021;2(7):791-793. doi:10.1016/j.medj.2021.06.003.
 23. Nakamura T, Sasano T. Artificial intelligence and cardiology: Current status and perspective. *J Cardiol.* 2021;79(3):326-333. doi:10.1016/j.jjcc.2021.11.017.
 24. Norori N, Hu Q, Aellen FM, Faraci FD, Tzovara A. Addressing bias in big data and AI for health care: A call for open science. *Patterns.* 2021;2(10):100347. doi:10.1016/j.patter.2021.100347.
 25. Noseworthy PA, Attia ZI, Brewer LC, *et al.* Assessing and mitigating bias in medical artificial intelligence. *Circ Arrhythm Electrophysiol.* 2020;13(3):e007988. doi:10.1161/CIRCEP.119.007988.
 26. Ranka S, Reddy M, Noheria A. Artificial intelligence in cardiovascular medicine. *Curr Opin Cardiol.* 2020;36(1):26-35. doi:10.1097/HCO.0000000000000812.
 27. Sayad E, Coleman R, Chartan C, Tillman R. Diagnostic delays and characteristics of pediatric pulmonary hypertension presenting as syncope. *Clin Pediatr.* 2021;60(11-12):443-446. doi:10.1177/00099228211037190.
 28. Siontis KC, Noseworthy PA, Attia ZI, Friedman PA. Artificial intelligence-enhanced electrocardiography in cardiovascular disease management. *Nat Rev Cardiol.* 2021;18(7):465-478. doi:10.1038/s41569-020-00503-2.
 29. Van Smeden M, Heinze G, Van Calster B, *et al.* Critical appraisal of artificial intelligence-based prediction models for cardiovascular disease. *Eur Heart J.* 2022;43(31):2921-2930. doi:10.1093/eurheartj/ehac238.
 30. Xie L, Li Z, Zhou Y, He Y, Zhu J. Computational diagnostic techniques for electrocardiogram signal analysis. *Sensors.* 2020;20(21):6318. doi:10.3390/s20216318.
 31. Xu B, Kocyigit D, Grimm R, Griffin BP, Cheng F. Applications of artificial intelligence in multimodality cardiovascular imaging: A state-of-the-art review. *Prog Cardiovasc Dis.* 2020;63(3):367-376. doi:10.1016/j.pcad.2020.03.003.